Lecture Notes on Data Engineering and Communications Technologies 192

Sanjay Misra
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Artificial Intelligence of Things for Achieving Sustainable Development Goals

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Preface

Artificial Intelligence of Things (AIoT) is a new field of study that can be used in various domains and yield numerous benefits. Particularly, AIoT combines Artificial Intelligence (AI) and Internet of Things (IoT) technologies to create an intelligent and autonomous network of interconnected devices, services, and systems. Due to its nature, AIoT can be used to achieve the Sustainable Development Goals (SDGs) set by the United Nations. Currently, ensuring the achievement of SDGs is essential for people's well-being, the planet's prosperity, and for human development.

In the context of AIoT, several other new technologies can also be integrated to further increase its impact toward meeting the SDGs. Such technologies include but are not limited to AI, IoT, big data, AI-based and IoT-based cloud computing, Machine Learning (ML), Deep Learning (DL), and blockchain. Hence, it is important to understand how the fusion, integration, advancements, and impact of these technologies can affect the achievement of SDGs.

To understand AIoT and its role in SDGs, it is necessary for it to be examined from different dimensions due to its broad scope and complexity. Hence, analyzing the technologies of AI, IoT, and AIoT in the context of different SDGs is imperative for this field of study to advance further.

This book aims to provide an overview and helpful insights into the fusion, integration, advancements, and impact of AIoT in the context of achieving SDGs. Hence, the chapters contained within the book involve AI, IoT, and AIoT and examine how their adoption and integration can increase sustainability and help meet the SDGs. The chapters explore the use of AIoT in achieving society and well-being-related SDGs, industrial sectors, infrastructure, and economy-related SDG, and natural resources and environment-related SDGs. This book consists of 18 chapters written by 49 authors from 14 different countries. A summary of each chapter is provided below.

Lampropoulos et al. examine the role of AIoT in attaining a circular economy and in achieving SDGs for a sustainable future in their chapter entitled "***Reconsidering a Sustainable Future through Artificial Intelligence of Things in the Context of Circular Economy***". The chapter goes over the importance of achieving SDGs and the impact that the circular economy can have. Additionally, the 4R sustainability framework (and rethink) is suggested and examined through a sociocultural, technical, economic, environmental, political, legal, ethical, and demographic (STEEPLED) analyses. The chapter focuses on the role of AI in achieving SDGs and discusses its influence in creating a circular economy.

Thamik et al. explore the capabilities of AI and IoT technologies to help meet SDGs in their chapter entitled "***The Digital Paradigm: Unraveling the Impact of Artificial Intelligence and Internet of Things on achieving Sustainable Development Goals***". The chapter provides an overview of SDGs and AIoT and discusses the related challenges and opportunities. The authors focus on the role of AIoT in achieving specific SDGs and go over other related and recent technologies (e.g., machine learning, deep learning, IoT platforms, computer vision, and natural language processing). The influence of intelligent systems, blockchain, and cyber-physical systems in achieving SDGs is also examined. Additionally, ethical and governance issues related to AIoT for SDG achievement and the potential risks and benefits are discussed.

López-Vargas et al. explore how AIoT can assist in alleviating energy poverty in the context of SDG 7 in their chapter entitled "***The role of the Artificial Intelligence of Things in Energy Poverty alleviation***". Focusing on the impact of AI and IoT in addressing the challenges of energy poverty, the state-of-the-art is presented. The chapter goes over AIoT-based approaches for energy poverty characterization and presents recent AIoT applications for thermal comfort characterization. The findings of the study are summarized in an in-depth discussion.

Alaba et al. look into how renewable energy integration and energy efficiency in the context of SDGs can be achieved through AIoT-enabled Smart Grids in their chapter entitled "***AIoT-Enabled Smart Grids: Advancing Energy Efficiency and Renewable Energy Integration***". The authors go over the AIoT development, present a conceptual framework for AIoT-enabled smart grids, and discuss how AI algorithms can be integrated into IoT devices to improve energy management and grid stability. Suggestions on how renewable energy can be integrated into AIoT-enabled smart grids are offered. Best practices and mitigation strategies are provided to address the current security concerns and challenges and to ensure reliable operations. Finally, the chapter discusses policy implications and regulatory frameworks.

Barik et al. examined the use of digital twins and AI techniques in nuclear power plants in the context of SDGs in their chapter entitled "***Achieving SDGs using AI Techniques and Digital Twins for Nuclear Power Plants: A Review***". The authors present an overview of nuclear power plants and go over the use of digital twins for achieving SDGs. Moreover, the role of AI tools in nuclear power plants is presented and the impact of digital twins on SDGs is highlighted. The open issues and challenges are discussed, suggestions for solutions are given, and recommendations for future studies are provided.

Di Vaio et al. focus on how AIoT can influence the digital transformation in decarbonizing processes as well as the challenges for the non-financial disclosure on the decarbonization practices adopted by the enterprises in their chapter entitled "***Carbon and Decarbonization Disclosure: Role of Responsible Innovation in***

Adoption of Artificial Intelligence of Things towards SDGs". More specifically, the chapter conceptualizes carbon disclosure with different levels of performance paradigm and presents the concept of carbon disclosure and performance by incorporating financial, operational, and sustainable performance reporting through the lens of institutional, legitimacy, and stakeholder theories. The role of AIoT in decarbonization practices is analyzed and the relationship between AIoT and responsible innovation to achieve SDGs is discussed. Finally, a conceptual framework of carbon disclosure and decarbonization focusing on SDGs is presented.

The chapter entitled "***Artificial Intelligence of Things (AIoT) Solutions for Sustainable Agriculture and Food Security***" examines the significance of AIoT in achieving food security and sustainable agriculture. The chapter goes over the role of AIoT in sustainable agriculture, discusses supply chain management, presents the existing barriers and challenges, and suggests solutions to overcome them. The authors also examine the AIoT, machine learning, 5G, and edge computing applications in agriculture. Additionally, it presents real-world implementations, highlights best practices, and discusses regulatory considerations and policy.

Kusharki and Muhammad-Bello focus on achieving sustainable crop disease management through AIoT-enabled precision agriculture and using graph attention neural networks in their chapter entitled "***AIoT-Enabled Precision Agriculture for Sustainable Crop Disease Management: Advancing SDGs through Graph Attention Neural Networks***". The chapter goes over the role of crop diseases, AIoT in agriculture, multi-object techniques, and graph attention networks. Additionally, the use of AIoT in graph attention networks to attain precision agriculture and cost-effective crop monitoring systems is discussed. Their suggested model combines Fast R-CNNs, Mask R-CNNs, and RetinaNet to detect healthy or rust-infected wheat samples, and a series of experiments are conducted and analyzed.

Ramesh et al. examine how healthcare data can be secured using IoT and blockchain with federated learning models in the context of sustainable Healthcare 5.0 and SDG 3 in their chapter entitled "***Sustainable Healthcare 5.0: Integration of IoT and Blockchain Technology with Federated Learning Model for Securing Healthcare Data***". The chapter provides an in-depth look at IoT, federated learning, and blockchain and presents the state-of-the-art of Healthcare 5.0. The findings of recent studies are presented and a model architecture is proposed. The experimental analysis of the model is explained and the results are presented. An elaborate discussion on how these technologies can help achieve SDG 3 and sustainable Healthcare 5.0 is provided.

Abubakar et al. focus on enhancing diabetes and heart disease diagnosis in resource-limited settings using IoT-enabled machine learning in the context of SDG 3 in their chapter entitled "***IoT-Enabled Machine Learning for Enhanced Diagnosis of Diabetes and Heart Disease in Resource-Limited Settings***". The chapter goes over the use of IoT-enabled machine learning in healthcare and presents the design and analysis of a proposed system and model for enhanced diagnosis. Analysis regarding the performance metrics of the model is conducted. The results are discussed and suggestions on how IoT-enabled machine learning can help achieve SDG 3 are provided.

Vijarania et al. focus on the healthcare domain and on achieving SDGs and increasing cyber security through AIoT in their chapter entitled "***Achieving Sustainable Development Goals in Cyber Security using AIoT for Healthcare Application***". The chapter goes over the findings of recent literature and presents the state-of-the-art in cyber security within the healthcare domain. Additionally, AI, blockchain, and cloud computing are presented and their role in cyber security is explored. Cyber risks and threats as well as security measures in healthcare are described. Finally, the relation of healthcare cybersecurity to meet SDGs is discussed.

López-Belmonte et al. focus on the use of AI and machine learning to support and enhance teaching and learning in the context of SDGs 4 and 11 in their chapter entitled "***Machine Learning as a Methodological Resource in the Classroom***". The authors present the state-of-the-art and go over their application and experiment in detail. The chapter also discusses AI projects that use LearningML and Scratch in education as well as the use of chatbots. Additionally, the experiment process which involved primary education students is described, and the results are analyzed and compared to those of the literature. An in-depth discussion regarding the use of AI and ML to achieve SDGs 4 and 11 is provided.

Nozari et al. explore how AIoT-based intelligent systems can enhance sustainable marketing in their chapter entitled "***A Framework for AIoT-based smart sustainable marketing system***". The chapter presents the state-of-the-art regarding sustainable marketing in the context of SDGs and goes over the specifications of AIoT. Additionally, the concept of digital and sustainable development is analyzed in detail. The role and impact of AI, IoT, and AIoT in sustainable marketing are described through in-depth discussions. Insights into how AIoT and sustainable marketing can contribute toward achieving SDGs are given.

The chapter entitled "***Enabling Sustainable Transportation through IoT and AIoT Innovations***" examines the use of IoT and AIoT innovations to achieve sustainable transportation. The authors go over how AIoT and IoT can affect urban planning in the context of transportation and discuss how IoT sensors can enable environmental monitoring. AIoT-based parking systems and safety precautions are also examined and actions to encourage environmentally-friendly modes of transportation are presented. Additionally, the authors through an in-depth analysis of relevant case studies and practical applications showcase how AIoT can be used to achieve sustainable transportation and the benefits that can be yielded through its integration. Challenges and issues are also presented and suggestions to improve the security of operations are provided.

The chapter entitled "***Investigating key dimensions and key indicators of AIoT-based supply chain in sustainable business development***" focuses on AIoT-based supply chain and examines its key dimensions and indicators to achieve sustainable business development. The chapter goes over relative transformative technologies in the context of supply chain and transportation and puts emphasis on AIoT. Additionally, the role and use of AI, IoT, and AIoT in sustainable business development are thoroughly discussed. Insights into AIoT-enabled devices and how they can assist in meeting SDGs are also provided.

Barik et al. explore how societal applications can be improved using intelligent technologies as well as AIoT and its trust models in their chapter entitled "***AIoT and its trust models to enhance societal applications using intelligent technologies***". The chapter presents the role of AI in IoT as well as the related to their integration trust models. Additionally, the influence of digitization on SDGs and the security benefits that the digitization of AIoT can yield are discussed. Challenges and strategies to enhance security capabilities for achieving SDGs are presented and an in-depth discussion on AIoT and its trust models to improve security is provided.

The chapter entitled "***Advancing Democratic Governance with AIoT-Enabled E-Voting: A Case Study of Covenant University's Departmental Associations in Alignment with SDG 16***" looks into how AIoT-enabled e-voting can help advance democratic governance in the context of SDG 16. The chapter goes over the use of AIoT and the role of voting in society and presents insights into the relevant literature. Additionally, the design and analysis of a proposed system are presented in detail. The proposed system performance is examined and evaluated and an in-depth discussion of the results is presented.

The chapter entitled "***Cyber Resilience for SDG Towards the Digitization: An Imperial Study***" examines AIoT and cyber resilience for achieving SDGs toward digitization. The chapter provides a holistic view of cyber security and resilience as well as digitization and SDGs and offers recommendations for cyber resilience in cyber security. Additionally, cyber resilience strategies and related technologies (e.g., AI, IoT, blockchain, etc.) to achieve SDGs are presented. An in-depth discussion on the use of AIoT to achieve sustainable growth in digitization is provided. The open cyber resilience challenges in the context of sustainable development and digitalization are analyzed.

As AIoT advances, its capabilities and potentials as well as the domains of its being applied are increased. Due to the benefits, it can yield AIoT can transform several sectors and offer new solutions as well as provide novel solutions to each of the 17 SDGs. Therefore, the role of AI, IoT, and AIoT in achieving SDGs is significant. Through the achievement of the SDGs the sustainable development of humanity and the planet is ensured for this and future generations. We hope that this book will serve the community who aspire to use AIoT and who strive to achieve SDGs.

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Reconsidering a Sustainable Future Through Artificial Intelligence of Things (AIoT) in the Context of Circular Economy

Georgios Lampropoulos, Harjinder Rahanu, Elli Georgiadou, Dimitrios Siakas, and Kerstin Siakas

Abstract To assure a sustainable future for current and future generations, the achievement of the 17 Sustainable Development Goals (SDGs) which was set by the United Nations is imperative. Hence, a fundamental social and cultural shift toward resource efficiency and more sustainable lifestyles is required. In this context, the need for a circular economy is becoming more evident. New technologies can assist in meeting SDGs and achieving an effective circular economy. Particularly, Artificial Intelligence (AI) and Internet of Things (IoT) are critical technologies for fulfilling these goals. The combination of AI with IoT leads to the Artificial Intelligence of Things (AIoT) which has the potential to further facilitate the transition toward and amplify the benefits for a sustainable future. This chapter aims to examine how AI can support the achievement of SDGs and realization of a circular economy. Additionally, the 4R sustainability framework (Reduce, Reuse, Recycle, and Rethink) is presented as a proposed extension of the 3R principles. To assess its suitability, a Sociocultural, Technical, Economic, Environmental, Political, Legal, Ethical, and Demographic (STEEPLED) analysis is conducted. The need to educate the younger generations and re-educate adults to achieve changes in attitudes and mindsets toward

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sustainability was highlighted as a vital process. The need to further improve adaptability and reusability of resources emerged as a requirement to effectively maximize the 4Rs. AI emerged as a determining factor in achieving SDGs and creating a circular economy.

Keywords Sustainability · Sustainable development goals · Circular economy · Artificial intelligence · Artificial intelligence of things · Sustainable development

1 Introduction

All Member States of the United Nations endorsed the 2030 Agenda for Sustainable Development which contains a shared mission regarding peace and prosperity for the human kind and the environment (United Nations 2015). Based on the definition provided by the World Commission on Environment and Development (1987), sustainable development is characterized as "*the development that meets the needs of the present without compromising the ability of future generations to meet their own needs*". In total, 17 Sustainable Development Goals (SDGs) were developed to be met through a global partnership among all countries. The 17 SDGs focus on goals related to the environment, to wellbeing, economic growth, work, social justice, health, as well as politics. It is recognized that "*ending poverty and other deprivations must go hand-in-hand with strategies that improve health and education, reduce inequality, and spur economic growth – all while tackling climate change and working to preserve our oceans and forests*" and "*are determined to take the bold and transformative steps which are urgently needed to shift the world onto a sustainable and resilient path*" (United Nations 2015).

The 17 SDGs and 169 targets set show the ambition and large scale of the universal 2030 agenda for Sustainable Development (Visvizi 2022). The SDGs are integrated and indivisible and they both directly and indirectly impact on the social, environmental, as well as economic dimensions of sustainability and sustainable development, which imply an endeavor to satisfy the existing needs without risking future generations' needs. Based on the 169 targets, it can be inferred that growth alone is not a straightforward goal, but a goal that is sustainable, equitable, and beneficial to everybody regardless of class, race, gender etc.

The SDG Report, which offers a global overview about the latest available data of the progress regarding the adoption and application of the 2030 Agenda for SDG, states in its foreword that "*As the world faces cascading and interlinked global crises and conflicts, the aspirations set out in the 2030 Agenda for Sustainable Development are in jeopardy*" (United Nations 2022a). Based on current data, the report offers proof of the damaging influence of simultaneous crises, such as COVID-19, climate change, conflicts, and wars which are dangerously affecting all the SDGs including impacts on food and nutrition, health, education, the environment, as well as peace and security.

Furthermore, to maintain our current way of life, the natural resources which are used surpass the limits of what the Earth can produce. More sustainable solutions need to be discovered and implemented regarding how humans use natural materials, energy, as well as resources. This, however, requires a sociocultural transition, as highlighted in the 2030 Agenda for SDG. Achieving a circular economy may help meet the 17 SDGs as the circular economy aims at addressing global issues and challenges related to nature (e.g., climate change, waste, pollution, and biodiversity loss, etc.) in a systematic manner. The circular economy aims at implementing a design-based approach regarding optimal use of natural resources, effectively circulating materials and products, regenerating and rejuvenating nature, as well as minimizing and eliminating waste and pollution. The circular economy concept comes from a structured and systematic thinking approach which aims at imitating natural systems that are characterized by adaptivity, complexity, openness, optimization, and resilience (Fehrer and Wieland 2020; Siakas et al. 2023a). Due to its potentials, the circular economy has been increasingly promoted in various sectors to achieve environmental sustainability and minimize pollution and waste (De Angelis 2020). In the context of the circular economy, products, services, resources, and materials remain in circulation for as long as possible. The circular economy is a viable approach for overcoming environmental challenges (e.g., Anthropocene epoch) and constitutes a key aspect in achieving SDGs.

To ensure a sustainable future, effective waste management is imperative. Until the late twentieth century, the main waste measures in Europe, Japan, as well as the United States were the so called "*Back-Yard-Dumping*" and "*End-of-Pipe Approach*" (Sakai 2020). Uncontrolled landfill and incineration together with illegally dumped and abandoned piles of waste all over the world were noticed in 1970–1980s needing enormous costs for remediation. It was gradually understood that regional and global sustainability would not be achieved within the framework of the traditional waste treatment. As a result, the concept of waste prevention and recycling appeared.

The main process in the circular economy is the hierarchical waste management process which contains three key actions commonly referred to as 3R Principles, that is, Reduce, Reuse, and Recycle (United Nations 2022b). In the G8 summit which took place in Tokyo in 2005 the 3R initiative was launched as an attempt to transition toward creating a sound material-cycle society. An important issue in the waste management process is to maintain an adequate balance among consumption, reuse, and recycling. If consumption is reduced, the rate of reuse and recycling will also be reduced. In addition to reduction of product consumption, a reduction of energy and water is also needed to cater for future generations. The primary purpose of reusing old things either by modifications, donations or second-hand offerings and use, is to minimize the amount of waste. Recycling is a process in which the discarded items are transformed into new ones. Each measure of 3Rs enables waste reduction and energy conservation (Sakai 2020). Waste treatment plants and social resources (social connections and interaction between social structure and individuals) pave the way for meeting the aims of the circular economy and a sustainable future.

In this context, Artificial Intelligence (AI), Internet of Things (IoT), as well as Artificial Intelligence of Things (AIoT) can help meet the goals of the circular economy and of the SDGs. Particularly, AI refers to the development of systems endowed with intellectual processes that can mimic human behaviors and way of thinking and autonomously perform actions and tasks related to intelligent beings (Lampropoulos 2022; Russell 2010). AI systems are characterized by their reasoning and learning capabilities as well as their rationality and adaptability (Lampropoulos et al. 2022; Zhang and Lu 2021). Hence, AI can contribute toward the realization of sustainable development (Goralski and Tan 2020; Lampropoulos 2023; Vinuesa et al. 2020). IoT is a global and dynamic network of interconnected devices, services, objects, and systems (Atzori et al. 2010; Lampropoulos et al. 2018; Li et al. 2015). These "things" can autonomously and securely sense, communicate, and interact with one another as well as with their environment (Lampropoulos et al. 2019; Lampropoulos and Siakas 2022; Xu et al. 2014). Thus, IoT constitutes a vital component in achieving SDGs (Lopez-Vargas et al. 2020; Villiers et al. 2021). When embedding IoT in intelligent processes, AIoT can be realized. The adoption of these technologies in the context of the circular economy can enrich and accelerate the transition toward a more sustainable and greener future (McKinsey 2019). Thus, the potential of AI is too immense to be neglected (Sætra 2022).

Consequently, this chapter aims to explore how AI can support the achievement of SDGs and the realization of a circular economy and propose the 4R sustainability framework. Hence, in Sect. 2, the concept of the CE, the 3R principles and the proposed 4R sustainability framework are presented. In Sect. 3, a Sociocultural, Technical, Economic, Environmental, Political, Legal, Ethical, and Demographic (STEEPLED) analysis of the 4R sustainability framework is showcased. In Sect. 4, the key AI aspects in achieving SDGs and the goals of circular economy are presented. Finally, in Sect. 5, conclusive remarks and suggestions for future lines of research are provided.

2 Circular Economy and the 4R Sustainability Framework

In this section the concepts of the circular economy and the 3R principles are presented. Additionally, it goes over the proposed 4R sustainability framework. Their interrelation with and role in achieving SDGs are also discussed.

2.1 The Circular Economy

In recent years, the interest in the circular economy and the shift from a linear to a cyclic system for reusing, remanufacturing, and recycling materials has gained ground. By using the circular economy as a means to achieve climate goals, circular economy also contributes to the SDGs, particularly regarding SDGs related to energy, production, consumption, and waste.

Schroeder et al. (2018) examined the relevancy of the circular economy practices in the implementation and achievement of the SDGs. Their results confirmed that the circular economy practices contribute to achieving a significant number of SDGs. The strongest relationships were found to exist between the circular economy practices and the targets of Clean Water and Sanitation (SDG 6), Affordable and Clean Energy (SDG 7), Decent Work and Economic Growth (SDG 8), Responsible Consumption and Production (SDG 12), as well as Life on Land (SDG 15). In addition, Industry, Innovation and Infrastructure (SDG 9) is of particular importance, since any success in achieving this goal will have important ripple effects for the other goals (Truby 2020).

Dufourmont et al. (2020) argued that the circular economy supported by resilience thinking is a means to achieving an ecologically safe and socially just result. They identified the circular economy elements that are essential within the context of education, culture, legal systems, values, quality of life, behavioral norms and political and governance considerations. Taking this into account was a main factor for considering that the 3Rs need to be extended with a fourth R, namely RETHINKing. The process of RETHINKing is the starting point for any development. In the case of the SDGs, everyone needs to RETHINK how we consume resources, materials, and energy nowadays. A social and cultural shift contributed by every single person is imperative so that society can actively contribute to the transformation to a more sustainable future.

2.2 The 3R Principles

Based on the nature of human life, waste resulting in pollution is constantly produced (Samiha 2013). When it comes to sustainable development, the 3R principle seeks to maintain the natural resources for future generations by reducing their use, reusing and recycling as much as possible. Waste reduction decreases pollution and prevents the environment contamination. The 3R principles are considered as the most proper way of waste disposal (Daniel 2003). A policy is referred to as "*zero waste*" when it adopts and integrated all of the 3R principles to achieve zero warming and zero disposals from waste (Baba et al. 2020). It is a holistic concept of waste management recognizing waste as resources which were produced during the interim resource consumption process phase. By decreasing global resource requirements, we need to re-consider today's resource and product management. Achieving zero waste requires a complex infrastructure, a change in mindsets, and innovative solutions.

2.3 The 4R Sustainability Framework Depicted

In this chapter, a fourth R, RETHINK, is presented as an extension to the existing 3R principles (Reduce, Reuse and Recycle) (United Nations 2022b), related to the circular economy and the SDGs interrelated to the environment.

In Fig. 1, the suggested 4R sustainability framework is presented. The proposed framework has the existing 3R principles (Reduce, Reuse and Recycle) at its core and extends the principles by including a fourth R, RETHINK, and highlighting the need for changing mindsets. It is proposed that no matter the aim, RETHINKing involves evaluating and quantifying the results. Additionally, this study argues that the RETHINK can be considered and deployed by using a STEEPLED analysis.

There are numerous routes to be followed to achieve the 4R Sustainability framework. The position of RETHINK denotes the need and intention to always reconsider and repeat steps as necessary. RETHINKing includes a STEEPLED Analysis (Georgiadou et al. 2021a) to extend the 3R sustainability model. A STEEPLED analysis urges decision-makers to consider how each factor will impact society and how the results of Reduce, Reuse, and Recycle will fit into future circular economy scenarios. The influence, either negative or positive, of each macro-environmental factor can be determined and understood and thus, formulated strategies and respective remedial actions should be taken in terms of the 3Rs. The centrality of RETHINKing highlights the need to constantly review, analyze, measure, learn, and improve (Siakas et al. 2023a).

It is assumed that sustainability is paramount for progressing toward the circular economy. The shift toward circularity involves numerous benefits, including the creation of new value propositions. Optimizing how resources could be best used enables enterprises to innovate by creating new value propositions to appeal to increasingly aware consumers who seek for cleaner, healthier, greener, and more humane and equitable lifestyles. As argued above, reusing, recycling, and reducing materials, resources, and knowhow are desirable, and that their impact can be both specified and quantified. Georgiadou et al. (2021a) used a STEEPLED analysis for reviewing and extending the Software process Improvement (SPI) Manifesto while Siakas et al. (2023b) focused on analyzing system failures through a STEEPLED

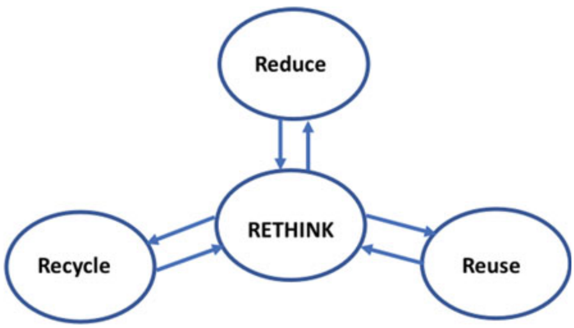

Fig. 1 The 4R sustainability framework

analysis. These eight dimensions help tackle perplex challenges, systems, and process which can further improve services, outputs, products, and outcomes. In the following sectors, the STEEPLED dimensions with regard to the 4R Sustainability framework are being analyzed.

3 Sociocultural, Technical, Economic, Environmental, Political, Legal, Ethical, and Demographic (STEEPLED) Analysis

This section presents a STEEPLED analysis of the proposed 4R sustainability framework. Particularly, it examines it from eight different dimensions.

3.1 The Sociocultural Dimension

The Sociocultural dimension is particularly important in the current globalized and multicultural workforce which collaborate and communicate with colleagues from the same or other organizations in the same or in different countries in a distributed mode. Therefore, this dimension involves the influences, effects, and inspirations that derive from different cultures. Resistance to change and to knowledge sharing are cultural characteristics that affect the quality of decisions, actions, and outcomes (Georgiadou et al. 2011).

In modern society, emergent properties and behaviors of individuals and organizations are challenging sociocultural factors exerting significant impact on decisions, actions, and outcomes.

The acquisition and use of new technologies and methods of working present challenges in dealing with the uneven distribution of wealth and opportunities. Enormous differences in education levels and cultural norms present barriers toward changing mindsets and behaviors. On the one hand, there is excessive waste (no or low levels of Reducing (R1), Reusing (R2), or Recycling (R3)) in what have come to be known advanced economies. On the other hand, in the developing economies, there is no or low opportunity to acquire knowledge, material goods, and technologies. In advanced economies, direct and fast communication with text, voice, and image is enjoyed through the internet and social media. A UNESCO report (Markelova 2005) revealed that "*more than 750 million adults around the world were illiterate – and two-thirds of them women. Another 250 million children of primary school age do not have a grasp of basic literacy skills*".

In recent years, there is a lot of discussion and research into information and digital literacy (Georgiadou et al. 2015, 2016, 2021b). Inevitably in the CE, new technologies demand competencies in the use of the technologies and the ability to discern the correctness of information and the safe navigation through misinformation, disinformation, and mal-information.

3.2 The Technical (or Technological) Dimension

The Technical dimension involves the analysis of variables concerned with the development and availability of relevant technologies. Over the course of time, factors relevant to the practical metrication and maintainable implementations of processes or products are also included and analyzed within the technical dimension. (Berki et al. 2018). In the light of the 4R Sustainability framework, innovative technologies for recycling, reducing and reusing are increasingly used. Hojnik et al. (2023), for example, argued that digitization improves the control over eco-innovation and enhances manageability and transparency. They asserted that digitization has enabled businesses to develop new services and products with less harmful effects on the environment and to optimize existing products and services in more sustainable ways.

Furthermore, Industry 4.0 seeks to transform traditional industries, manufacturing, and infrastructure into intelligent ones by integrating and combining novel smart technologies, such as AI, IoT, AIoT, cloud computing, blockchain, Cyber-Physical Systems (CPS), etc. (Awan et al. 2021; Reshad et al. 2023). These technologies can also facilitate the transition toward a circular economy and further enhance its benefits (Siakas et al. 2023a). On the other hand, Industry 5.0 capitalizes on humans and machinery to improve human–machine interaction and enables monitoring in real time. Industry 5.0 also aims to create more personalized to customer preferences and needs products and services and increase their quality by assigning tasks that require critical thinking to humans and tasks that are characterized by monotony and repetitiveness to machines (Reddy et al. 2021).

3.3 The Economic Dimension

The economy is constantly changing. Its growth or decline is influenced by several factors, such as gross domestic product (GDP), inflation, distribution channels, tax policies, unemployment, local and global economy, trends, growth and recession, interest and exchange rates, as well as supply and demand. To ensure the survival and success of a business, it is important for external economic developments to be matched in product launch strategies and in capital investment and specific refinements should take place.

Learning and using new tools, processes, and approaches often requires a steep and long learning curve for an individual to specialize in using them. Hence, it is important to focus on leadership aspects, effective training, and distributing tasks. In this context, the economic dimension involves the level at which an organization expands by training and hiring new staff, joining ventures with other organizations, or outsourcing (Georgiadou et al. 2020).

An economic view of society takes value creation activities and value-based decisions. In the context of software engineering, game theory can define socioeconomic situations following mathematical models and can be adopted to examine, identify, and analyze potential concerns, issues, and challenges by developing different mechanisms (Yilmaz et al. 2010).

3.4 The Environmental Dimension

The transition toward circularity includes a multitude of environmental benefits, such as reducing the environmental footprint. By designing products and by considering reusability, recyclability, and industrial symbiosis, businesses will effectively reduce their environmental footprint and eliminate pollution and waste. Goal 13 of the 17 SDGs is directly related to the environmental dimension. It involves the urgent actions required to address and overcome environmental problems (e.g., climate change) and the evaluation of their potential impact.

Raja et al. (2018) emphasized that within the concept of sustainability, people, the planet, and general profits are key aspects. Additionally, they argued that "*climate change requires conceptualizations of the interactions between human actions and social structure on the one hand and ecosystem dynamics on the other*".

The SDGs 2022 report (United Nations 2022a) states that "decades of misuse, poor management, over extraction of groundwater and contamination of freshwater supplies have exacerbated water stress. In addition, countries are facing growing challenges linked to degraded water-related ecosystems, water scarcity caused by climate change, underinvestment in water and sanitation and insufficient cooperation on transboundary waters". SDG 6 is directly connected with the environmental dimension due to its goal of ensuring access to sanitation and water for everyone.

3.5 The Political Dimension

The political dimension concerns aspects that are required to ensure and promote peace, justice, and inclusion in society. The related SDGs are monitored by the United Nations High-Level Political Forum on Sustainable Development (HLPF). HLPF is an annual forum which is organized by the United Nations Economic and Social Council (ECOSOC). Sustainability can be viewed from political, socioeconomic, sociocultural and sociopolitical dimensions. Niskanen and McLaren (2021) provided a broader analysis of the ideologies, interests, and institutions involved regarding future expectations and opportunities for repair and circularity. One of the SDGs mainly related to the political dimension is SDG 16.

3.6 The Legal Dimension

A legal guide to the SDGs was embarked on in 2015 by Advocates for the International Development (A4ID) (United Nations 2016). A4ID is a global charity that works in partnership with leading worldwide law firms. A4ID aims at creating a guide which outlines key components and elements that connect SDGs and current legal concepts and framework within a broad global sense. Moreover, the guide points out the vital role of the law in ensuring the achievement of SDGs and focuses on policy makers. The A4ID arranges trainings and events and delivers pro bono legal services related to the SDGs.

3.7 The Ethical Dimension

According to Rahanu et al. (2021), RETHINK includes an End User License Agreement (EULA) to extend the 3R sustainability model shown. A set of logically related steps for carrying out an ethical/legal analysis was presented in a framework by Kallman and Grillo (1996). The related steps are summarized and presented below:

- *Step 1*: "List the effects/challenges/impact of the issues under consideration".
- *Step 2*: "*Identify the stakeholders (those affected by the issues raised in Step 1)*". *Persons, such as customers, employees and citizens, who have responsibilities toward an organization and/or society and an interest in its success can be regarded as stakeholders.*
- *Step 3*: "Identify stakeholder obligation/duty to do or not to do something". Stakeholders have different obligations/duties depending on their position in the organization/society. However, all persons can contribute to a better world with sustainable living and consumption.
- *Step 4*: "Apply normative ethical/legal principles for the purposes of substantiation". Ethical/legal principles need to be communicated and transmitted to all members of a society. Society as a whole has the responsibility to create common ethical values for its members.

In conducting EULA, stakeholders should be consciously aware of the context of the sustainability framework of the moral and legal duties and obligations they have, as well as of the rights of others. Thus, ethical themes such risk and reliability, privacy, rights, equity, life quality, access, and use of power permeate the decisions made concerning Reduce, Reuse, and Recycle.

3.8 The Demographic Dimension

Hojnik et al. (2023) suggested that businesses in order to stay ahead of competition, they adjust and modify their services and products based on the demographic trends to meet the new requirements. They argued that demographic changes bring about changes in the way society perceives the circular economy and eco-innovations. Soukopova et al. (2017) found that demographic characteristics are predictive of the amount of waste residents generate. For example, older generations create more household waste. Similarly, Smol et al. (2018) identified that younger generations are more accustomed to circular economy and environmentally friendly behaviors and actions.

Mukucha et al. (2023) carried out a recent study on the tendency to reuse plastic bags instead of cotton and paper found no difference in terms of demographics (age, gender, country of residence). This is encouraging as it reveals that change of mindsets and behaviors is possible.

4 Using AI to Support the Achievement of SDGs

This chapter explores how AI can be used to help achieve different SDGs. More specifically, it examines the role of AI in Zero hunger (SDG 2), Quality education (SDG 4), Affordable and clean energy (SDG 7), and Sustainable cities and communities (SDG 11).

4.1 AI and Zero Hunger (SDG 2)

Based on the expectations of the United Nations, the global population is to reach 9.7 billion by the year 2050. It warns that sustainable ways must be found to both produce and distribute food, otherwise the risk of widespread hunger and food insecurity is imminent (United Nations 2023).

Kugler (2022) reported on how intelligent systems that use AI, machine learning (ML), and deep learning (DL), are exploiting large volumes of data datasets and robust computer science methods to increase boost farm productivity and yields, improve food supply chains, and prevent diseases from destroying crops. Vågsholm et al. (2020) reported on numerous novel technologies and AI solutions that can be used to address issues of food security, safety, and sustainability. Table 1 presents some examples of information technology (IT) and AI solutions that are being used to address these issues.

The solutions identified in Table 1 address the ethical themes of Quality of Life (QoL), Risks and Reliability, and Equity and Access, which should permeate the

Table 1 Examples of IT and AI solutions that are being used to address issues regarding food security, safety, and sustainability

Issue	IT/AI solution
Reduction of Food Loss and Waste to improve food security (Vågsholm et al. 2020)	Poyatos-Racinero et al. (2018) identified specific sensor categories that address issues related with product freshness, time–temperature indicators (TTI), food package integrity, and identification tags. Through the use of these sensors, intelligent packaging can be developed to reduce food waste Zhang et al. (2020) proposed e-commerce platforms that capitalize on big data infrastructure. These platforms would enable food supply chain efficiencies and customer behavioral insights to be realized by gathering, examining, and drawing meaningful insights from diverse data sources and analyzing them in real time
Increasing Crop yields	Javaid et al. (2023) identified numerous AI applications in the agriculture sector including increasing crop yields. By using technologies (e.g., IoT, data analytics, etc.) and sensors, a number of AI applications can assist in, amongst other things, predicting weather and plant diseases, monitoring crop and soil, identifying wasteful resource consumption patterns, guiding on water management, and detecting anomalies and impurities. Resulting, thus, in improving agricultural efficiency Quantilus (2022) reported on scientists who use AI to create new crop variations which are more resilient to diseases and pests, can be farmed even in extreme weather conditions, and demand fewer fertilizers and smaller water quantities
Distributing food more efficiently	Alabi and Ngwenyama (2023) advocated the use of smarter, digital food supply chains to improve food security and negate disruptions. The authors identified the following technologies to achieve this:
	1. New supply chain technologies deployment (e.g., blockchain, AI, ML, DL, data analytics, etc.)
	2. The use of Cloud based technologies can support full food supply chain visibility and asset movement (Terblanche 2021)
	3. Application of Industry 4.0 model, where digitalization and interconnectedness are achieved through the use of technologies, such as cognitive computing, IoT, CPS, and cloud computing

decisions made concerning Reduce, Reuse, and Recycle in using AI to support the achievement of zero hunger sustainable development goal.

4.2 *AI and Quality Education (SDG 4)*

In an attempt to reveal how how AI can support the SDGs and benefit the society as a whole, Luckin et al. (2016) presented lucid arguments for the use of AI in Education (AIEd). In another study, Zawacki-Richter et al. (2019) showcased an extensive research overview regarding the adoption and use of AI applications in higher education. Four key areas of AIEd emerged from their study. These areas involve the use of AI in institutional, academic, and administrative support services.

Particularly, these areas are: (1) intelligent tutoring systems (ITTs), (2) assessment and evaluation, (3) adaptive systems and personalization, as well as (4) profiling and prediction.

Chaudhry and Kazim (2022) presented the findings of an overview regarding the use of AI in Education based on perspectives from both academia and industry. The authors highlighted the research emphasis on reducing the workload of teachers, contextualizing learning for students, improving evaluations, and developing ITTs. Similarly, Chassignol et al. (2018) argued that AI will change and reshape the education landscape via four broad categories: (1) technology enhanced assessment, (2) communication between students and educators, (3) innovative teaching methods, and (4) customized educational content.

When applying AI solutions in the education domain, attention should be given to the ethical theme of Equity and Access, which should permeate the decisions made concerning Reduce, Reuse, and Recycle in the use of AI to support education quality (SDG 4). UNESCO (2023) promotes digital learning and the transformation of education via the deployment and exploitation of AI. But it alerts developers and policy makers to the multiple risks and challenges that AI brings, including the technology role in overcoming existing inequalities concerning access to "*knowledge, research and the diversity of cultural expressions and to ensure AI does not widen the technological divides within and between countries*". UNESCO advocates the promise of "*AI for all*" in this AI technological revolution in education.

4.3 AI and Affordable and Clean Energy (SDG 7)

It was highlighted in a recent report by the United Nations (2021) that in 2021 one fifth of the global population did not have access to electricity. The United Nations argued that due to the drastic increase in energy consumption and demand, the use of renewable energy sources must be increased. Salim et al. (2018) stated that the concept of sustainable production and consumption of energy needs to balance the negative externalities (reducing resource utilization, energy usage, waste, and pollution), on one hand, with maintaining economic prosperity and social well-being on the other. Ediger (2019) argued that to overcome the difficulties and challenges caused by the conventional energy plants (e.g., fossil fuels) it is important to transition toward renewable energy resources.

Hannan et al. (2021) stated that AI plays an essential role in increasing "*RE utilization and contribution to the energy mix, as well as the potential to revolutionize the RE sector*". Table 2 presents examples of AI applications and approaches that are being used to optimize RE resources production, consumption, and distribution.

When applying AI solutions in the RE domain particular attention should be placed to the ethical themes of Risks and Reliability and Equity and Access, which should permeate the decisions made concerning Reduce, Reuse, and Recycle in using AI to assist in meeting the goal of Affordable and Clean Energy (SDG 7). Jones (2018) reported on the need to use large computing centers to further advance AI technology

Table 2 Examples of AI solutions that are being used to develop renewable energies

Reported in	AI applications and approaches
(Zahraee et al. 2016)	By integrating AI solutions and applications in the renewable resource domain, the overall energy efficiency, safety, and reliability can be improved. Additionally, the impact on the environment and the overall costs can be reduced. The integration and digitalization of smart grids and microgrids that more effectively produce, manage, and distribute energy resources can be enhanced
Chatterjee and Dethlefs (2022)	The use of AI-based solutions to monitor and analyze issues in solar panels and turbine blades, via the use of computer vision techniques and data analytics. To develop more effective AI models to achieve corrective and predictive maintenance, data from historical failures caused by sensors in solar panels or wind turbines can be used

and research as well as AI-based products, which, in turn, can have a very high energy consumption rate and carbon footprint. The author estimated that the total electricity demand for ICT infrastructure could require up to 20% of the total world electricity demand by 2030. Hence, the transition toward greener energy resources and ICT infrastructure is ethically essential (Karnama et al. 2019).

4.4 AI and Sustainable Cities and Communities (SDG 11)

According to the United Nations Development Programme (UNDP), over half of the world population currently live in cities and it is estimated that by 2050 that number will increase to two-thirds of all humanity (United Nations Development Programme 2023). Therefore, the UNDP argued that it would be impossible to achieve sustainable development without changed the way cities are designed, build, and managed.

Allam and Dhunny (2019) reported on how urban centers are increasingly using new technologies to overcome issues related to "*society, ecology, morphology, and many others*". Among other technologies, smart cities incorporate sensors and big data through the IoT. The AI-based analysis of data deriving from such sources brings new opportunities in the city organization and management, contributing to the concepts of urban fabric, sustainability, and livability, along with opportunities for economic growth.

Singh et al. (2020) stated that smart cities can contribute toward the development of a more intelligent society by deploying and exploiting new technologies. They advocated that the adoption and integration of blockchain technology has contributed toward "*a paradigm shift to a new digital smart city ecosystem*". The convergence of AI and blockchain technology is revolutionizing the smart city network architecture to build sustainable ecosystems. Bokhari and Myeong (2022) highlighted that using AI-based solution to analyze big data deriving form smart cities could enhance autonomous decision-making systems. Gupta and Degbelo (2022) identified examples of how the integration of AI to monitor and manage resources and systems in smart cities has contributed toward the achievement of sustainable cities.

The AI solutions in the realm of sustainable cities address the ethical themes of Quality of Life, Risks, Privacy and Reliability, and Equity and Access, which should permeate the decisions made concerning Reduce, Reuse, and Recycle in using AI to assist in developing sustainable cities and communities (SDG 11). Pastor-Escuredo et al. (2022) stated that the ethical danger of digital technologies deployed in smart cities is that they have an impact at both a societal and individual level, "*posing several risks including a more homogeneous and predictable humankind*".

5 Conclusions

The aim of this study was to reveal how AI can support the creation of a circular economy and help achieve SDGs to benefit society. The proposed 4R sustainability framework, which was based on the 3R principles, concluded in the RETHINKing of values and actions to transition to a circular economy. The circular economy focuses on using natural resources more efficiently; hence, it coincides with several of the SDGs. A change in mindsets is necessary to develop a viable re-modelling approach of deep-rooted practices; thus, the transition should be associated with appropriate sociocultural frameworks and policy debates. Understanding consumers' cultural behaviors is essential for this transformational change. Additionally, changes must be made on an individual and local level to address the global challenges. Hence, the wider sociocultural transition should be met with appropriate individual actions and initiatives. This transformational change can result in better performance, improved engagement, and higher levels of innovation and creativity. AI and AIoT are significant components in creating a circular economy and achieving SDGs which, in turn, will result in a sociocultural transition.

Rethinking requires changes of mindsets and attitudes starting from raising awareness through educating the younger generations and re-educating adults who may be more set in their ways of thinking and often not open to new ideas. Additionally, to maximize any of the 3Rs (Reduce, Reuse, Recycle), it is necessary to increase reusability and adaptability of products, organize resources and knowhow into small and independent packages so that changes are controllable without generating a ripple effect of uncertainty.

It is simplistic to look for technological solutions without understanding the human centered environment. It is only through combining the "*human-centered and collectiveness-oriented digital development*" which can result in the development of new ethical social models (Pastor-Escuredo et al. 2022). Thus, it is necessary to combine ethical principles with the digital innovation undergoing in all the dimensions of sustainability. Vinuesa et al. (2020) proposed that to achieve sustainable development, the deployment of AI needs to be further promoted and supported by regulatory insight and oversight. They concluded that failure to do so could result in gaps in "*transparency, safety, and ethical standards*".

Future work will concentrate on the required changes to attain a sociocultural transition toward achieving a circular economy and SDGs. Other actions will focus on validating the suggested 4R sustainability framework by conducting case studies within enterprises and industries in cross-country and cross-cultural settings.

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The Digital Paradigm: Unraveling the Impact of Artificial Intelligence and Internet of Things on Achieving Sustainable Development Goals

Hanane Thamik, Juan David Figueroa Cabrera, and Jiang Wu

Abstract The UN General Assembly established the Sustainable Development Goals (SDGs) in 2015, with a target year of 2030. The goals address three critical aspects of community development: social diversity, environmental protection, and economic prosperity. The aim of this chapter is to discuss the role of AIoT in achieving long-term development goals. Firstly, we describe the "Introduction to Artificial intelligence of things (AIoT) and SDGs" and provide an overview of AIoT and SDGs, including definitions, concepts, and objectives. It also discusses AIoT potential to help achieve the SDGs, as well as the challenges and opportunities. Then, we discussed the "Applications of AIoT for SDGs," delves into how AIoT can be used to achieve specific SDGs like environmental protection, renewable technology, sustainable farming, water and hygiene, and smart development and communities. Machine learning, deep learning, natural language processing, computer vision, and IoT platforms are also covered in this chapter. It also looks at the challenges and opportunities associated with using these technologies to achieve the SDGs. After that, "The role of big data, cyber-physical systems, intelligent systems, and blockchain in SDGs," are discussed. In this, we examine the role of big data analytics, cyber-physical systems, intelligent systems, and blockchain technology in achieving SDGs. It also discusses the difficulties and limitations of using these systems to achieve long-term development goals. Then, "Ethics and Governance of AIoT for SDG Achievement," is explained which discusses the ethical and governance issues associated with AIoT for SDG achievement. It also investigates the potential risks and benefits of AIoT and offers recommendations for ethical and responsible AIoT development and deployment. At the last, we discuss the "Future

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Directions and Challenges of AIoT for Sustainable Development Goals," In this, we also look at the potential of emerging technologies and trends like edge computing, blockchain, and 5G, as well as the difficulties of scaling up AIoT applications for broader impact. At the end, a conclusion is drawn on the basis of these chapters.

Keywords Artificial intelligence of things · Sustainable development goals · Big data · Cyber-physical system · Intelligent system · Blockchain

1 Introduction

The Sustainable Development Goals (SDGs) were established by the UN General Assembly in 2015 and have a target year of 2030 (Sachs et al. 2019; Tsalis et al. 2020). SDGs aim to improve social diversity, protect the environment, and promote economic prosperity (Salam 2020). These objectives are crucial for creating sustainable communities, and the United Nations' SDGs have become one of the most widely used frameworks for achieving them. The SDGs were developed through a collaborative effort involving government, corporations, and academics. Millennium Development Goals (MDGs), which consisted of 8 goals and had 2015 as its target year, were replaced with SDGs, comprise 17 objectives and provide a comprehensive approach to achieving sustainable community development (Kumar et al. 2016; Sætra 2021). The SDGs focus on people, planet, prosperity, peace, and cooperation, while human rights are about protecting fundamental rights and freedoms. Although they are connected, they have distinct differences (Branch 2011). The SDGs can appear unattainable since they are so ambitious and inclusive (Pekmezovic 2019). But nonetheless, they are continued in order to support progressive methods of advancement (Alkire and Jahan 2018). Intelligent Connectivity is a technology that can greatly assist in achieving SDGs. By combining technical enablers like AI, 5G, IoT, Cloud, and Blockchain, a powerful system is created to address sustainable development challenges. These components are discussed below:

- **5G**: 5G technology provides three service sets: Enhanced Mobile Broadband (eMBB) for fast data transfer, Ultra-Reliable Low-Latency Communication (URRLC) for high reliability and low latency, and Massive Machine Type Communications (mMTC) for large device support with low power consumption. These sets have the potential to transform how we use and communicate with technology (Shafique et al. 2020).
- **Cloud**: Cloud contains multiple applications, faster processors, and memory space for running and scaling AI and data analytics through services like Software-as-a-Service, Infrastructure-as-a-Service, and Platform-as-a-Service (Tuli et al. 2019).
- **AI**: AI enables the use of machine learning algorithms to analyze data for various purposes, including real-time or almost real-time applications. AI can perform tasks such as making predictions, recognizing patterns, classifying data,

and making decisions based on the analysis. These capabilities make AI an important tool for a wide range of industries, including healthcare, finance, and transportation, among others (Chamola et al. 2020).
- **IoT**: IoT is a network of connected devices with sensors that communicate online. The sensors gather data for AI systems, while other components, like controllers or robots, execute AI commands. This system creates efficient decision-making in many fields (Weyrich and Ebert 2016).
- **Blockchain**: Blockchain, also known as Distributed Ledger Technology (DLT), connects data blocks cryptographically, records transactions over time, and links each block to the next. It creates a secure and transparent data stream that can serve as a powerful enabling technology for AI applications and analytical tools (Weyrich and Ebert 2016).

Although technology is even now in its early stage, intelligent connectivity is anticipated to introduce breakthroughs, increase efficiency, and hasten the creation of new firms that will have a substantial impact on socioeconomic growth (World Economic Forum 2020). By 2035, 22.3 million new employment and improved internet connectivity brought on by 5G technology are projected to generate \$3.6 trillion in economic production and \$13.2 trillion in total global economic value across all sectors of the economy. One-third of the economic output comes from the manufacturing sector, while the remaining one-third comes from wholesale and retail, construction, information and communications, and public services (IHS Markit 2019). The first trillion of dollars must go towards the global building of 5G networks, though. Businesses want to enter the 5G market first, but to do so, collaboration will be necessary to hasten the technology's development.

The carbon footprint of the mobile industry is far smaller than the reduction in greenhouse gas (GHG) emissions achieved by mobile technology. Mobile services are used by approximately five billion people, while mobile internet is used by four billion people. By facilitating digital services and boosting connectivity, mobile technologies have brought about several benefits for the economy, society, and environment, and they have also helped to achieve all 17 SDGs (Dar and Naseer Ahmad 2022).

Over the past 20 years, mobile technology has made a substantial contribution to both economic and social development. Intelligent Connectivity, which integrates advanced technologies like 5G, AI, IoT, cloud computing, and blockchain, has the potential to revolutionize human society and support the sustainable development goals. The COVID-19 pandemic has highlighted the importance of intelligent connectivity for supporting vital socioeconomic activities. Real-time data gathered by IoT sensors and analyzed by AI on cloud platforms through 5G connections can optimize resource management and positively impact all 17 SDGs, from poverty reduction and environmental protection to social justice and gender equality. But still, the effective mass acceptance and deployment of 5G will have a significant impact on how Intelligent Connectivity affects the SDGs. Therefore, it is crucial that organizations engaged in public–private partnerships, industry groups, network operators, and regulators continually consult to address the issues posed by its global deployment. This will enable the fullest possible use of the 5G opportunities for all Goals.

The aim of this chapter is to highlight the capability of AI and IoT technologies to contribute to sustainable development and to provide a roadmap for policymakers, practitioners, and researchers interested in leveraging these technologies for positive change. The structure of the chapter is as follows. Firstly, we discussed the "Introduction to Artificial Intelligence of Things (AIoT) and Sustainable Development Goals (SDGs)" and provides an overview of AIoT and SDGs, including their definitions, concepts, and objectives. It also discusses the potential of AIoT to achieve the SDGs, along with the challenges and opportunities. Then we discussed about the "Applications of AIoT for Sustainable Development Goals." We try to provide a detailed explanation of how AIoT can be applied to achieve specific SDGs, such as environment, clean energy, sustainable agriculture, water and sanitation, and sustainable cities and communities. This chapter also discusses the various technologies and tools used in AIoT, such as machine learning, deep learning, natural language processing, computer vision, and IoT platforms. This chapter also examine the challenges and opportunities of using these technologies for achieving SDGs. After that, we briefly explained "The role of big data, cyber-physical systems, intelligent systems, and blockchain in SDGs" in which we discuss the role of big data analytics, cyber-physical systems, intelligent systems, and potential of blockchain technology in achieving sustainable development goals. It also discusses the challenges and limitations of using these systems for sustainable development goals. Then we explained the "Ethics and Governance of AIoT for Sustainable Development Goals" in which we discuss the ethical and governance issues related to AIoT for achieving SDGs. It also examines the potential risks and benefits of AIoT and provide guidelines for ethical and responsible AIoT development and deployment. At the last, we discuss "Discussion, Challenges, and Future Directions" in which we argue about the future directions and challenges of AIoT for achieving SDGs. We also examine the potential of emerging technologies and trends, such as edge computing, blockchain, and 5G, and the challenges of scaling up AIoT applications for broader impact. The applications of these technologies for attaining SDGs are discussed in the next section.

2 Applications and Technologies of AIoT for SDGs

2.1 AIoT and Infrastructure Development

The scale of development of a society is determined by infrastructure, which serves as the foundation for various services and economies. Infrastructure enables the growth of fundamental amenities such as housing, sanitation, transportation networks, and power-generation amenities, among others. As a result, the SDGs' essential and most important component is the development of infrastructure. Common SDG objectives include having access to amenities like good health, universal access to education, clean water, food, and sanitation, among others. The only way to facilitate these is with the help of infrastructure upgrades. Civil infrastructure should never be seen as a standalone asset, ideally. Sustainable infrastructure provides economic, environmental, and social sustainability, making it a vital component of sustainable development. Power plants, healthcare facilities, water bodies, and their associated systems should be considered as interconnected entities. By using eco-friendly building methods and practices, sustainable infrastructure helps alleviate pressure on the environment. The issue of social sustainability can be dealt with automatically when everyone has equitable access to infrastructure. With time, the Intelligent Internet of Things will play a larger role in civil infrastructure (Bertino et al. 2021). In the context of the construction field, intelligent IoT can be used in a variety of applications. To address this, a labour management system is necessary, which can be facilitated by IoT and AI technology. Smart tags and other IoT devices can be used as identification systems for workers, while AI integration can provide administrators with critical data such as the number of workers, task duration, and break times. Such systems' capacity to be operated remotely is their main benefit. These systems can also guarantee the best possible use of human resources. IoT also plays a significant role in environmental safety management (Soltanmohammadlou et al. 2019). The construction industry needs safety management systems to reduce the damage caused by accidents at work sites. The system can employ sensors such as proximity sensors that can alert people in hazardous areas or small cameras that allow for real-time video monitoring (Chung et al. 2020). By connecting IoT devices with AI technology in a high-speed network, hazard alerts can be generated to improve safety management systems at work sites. Anomaly detection processes can be utilized to identify potential triggers for serious mishaps. Additionally, IoT devices have proven to be effective in managing supply chains (Ryan et al. 2013). Technologies such as RFID labels can be utilized to determine the availability of resources at work sites (Chung et al. 2020).

If the quantity of resources exceeds a predetermined ideal level, the system will therefore generate alerts automatically. This makes it easier to remotely monitor the resources and ensure their availability. We can ensure that resources are being used to their full potential thanks to the precise data on their availability and consumption. Resource expense and wastage are significant challenges for the construction industry in most developing countries. We can achieve SGDs by using such strategies to eliminate ineffective resource management. IoT can also be applied to the monitoring of building structures. Such solutions can be used on a regular basis as well as during building time deployments. Simply put, structural health monitoring (SHM) is the process of regularly assessing the durability of commercial and industrial structures to ensure that they are safe for habitation by people. Long-term, this approach lowers maintenance costs while also improving local resident safety (Di Nuzzo et al. 2021).

2.2 AIoT and Health Care Sector

The health care industry is another area that should be examined in conjunction with civil infrastructure. Systems that improve, conserve, or renew health while minimizing their harmful effects on the environment and utilizing every opportunity to restore or improve it for the benefit of the health and well-being of both the present and future generations are considered sustainable health care systems. Health care activities have a substantial impact on the environment and put pressure on it, according to extensive study. It can range from producing poisonous to regular garbage, wasting a lot of water, using a lot of energy, and even producing an increasing amount of e-waste on the technical side. When it comes to energy saving and e-waste minimization, the modern technologies are quite effective (Amin and Hossain 2021). Additionally, it aids in cost reduction and supports a few other beneficial sector developments. The perception of health care is being transformed by AIoT.

The utilization of personal health assistants, remote health monitoring systems, helping robots, and other support systems are progressively enhancing sustainable healthcare through AIoT (Mandal et al. 2021). One such significant technological progress is the administration of telemedicine. It is common practice to rely heavily on regional healthcare facilities with specialized engineers and tools to conduct specific activities or produce health diagnosis. This has an immediate impact on its accessibility to those in need because medical personnel shortages are a serious problem in distant locations (Nasralla 2021). The goal was to employ AIoT technology to create systems that could detect serious illnesses or other problems in a person. The system was much more effective than its human counterpart at gathering, processing, and drawing conclusions from patient data on its own. The oddity is that because the system had a certain amount of autonomy, it could be used by non-technical individuals. The low-cost system provides easy access to the underprivileged class, promoting health care equity in society (Hameed et al. 2020). The most recent iterations of wireless body networks known as Medical Super Sensors, equipped with enhanced memory and communication capabilities, can retrieve vital patient data, including blood pressure, ECG, and cardiac rate. An AI-based module might be used to mine and summaries the data gathered from these sensors, simplifying the process. These models can handle the challenges brought on by such a large amount of data since they are learning and evolving (Hajar et al. 2021). High-end DSSs can assist doctors in selecting the most practical diagnostic process for their patients based on their medical history. Like this, wireless wristbands could spare patients from lengthy lines at registration and lab counters. Hence, it is possible to use clinical resources and medical staff to their full potential, resulting in a greater number of beneficiaries.

The coordination and controlled communication of the stakeholders are key to the success of IoT-based health care systems, and these systems play a big part in how easily dangerous occurrences may be handled. The application of surgical robots is a boon for humanity since they enable complex procedures to be practiced beforehand and provide clinicians a better intuition about their working environment (Wang and

Wang 2021). Doctors can perform remote surgeries with the help of computers, and IoT-enabled devices may make it easier to monitor the patient's recovery. With the development of the Internet of Robots, these telesurgeries are becoming increasingly widespread these days. Robots may perform additional roles like patient bystander and mental therapist, besides performing procedures in certain medical cases.

2.3 AIoT and Intelligent Transport Systems

Intelligent Transportation Systems (ITS) typically function by keeping a constant flow of data among vehicles and structures along the route. ITS encompasses a larger range of technologies than only automatic driving. These technologies are frequently regarded as essential to achieving SDGs because to their high capacity to guarantee the long-term optimal use of available resources. The list of advantageous characteristics is broad and includes improvements in experience quality, enhanced road capacity, vehicle productivity, and increased vehicle usage. The odd thing about these systems is that they mostly manifest their impacts at the vehicular level. But nonetheless, ITSs can serve as a foundational element for the slow growth of cities, businesses, and other structures at many levels of the transportation sector (Sumalee and Ho 2018). According to extensive study, contemporary intelligent transportation technologies have significantly reduced greenhouse gas emissions, improved fuel efficiency, and cut travel times without compromising the mobility of common people who cannot buy such systems. While electricity and resource efficiency are two of the top necessities for emerging societies, further advancements in cutting-edge transportation-based innovations will enable them, facilitating the sustainable growth of the entire country. There are no greater and more straightforward examples of real-world AIoT application situations than ITS. Every one of these systems uses AIoT methods in some capacity. To create a safe and energy-efficient environment with less traffic, smart roads use cutting-edge technologies such as sensors, cameras, and solar and wind-powered devices ITS (Balasubramaniam et al. 2017). Smart fueling facilities, parking, and traffic lights are just a few examples of connected entities. These technologies help vehicles gain a sense of their environment while roadside infrastructures facilitate ITS (Trubia et al. 2020). AIoT devices have the advantage of identifying trends in data from numerous stakeholders and using that information to improve their future function, thanks to their bidirectional nature. Each participant could act more intelligently and better as the number of these stakeholders increasing (Sen et al. 2020). With the integration of cleverly designed smart vehicles, smart transportation networks can only be claimed to be finished. Autonomous vehicles are expanding more quickly thanks to a balanced combination of AI and 5G connection developments. The renowned automakers began making investments in these kinds of automobiles in 2013. Identification and management of the environmental parameters provide the key challenge for these vehicles. IoT sensors gather data for fog/cloud-based buffer layers, ensuring low latency. Self-driving cars promote the growth of supporting resources and infrastructure, enabling them to travel autonomously and safely (Khayyam et al. 2020). Another benefit of such vehicles is that they efficiently use resources, both direct resources like fuel and indirect resources like parking spaces and road usage, making them perfect for sustainable resource use. Additionally, they support the creation of intelligent transportation systems and navigation strategies that guarantee time management (Bertino et al. 2021).

2.4 AIoT and Smart City

A smart city is an approach based mostly on Information and Communication Technologies (ICT) that aims to create, implement, and promote sustainable development practices while addressing the growing problems associated with urbanization. ITS and smart cities are inseparably linked together like the two halves of a coin. Only at well-established former cites is the latter's full deployment feasible. The foundation of smart cities is AIoT application. Efficiently creating a Smart City system with improved standards of living, sustainable development, and higher resident productivity is possible with the use of this technology (Kashan Ali Shah and Mahmood 2020). It provides a stable foundation for the interaction of multiple technologies. In the framework of sustainable development, smart cities also offer several benefits (Ullo and Sinha 2021). One such important one is climate control. They frequently use cutting-edge technology, which suggests reduced overall energy use. The majority of AIoT devices are very effective and power efficient. As a result, these cities generally have very low carbon footprints, promoting environmentally friendly growth and greener living. Moreover, it has a significant impact on society (Ramesh et al. 2020). Smart city projects strive to create an inclusive society that offers equal opportunities for all residents to succeed, with the sole aim of improving their quality of life.

A smart city replaces conventional methods with numerous smart systems, including smart transportation, roads, health care, infrastructure, waste management, and more. These implementations will all be made with AIoT components, and their combined control will be used to govern operation (Syed et al. 2021). Standard communication protocols will be used by these networks while communicating, and an intelligent system will make decisions. Due to their usage of one or more of the above-mentioned technologies, smart cities can be thought of as a synthesis of them all. Smart technologies, smart businesses, smart services, and smart living are all parts of a smart city. IoT's role in various applications is to install devices and connect them to the internet, allowing for data exchange and communication. AI plays a place in information mining and related tasks like data management, tracking, monitoring, and location-based tasks. Depending on the application, they also use a variety of devices, including sensors, cameras, tags, and so on (Kamruzzaman 2022). A "smart city" cannot be created by just installing these features; rather, their cooperation at a greater level of IoT development is necessary (Lv et al. 2021). Other technological development needs also arise because of the growth of smart cities. Another process used in smart cities is smart energy. The dense population of a smart city necessitates significant energy consumption as well. The long-term needs of such settlements cannot be met by relying on conventional energy sources. Thus, smart cities typically use intelligent energy-use strategies. To ensure optimal energy utilization, energy-efficient equipment is used throughout the city. IoT devices are preferred for this purpose since they use minimal energy while still performing the same tasks as other devices. AI is also used in scenarios involving energy conservation. Smart cities use AI programmed to monitor energy use, identify energy leaks, and other tasks (Chauhan et al. 2022). Additionally, they use a variety of sustainable energy producing techniques in place of non-renewable ones. In these advanced cities, renewable energy sources like solar and wind are widely used. As a result, this feature of smart cities is crucial for the community's sustainable growth. The majority of applications will utilize AI and IoT to varying degrees in homes as well (Kashan Ali Shah and Mahmood 2020). Countless applications of IoT exist in domestic settings, including face recognition and biometric identification systems at entrance points, as well as smart home products and home automation systems.

2.5 AIoT and Agriculture

IoT has been used in agriculture for a while, artificial intelligence is a newer technology in this field. The primary difference is that previous methods lacked live data being sent to the sensors. Traditional systems, on the other hand, tended to employ previously acquired data to perform operations on and draw conclusions later. AI is enhancing agriculture by improving sensor and technology combinations, leading to better real-time jobs. These devices can be linked to centralized or cloud servers, storing data and enabling remote system control. Basic applications, such as plant hydration and disease diagnosis, can now be easily used by new farmers. Real-time duties like irrigation systems can also be modernized, including controlling water tank levels and watering plants (Boulouard et al. 2022). Because AIoT systems are so widely available, their importance in agriculture is not simply confined to one stage but rather permeates all of them, from determining how much time must be spent at each stage to producing a finished good. A second green revolution is occurring with the use of AIoT technologies to agriculture. From the standpoint of a farmer, these methods offer a variety of advantages. Long-term cost-effective solutions are provided, and farmers are enabled to make better decisions by employing correct data and supporting technologies (Mora et al. 2020).

These are just a few of the most fundamental features of smart greenhouse systems, and how well each one of these functions is carried out depends on the kinds and numbers of sensors being employed. Various sensors are utilized in agricultural processes, such as the relative humidity sensor, ambient air temperature sensor, soil moisture content sensor, PH sensor, CO_2 sensor, and others. A control component, such as a multi-controller, serves as the "brain of the system," and a connectivity component, such as Wi-Fi routers, Wi-Fi modules, or cloud connectivity, enables data flow between the system and the outside world (Ullo and Sinha 2021). The industry's interest in this topic is expanding as more remote agricultural control is used today. In remotely managed farming situations, the user can keep an eye on the farm or greenhouse around-the-clock from a distance and take the appropriate action without having to be present physically. Such systems would include a concoction of many technologies that aid in data collection across all domains, and carry out required duties when instructed (Ibrahim et al. 2019). Such systems include automatic watering, fertilization, and other maintenance procedures. Automated irrigation and fertilizing systems are closely linked to remote access farming systems, using sensor data to determine soil moisture and nutrient levels to perform operations. These systems can function both with and without human assistance, with specific values set and AI techniques activating the system when the threshold value is reached, such as fertilizing or hydrating the land (Raut et al. 2018). For forecasting, systems look for specific circumstances that may have led to specific ailments in the past. These occurrences are frequently referred to as "triggers," and properly trained models can recognize them.

These applications are simple to execute because they don't need any additional hardware because fields and greenhouses are constantly monitored in smart agricultural systems. Their excellent precision enables quick decisions and simple application of necessary remedies. Also, the systems' autonomy enables even inexperienced farmers to learn the same disease-related concerns as more seasoned ones (Ouhami et al. 2021). Another benefit is that, regardless of the user's level of experience, the traditionally laborious agricultural procedures may now be completed with simplicity. In addition, adequate use of agricultural resources and land should be a top priority when it comes to an expanding economy. The technologies mentioned enable us to utilize water, fertilizers, and other resources to the fullest, assisting us in our pursuit of sustainable agriculture. The introduction of all these technologies will also make the agricultural industry very alluring to newcomers.

Moreover, the role of big data, cyber-systems, and blockchain technology in achieving SDGs are discussed in the next section.

3 The Role of Big Data, Cyber-Physical Systems, Intelligent Systems, and Blockchain in SDGs

3.1 Big Data and SDGs

Rapid and ongoing technical development in recent years has generated almost infinite amounts of information. By 2020, it is predicted that every individual on Earth would produce 1.7 MB of data every second, resulting in a daily data production of about 2.5 quintillion bytes (Handoko et al. 2020).

Big Data is the product of this data flood or information overload. Every part of the digital economy depends on the resulting analytics, and it is commonly understood that data-driven decision making has great potential and is becoming increasingly important. Many studies have been done to show and demonstrate how these data can be used effectively. Many studies, statistics, and data are needed to achieve the Sustainable Development Goals. These data must be valuable, informative, timely, appropriate, and sufficient because they are required to formulate plans and important decisions. At every stage of the decision-making process, data literacy needs to be established and statistical volume needs to be further solidified (Hassani et al. 2021). It will take a lot of cooperation between data makers and users from diverse data solutions to reach the goal of sustainable development (Joshi 2021). Using cutting-edge technologies will be necessary for both producing and utilizing data and statistics. To review are several different SDG indicators. Because Big Data complements the traditional data sources, businesses may more easily keep track of development plans with its assistance. In terms of country development policies, the SDGs feature precise, time-bound, and quantitative targets. Maybe more than 230 SDG indicators exist. However, many of these variables need to be properly disaggregated by many factors, including age, gender, geography, and more. NSS, or National Statistical Systems, needs precise data.

3.2 Cyber-Physical System and SDGs

CPSs improve physical system potential by integrating computations and communications to govern and monitor physical processes through feedback loops. This enables computations to affect physical processes and vice versa (Wang et al. 2015). CPSs create a real-time connection among humans and physical systems, connecting devices with a network, sensors, actuators, and computers (Amato et al. 2021). CPSs consist of six essential components: sensors, actuators, power supply, digital and analog hardware components, network, and software. These technologies are highly adaptable and have a broad range of applications, including communications, energy, healthcare, infrastructure, manufacturing, military, robotics, and transportation, among others (Amato et al. 2021).

3.3 Intelligent Systems and SDGs

Digital tools that produce, use, transmit or source electronic data can aid in achieving the SDGs by ensuring sustainable economic growth. These tools can be characterized as digital sustainability, integrating the SDGs. Artificial intelligence and machine learning technologies are expected to contribute about 14% to the world economy by 2030, providing enormous value. We explore how digitalization can usher in sustainable development, creating a "Smart Green Planet" that offers resources while protecting the well-being of all citizens (George et al. 2021).

3.4 Blockchain and SDGs

The United Nations' SDGs outline the world's major problems, and it is critical to approach them systematically. This is especially true considering the COVID-19 pandemic's devastating influence on the SDGs. Digitization and technological engagement have become increasingly important in reducing human interaction and travel requirements (Barnes 2020). IoT data fed into blockchain can offer trusted and incentivized contributions towards SDG progress, providing a business opportunity for companies. The IoT is a system of mechanisms that communicate to maximize resource use and experience. A blockchain can track device measurements and transactions, concurrently recording and auditing various types of transactions. This is useful where trust is lacking (Issa et al. 2016). Private sector organizations are explicitly envisioned to contribute to global development and sustainability concerns by the United Nations 2030 Agenda for Sustainable Development (Lee et al. 2016). Established businesses can differentiate themselves from competitors and foster innovation in their operations and stakeholder relationships by participating in measuring and monitoring the SDGs (Tan and Low 2019); start-ups may also benefit from this opportunity. Combining business and sustainability goals can lead to "win–win" scenarios that advance both sustainable development and economic growth (Burritt and Schaltegger 2010). However, the ethical concerns regarding the use of these technologies are discussed in the next section.

4 Ethics and Governance of AIoT for SDGs

4.1 Ethical Benefits of AI and SDGs

AI's ethical concerns are often associated with immoral outcomes, which are central to the AI debate. However, it's worth noting that AI also offers numerous advantages. Many AI policy documents emphasize the financial gains that are expected to come from increased production and efficiency. The opportunities and benefits of AI are limitless for any industry, and it can discover and resolve difficult problems faster and more efficiently than prior approaches. Both the public and private sectors are extremely drawn to it. Governments and companies are utilizing various AI applications such as real-time response to cybersecurity threats, tracking of national spending patterns, automated investment decisions, self-driving cars, self-learning customer service, and digital personal assistants (Truby 2020). As a result, businesses and governments will progressively invest in expanding their AI skills to capitalize on its potential and boost revenue. Those who don't risk falling behind and losing out on investments and earnings as rivals adopt AI (Theis and White 2021).

Promoting greater wealth and well-being is the moral principle that improves people's quality of life and may be essential for human flourishing. The EU's High-Level Expert Group on AI states that AI is a promising method for promoting human flourishing, individual and societal well-being, and the common good, as well as driving advancement and innovation (Andreoni and Chang 2019). The International Risk Governance Center highlights that AI's analytical power, which allows it to process data that humans cannot, has the potential to improve ethics currently (Stahl 2021). AI offers various technical advancements such as linking data across domains and geographical barriers, identifying patterns, and providing quick and consistent results. These advancements can free humans from repetitive tasks and help us gain a better understanding of phenomena, promoting human flourishing. AI can also simplify the lives of busy professionals, for example, by reducing commute times and improving email spam filters (Stahl et al. 2023). There are growing efforts to use AI particularly for ethical goals, adding up to these instances of incidental ethical benefits, or advantages that result from the technological capabilities of AI. Currently, this is done under the banner of "AI for Good" (Berendt 2019). AI for Good faces the challenge of determining what defines ethical good. Shared ethical values, such as altruism, security, success, and self-direction, have been identified, despite differences in opinions in a pluralistic society (Karim et al. 2020).

4.2 Ethical Issues and SDGs

AI's machine learning characteristics bring up two main groups of ethical problems. The first is the opacity, unpredictability, and need for big datasets to train the technology, which raises concerns about privacy and data protection. It is challenging to predict how the system will respond to specific inputs, and past behaviors may not accurately predict future behavior. Informational privacy and data protection are crucial ethical issues. On the other hand, machine learning-based AI also poses data security risks since it requires access to significant amounts of data for training (Fabiano 2019). AI's pattern recognition abilities may pose privacy issues, even without direct access to personal data. For instance, a study (Çoban et al. 2021) claimed to determine sexual orientation from Facebook friendships. Big tech companies have faced investigations and hefty fines for various violations. Despite its ethical and scientific merits, AI can generate insights that raise privacy concerns (Stahl 2021). AI's capabilities have introduced unforeseen potential for the re-identification of anonymized personal data, presenting new data protection issues that may not be covered by current laws. This creates new ethical concerns, especially since AI can generate or use uncommon types of personal data, like emotional data (Ho et al. 2021; Nycyk 2020). AI systems can be vulnerable to novel security flaws, such as model poisoning attacks, which are closely related to data protection worries and cybersecurity issues in ICT (Costa et al. 2021). Moreover, novel vulnerability detection and exploitation techniques may be employed by these systems (Su et al. 2023). Countries' reluctance to regulate AI to attract technology businesses is a mistake. Regulatory intervention in line with internationally recognized standards can create a safer and healthier environment for AI to develop without the risk of overregulation

(Stahl 2021). By influencing and auditing AI design, it can manage current risks and anticipate future dangers while ensuring sustainable innovation.

5 Discussion, Challenges, and Future Directions

Without a doubt, regardless of the application areas, AI-enabled IoT will be highly relevant soon when considering the current trend. AIoT is a strong competitor for numerous applications dispersed throughout diverse instances due to its broad applicability. Data is expected to be the most expensive commodity in the future, and systems that can't use it will fail. One of the main challenges we encounter when integrating data-intensive AI into IoT devices is the components' limited memory and processing power (Nair and Sahoo 2021). IoT devices lack the ability to perform very complicated AI tasks, which often require large amounts of memory. One alternative that has been suggested is using cloud computing for AI-enabled IoT, as restricting the technology to purely IoT devices won't be enough to support its future. The Cloud appears more enticing as the best option to solving such problems due to its enormous popularity and availability (Stahl 2021). Despite all of this, research has shown that the combination of cloud computing and IoT is one of the least effective ways to address the issues raised thus far. It is mostly caused by the latency problems that these systems' data transport causes. It is inevitable that a system that relies on a Cloud server will require a fast network for ongoing data transfer. High data volume and significant latency are typical features of such systems. The benefits of IoT, such as speedy processing and mobility, which may have been the driving force behind picking the IoT architecture, will be rendered useless as a result (Abdulkareem et al. 2021). Edge computing and fog computing are introduced in this context. Edge computing involves using processors near the data source for processing, reducing the amount of data transmitted between the server and devices. This results in faster system operation with reduced latency, enabling real-time or near-real-time task completion. Fog computing shares a similar situation (Kalyani and Collier 2021). Hybrid environments that combine IoT, Fog, and Edge computing offer significant advantages for AI-enabled IoT systems. These paradigms allow for the expansion of AIoT setups to more data-intensive challenges, such as real-time video processing, navigation systems, and video analysis systems. This creates new opportunities for research in various fields (Nair and Sahoo 2021). Security is a key concern regarding the proposed methodology. The industry is undergoing a slow transition towards the future in terms of practical implications. One of the most radical transformations has occurred in the health care industry. Prior to the widespread adoption of AIoT, the use of wearable technology and personal care systems in healthcare was restricted to rudimentary assisting robots and decision support systems. It is anticipated that more portable wearable devices that can track many biological functions will soon be made available. Intelligent vehicle systems are another area that has seen significant transformation because of AIoT. Technology has advanced from simple auto navigation systems to the point where cars may now drive themselves without any assistance from a driver. The goal of the ongoing research is to advance technology by giving it more autonomy and the ability to work without assistance from humans. Smart greenhouses and automated farming systems are currently popular. Currently, these technologies can only be used indoors, and significant improvements are required before they can be used in open farming.

AIoT potential is not limited to any field, as research in the paradigm continues to evolve. While some well-known applications have been utilized, the full scope of AIoT remains to be seen. Before we can accurately examine the positive and bad effects of the technology, there is still much work to be done. Studying the system's sustainability aspect is important since, in the future, the reach of any technology will depend on its capacity to provide sustainable technological breakthroughs. By eliminating mundane activities, it can make work more enjoyable and productive for people, assist society and governments in making decisions without human bias, and advance the SDGs. For example, building technology to improve economic presence and combat exploitation and money-laundering (Hoang et al. 2021). SDG-compliant technology may be rejected by nations that have signed up to the SDGs. Governments have a good enough reason to do this since allowing noncompliant AI would prevent them from making any progress towards reaching the SDGs. As a result, the UN should take steps to develop a set of guidelines and requirements that all signatories must follow to implement through national laws, which would have a substantial positive impact on the SDGs globally. There may need to be strong limitations on some uses of AI: Joh gives the illustration of deadly autonomous weaponry in battle (Truby 2020). The ability of artificial intelligence to discover and shape itself through new experiences, leading to it taking on practically human features, is one of its main advantages (Najaf et al. 2021). Effective regulation of the kinds suggested would not completely prevent or punish all risks resulting from experimental AI. Rather, it is needed to be ensured that the AI is designed with a benefit to the SDGs in mind and that adequate safeguards are in place should the AI behave or produce decisions that are contrary to mandated principles, such as the benefit to the SDGs.

6 Conclusion

IoT, big data, smart systems, cloud computing, and block chain technology advancements are rapidly changing how established and mature business models operate. This will be opening up new opportunities for start-up businesses to innovate and for social enterprises (which have a stronger social purpose) to emerge. IoT technology makes it possible for numerous devices to relay information over a large network of users, enabling fast and accurate measurement of data (such as temperature, weight, carbon emissions, etc.). With the help of block chain technology, data may be reliably and immutably recorded, publicly reported, and maintained in integrity by being distributed to a network, fostering confidence in the data's veracity. These technologies' traits can offer creative approaches to managing and measuring operations. Likewise, there is a growing societal and commercial interest in supporting the UN

SDGs. The major social, environmental, and economic issues that must be resolved to create a successful and peaceful world are outlined in these objectives. Although there is enthusiasm in the SDGs, businesses frequently just engage with these objectives superficially, missing out on many opportunities. In the end, these reforms might open doors for start-ups and fresh social companies, as well as opportunities for innovation in established organizations. Nevertheless, because these technologies are located at the edge of the network, they lack the network security that devices placed within the network coverage can benefit from. As a result, security risks also materialize; in-depth investigation is necessary to solve those problems as well. Hence, the UN must take action to create a set of rules and specifications that all signatories must adhere to in order to execute through national laws, which would significantly benefit the SDGs globally. Proper implementation of the types proposed would not completely prevent or punish all risks resulting from experimental AI. This would guarantee that the AI is designed with the SDGs in mind and that adequate protections are in place should the AI function or generate decisions that are opposed to mandated ethics, such as the benefit to the SDGs.

In light of these developments, the United Nations must take proactive measures by creating a set of rules and specifications that all signatories must adhere to through national laws. Such a framework would significantly benefit the global implementation of the SDGs, fostering responsible and ethical utilization of these transformative technologies. While the proposed regulations and guidelines cannot completely eliminate or penalize all risks arising from experimental AI, they can ensure that AI systems are designed with the SDGs in mind and that adequate safeguards are in place should the AI function or generate decisions that contradict mandated ethics, including the advancement of the SDGs. By embracing responsible innovation and technology deployment, the UN can contribute to the realization of a more sustainable, inclusive, and prosperous future. “The Digital Paradigm” serves as a valuable resource for understanding the profound implications of AI, IoT, and other digital advancements on achieving the SDGs. It underscores the importance of strategic and holistic engagement with these technologies, emphasizing the need to balance innovation, societal impact, and security considerations. Through informed actions and global cooperation, we can harness the transformative power of these technologies to drive sustainable development and create a better world for present and future generations.

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The Role of the Artificial Intelligence of Things in Energy Poverty Alleviation

Ascensión López-Vargas, Agapito Ledezma-Espino, and Araceli Sanchis-de-Miguel

Abstract The Sustainable Development Goal 7 aims to ensure access to affordable, reliable, sustainable, and modern energy for all by 2030. It combines efforts to alleviate energy poverty with climate change action by setting worldwide objectives for boosting renewable and efficient energy consumption. Energy poverty is a significant problem in Europe that has worsened because of the Global Energy Crisis; the prevalence of energy poverty varies greatly throughout the continent, ranging from 0.3% to 27% of the population. After the COVID-19 outbreak, the Artificial Intelligence of Things has so far grown in significance and the research trends and emerging approaches using Artificial Intelligence of Things applications have been increasingly applied in the energy poverty context. There are not many works that use Artificial Intelligence of Things primarily to combat energy poverty. Nonetheless, several Artificial Intelligence of Things applications focusing on partial energy poverty features or on topics closely connected to energy poverty (income, energy prices, and building energy efficiency) have been released recently, allowing for the effective characterization of the issue. The primary objective of this chapter is to examine the role of the Internet of Things powered by Artificial Intelligence in addressing the issue of energy poverty. In this chapter, successful Artificial Intelligence of Things projects, in relation to the energy poverty and Sustainable Developments Goals are highlighted. After an exhaustive study, the Artificial Intelligence of Things has been determined to be a key actor to combat the current Global Energy

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Crisis and alleviate energy poverty. Future obstacles to the adoption of Artificial Intelligence of Things have been highlighted, and these include infrastructural gaps, societal issues, and cybersecurity.

Keywords Artificial intelligence of things · Energy poverty · Sustainability

1 Introduction

The consequences of the COVID-19 outbreak, as well as the increase in energy costs after the Russian invasion of Ukraine in February 2022, has resulted in an increase in European inhabitants suffering from energy poverty in 2023 (Guan et al. 2023). By 2030, the Sustainable Development Goal (SDG) 7 aims to ensure that everyone has access to affordable, reliable, sustainable, and modern energy. The SDG7 combines efforts to alleviate energy poverty with climate change action by establishing global targets for increasing renewable and efficient energy consumption. Energy poverty (EP) has not a universal definition; however, it is commonly defined as "*inability to keep adequate levels of heating, cooling and lighting*" in households (European Commission 2018, 2022). Over 35 million European Union (EU) inhabitants, or around 8% of the EU's population (ranging from 0.3% to 27% (United Nations Development Programme 2022)), were reportedly unable to sufficiently heat their houses in 2020, as stated by the European Commission (2022). Energy poverty is also intrinsically related to SDG11 "Sustainable cities and communities". Half of global population, that is, 3.5 billion people, today lives in cities, and this figure is expected to increase to 5 billion by the year 2030. Problems in cities accumulate, and it is there where more EP is emerging and also where more solutions could be implemented (Hogares Saludables Getafe 2021).

Although energy poverty is usually linked to the SDGs7 and SDG11, energy poverty is present and has an influence on all the objectives of the agenda. Some of the objectives that are most influenced by energy poverty are the SDG1 "End poverty in all its forms everywhere" because poverty is a multidimensional phenomenon and energy poverty is only one of the faces of poverty; the SDG2 "Zero hunger" because families suffering from energy poverty allocate a high part of their income to pay energy bills at the cost of reducing spending on basic products such as food; the SDG3 "Good health and wellbeing" because living in a house with inadequate temperatures in winter and summer, or with mold and humidity, directly influences the health of those who inhabit it; and SDG5 "Gender quality" because women are more likely than males to fall into energy poverty due to economic, physiological, and socio-cultural factors (European Economic and Social Committee 2022; Hogares Saludables Getafe 2021).

Using the Internet of Things (IoT) to carry out intelligent activities by applying Artificial Intelligence (AI) is referred to as "Artificial Intelligence of Things" (AIoT) (Nozari et al. 2022). AIoT applications result from the combination of AI algorithms with data from RFID sensors (radio detection technology), which provide information to be analyzed and add features such as tracking and quick alerts to enhance decision-making (Nozari et al. 2022). The Internet of Things used to be made up of networks of embedded sensors that gathered data and delivered it to a distant server before AIoT. Once arriving at the server, a data analysis would be performed, often involving the use of several AI techniques (Corchado Rodríguez 2021). Zhang and Tao (2020) reviewed advances and promising AIoT applications from different perspectives, outlining the problems that AIoT faces as well as some future research prospects. They stated that while deep learning has advanced fast in many perception domains allowing numerous AIoT applications, more work should be done to develop edge intelligence. The authors concluded that several quick, shrewd, environmentally friendly, and secure AIoT applications would likely profoundly alter our world in the future.

In recent years, the role of AI and IoT for sustainable development has been studied. According to López Vargas et al. (2020), over 85% of IoT implementations are in alignment with SDGs. Analogously, the analysis of the pertinent data carried out in Vinuesa et al. (2020) revealed that AI may operate as an enabler on 134 targets (79%) across all SDGs, often via a technology advancement that may allow to get beyond certain current constraints. Bronner et al. (2021) reflected on the fundamental impact of the AIoT on sustainability. The authors concluded that the triple bottom line, which consists of the three interconnected dimensions of profit, people, and planet, may be significantly supported by the AIoT. According to Bronner et al. (2021) the AIoT is essential to managing energy supply and demand in a future with distributed renewable energy producers such as photovoltaics. It was identified that AIot has the potential to act as a major player in the energy sector making smart buildings, decarbonizing the energy sector through increased grid efficiency, renewable energy integration, and decentralized energy trading, and reducing needless energy use through automated monitoring and management of heating and cooling systems.

The lack of real data to accurately characterize EP in an objective way is one of the primary issues in addressing the problem. Consensual data based on self-reported assessments of home living conditions determined in surveys and spending data obtained from surveys or government sources make up the major sources of data for evaluating EP. Direct measurements of energy-related and ambient variables are extremely infrequently employed for the characterization of EP in comparison to those two sources of data (Ruiz-Rivas Hernando et al. 2022). Some studies employ generated data (obtained by using simulations) since measured data needed to assess algorithms is not readily available (López Vargas et al. 2022). The amount of data aggregation affects the models produced; certain metrics require extensive disaggregated data (López Vargas et al. 2022), but this data is occasionally unavailable. The great advantage of using AIoT in the context of EP is that it enables the generation of realistic models with disaggregated information. This approach helps to characterize EP in a way that is adjusted to reality, allowing the detection of hidden EP situations.

The main purpose of this chapter is to analyze the impact of Artificial Intelligence integrated with the Internet of Things in tackling the challenge of energy poverty. This chapter's practical goal is as follows: Sect. 2 first reviews the most relevant past research that use AIoT in the field of EP relief. The description is then structured into many EP applications built over the last three years in Sect. 3, which offer AIoT approaches for characterizing EP. Section 4 focuses on the AIoT application for thermal comfort characterization. Section 5, the final part of the manuscript, summarizes the findings and contains the conclusion and future lines.

2 State of the Art: AIoT and EP Alleviation

The existing published literature on the application of AIoT to EP alleviation was reviewed and a bibliometric analysis was carried out. Since 2020 there has been an exponential increase in publications focused on AIoT application for alleviating EP. The most popular subject was the AIoT application for EP forecasting. In this Section, the state of the art was reviewed by applying a specific methodology. First, the specific objective of the EP research study is summarized. Databases used (if any) and IoT systems (and associated monitoring systems) are analyzed. The selected AI algorithms and the data intake mechanism are then briefly discussed. Finally, the results of the research and the roles of the AIoT to alleviate are analyzed.

Hurst et al. (2020a, b) published a study focused on estimating family poverty using data from gas smart meters. The authors evaluated a person's socioeconomic position and the amount of government aid they received for paying their bills using decision trees and cloud analytics. The area under the curve (AUC) classification for establishing socioeconomic class was 74.2%, while the AUC classification for assessing whether the family received government help was 88.1%. A Two-Class Decision Forest was employed in both scenarios. Using smart loggers, CAD data, and ML algorithms, Fergus and Chalmers (2020) presented a unique method of monitoring EP risk in households in 2020. The CAD payload data was collected every 10 s and contained the accumulated energy values. 1-dimensional convolutional neural networks (1DCNN) were selected for revealing local features along the time series data, and learnable kernel filters were used to build feature maps. Overfitting was reduced fitting networks parameters, exploring weight sharing and adjusting local connections. Every house linked to a smart grid underwent non-intrusive monitoring and customized activities of daily life monitoring to produce an EP indicator (via existing smart meters and CAD information). The work of Wang et al. (2021) combined data from socioeconomic surveys and remote sensing for predicting EP. A random forest model in combination with two geographic and environmental parameters were used to predict future levels of EP. The authors concluded that a machine learning (ML)-based strategy that combined remotely collected spatial and environmental data with socioeconomic indicators outperformed those that relied solely on socioeconomic indicators, identifying 90.91% of the districts with high EP.

It was observed following the assessment of the state of the art that there are few studies concentrating on the AIoT application for addressing EP (considering EP a multifaceted phenomenon). Decision trees and neural network-based algorithms were the most often used AI approaches for alleviating EP. It was concluded that one of the main shortcomings is the lack of real data captured by non-electric sensors of smart meters. The absence of real-time and remote EP monitoring generates a great scarcity of real data in this field, which means that many works obtain data via simulations (Bienvenido-Huertas et al. 2023) or surveys. Other works use data from IoT systems but only from a partial aspect of EP, which means that there is a lack of works to accurately characterize EP as a multifaceted phenomenon.

3 AIoT-Based Approaches for EP Characterization

There aren't many studies that use AIoT to address EP (see Sect. 2). In recent years, a considerable number of AIoT deployments have been published concentrated on partial elements of EP or problems directly connected to EP that allow to characterize the problem in an effective way. The last version of the "Energy poverty and vulnerable customers in the energy sector throughout the EU: policy and measure analysis" (Pye et al. 2015) policy report of the European Commission was published in 2021 and analyzed how European Member States define EP and vulnerable consumers, as well as the actions put in place to alleviate it.

According to Pye et al. (2015), EP is defined by three key elements (either together or separately): low wages, high energy prices, and poor building thermal efficiency. The three main causes of EP are high energy prices, low income, and insufficient building energy efficiency (Pye et al. 2015) and the relationship between these drivers is depicted in Fig. 1. These 3 factors are directly linked to the overlapping areas of the graph: energy affordability, housing patterns, and energy usage patterns. Energy costs rise because of high energy use, which has a negative impact on low-income households. In the same way, the typology of the heating system has an impact on the building's efficiency and energy costs.

The works that use AIoT techniques for modeling and describing EP are summarized in this section. The review adheres to the distribution shown in Fig. 1 and is restricted to works released between 2020 and 2023. Each of the three EP drivers mentioned in the literature (see Fig. 1)—low-income, high-energy costs, and inefficient buildings—has its own part in this section.

3.1 Socioeconomical Situation

Income largely determines the fraction of the population at danger of falling into poverty and is a crucial criterion for identifying and diagnosing EP (International Bank for Reconstruction and Development 2022). Low educational levels, family size and composition (lone parent households and large families are especially vulnerable), disability or illness (since it affects one's ability to find work), gender (women are more likely than males to be poor), belonging to a minority ethnic group, living in a rural or having restricted access to services are some factors that are associated

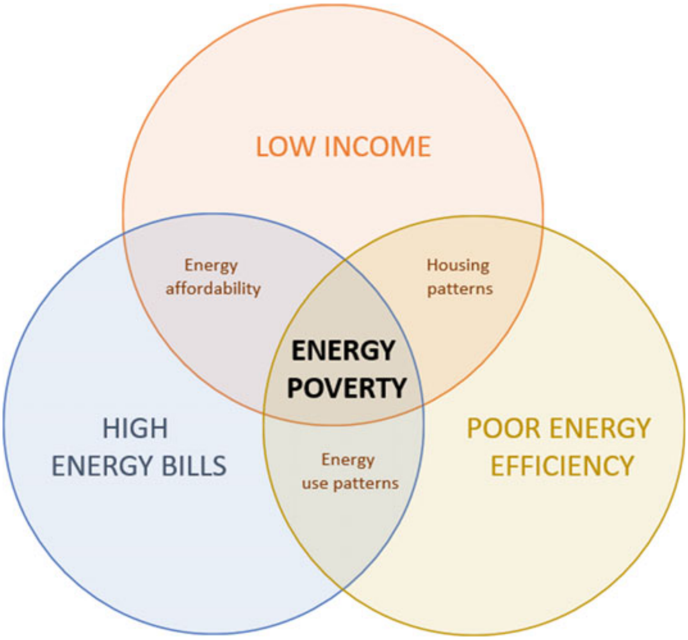

Fig. 1 Diagram for describing EP, encompassing important drivers and key indications (Pye et al. 2015)

with a low household income (and thus a higher risk of EP) (EAPN Website 2020). In this context, the number of research that applied AI algorithms on IoT data is minimal and the most studies developed were focused on identifying or anticipating poverty.

Usmanova et al. (2022) revised the most popular data sources used and studied AI applications in the context of poverty prediction. More than 35% of the reviewed papers included official local data in their analysis followed using data obtained from surveys (~15%). However, in recent years, data from remote sensors has been increasingly used in this context putting the usage of images in the fore. Figure 2 shows the frequency of data types used (including only the data obtained with IoT systems) in poverty prediction. Night-time light imagery (~17%) was the most used data. Google Earth images, high resolution daytime satellite imagery and land cover data were used in a third of the works that use data from IoT system so the use of images (often satellite) in the detection of poverty is highly remarkable. The authors determined that the use of remote data is highly beneficial in poverty prediction. On the AI techniques reviewed, when comparing linear regression and machine learning algorithms in this scenario, the latter proved more successful. Eventually, it was discovered that models with fewer variables had a higher predictive power.

Yeh et al. (2020) utilized publicly available satellite imagery and deep learning techniques to comprehend economic well-being. The researchers developed a CNN-based approach on satellite images achieving an accuracy rate of 81%. Their findings

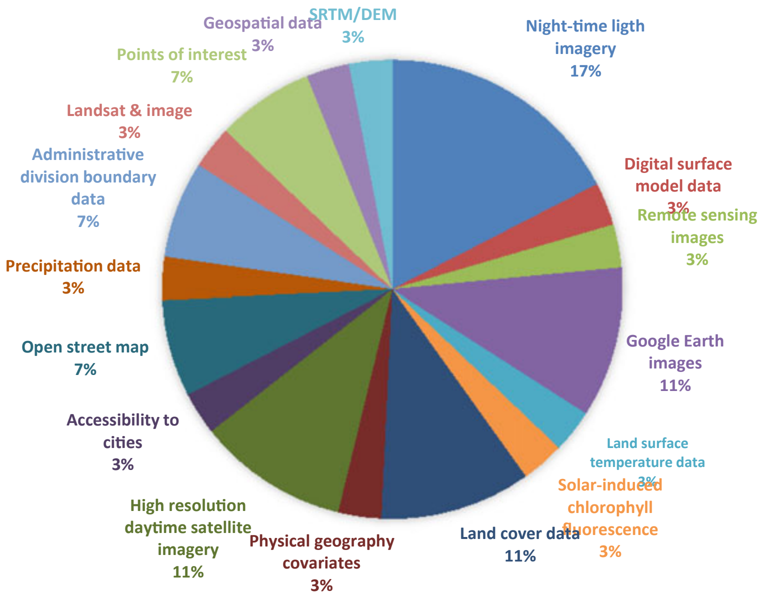

Fig. 2 Used IoT-data distribution in poverty prediction (Usmanova et al. 2022). The IoT data is used in approximately 50% of works reviewed by Usmanova et al. (2022)

showed that the deep learning algorithms utilizing satellite imagery to evaluate asset value is both scalable and accurate. Additionally, the consistent performance of the method on held-out nations indicates its potential to estimate wealth in countries where data is not readily available.

As conclusions, the AIoT integration has the potential to contribute significantly to poverty prediction and alleviation using socioeconomic data. By leveraging various data sources, including remote sensors and satellite imagery, AI algorithms can effectively identify and anticipate poverty patterns, offering valuable insights for targeted interventions. On the other hand, it was identified that the use of deep learning techniques jointly with satellite imagery enables accurate assessment of economic well-being and wealth estimation.

3.2 *High Energy Bills*

EP is highly associated with high energy expenses. According to the European Commission's "2020 Energy Prices and Costs" report (European Commission 2016), the average energy expenditure for the most impoverished European families was 8.3% of household income, whereas lower-middle and middle-income families spent 7.4% and 6.7%, respectively. In 2018, over 7% of European households couldn't pay their electricity bills (Eurostat 2020). Power outages and, in some situations, the emergence of unauthorized power connections are the final effects of not being able to pay bills. Both outcomes can be identified through bill discrepancies. Further links exist between EP and high energy costs. EP is typically the consequence of households not using enough energy to maintain a comfortable temperature. These situations can be clearly distinguished because of their unusually low bills in relation to the number of cohabitants. This factor is critical since short-term solutions to EP involve financial assistance to disadvantaged households who have been identified in order to help them pay their energy bills.

According to the European Commission report "Benchmarking smart metering deployment in the EU-27 with a focus on electricity" (European Commission 2011), in the year 2020, Member States rolled out around 45 million gas monitoring systems and 200 million smart meters for electricity measurements that were connected to telecommunications networks. Countries like Finland, Sweden, Italy, and Spain have already been deployed more than 80% of their smart meters. The data gathered by these smart meters provides valuable insights that can aid in mitigating EP. As a result of the large number of smart meters installed, several AIoT-based works have emerged, focusing on this area. The "high energy bills" driver is primarily comprised of energy cost, energy consumption, and billing irregularities and unpaid bills. While many AI-based solutions are available for forecasting energy expenses, no AI applications have been identified that utilize IoT system data related to energy cost. Therefore, this section has been divided into two subsections: energy consumption and billing irregularities and unpaid bills.

3.2.1 Energy Consumption

According to López Vargas et al. (2022), the electricity consumption forecasting was the most popular field for AI application related to EP alleviation in the last decade. Load forecasting involves estimating future loads using historical and present data. Forecasting loads in a smart grid is accomplished by considering consumer power use via smart energy meters and based on the time horizon, the AIoT application is different (Dewangan et al. 2023). There are different works dedicated to the calculation of energy consumption. There are many factors that influence the calculation of energy consumption, such as the climatic region in which it is worked out, the type of building or the number of cohabitants.

Fekri et al. (2021) used federated learning with Recurrent Neural Networks for forecasting distributed load using smart meter data. With federated learning (FL), an ML model was trained across several data holders, including edge devices and decentralized nodes. Data was kept locally, and only model changes were sent to the central server. The authors used numerous smart meter data dispersed across the network for load forecasting, and they trained a deep neural network without explicitly sharing data samples with the central server. 19 home users who each provided three years' worth of hourly energy consumption were used in the evaluation. Bolstad et al. (2022) demonstrated a practical application of eXplainable Artificial Intelligence (XAI) in day-ahead load forecasting in 2022. To achieve this, historical electric load and temperature data were transformed into daily samples of 24 features, corresponding to each hour of the day, and subsequently normalized to conform to the training data.

The most used AI method was neural networks-based algorithms (Lu et al. 2021), although aspects such as the lead time for predicting or the field of application may introduce differences. In addition, after exhaustive examination of the literature, it has been verified that the most common is to make predictions 24 h in advance. A significant area of attention has been load forecasting, which entails calculating future loads based on historical and current data. Applications of the AIoT for load forecasting vary depending on the desired time range and consumer power usage as measured by smart energy meters. Energy consumptions are usually included in this type of research, taking into consideration elements like climatic region, building type, and occupant count.

3.2.2 Anomalies in Energy Billing and Unpaid Fuel Bills

Utility bill arrears are a key indicator for detecting EP. Regarding this indicator, a high number of AIoT studies reviewed focus on the detection of Non-Technical Loss (NTL). NTL refers to "non-natural losses associated with the amount of unbilled electricity and unpaid billed electricity" (Viegas et al. 2017). Key indicators of the EP such as non-payments, thefts and other irregularities in bills are covered by NTL. As stated by the literature non-authorized connections, billing errors, meter manipulation or unpaid bills may be some of the causes of NTL. Yadav and Kumar (2021) carried out the review on the detection on NTL and electricity theft by using smart meters data and AI techniques. The authors concluded that the SVM and neural networks are the most used methods so far. These techniques are applied to fundamental aspects such as connection type and customer characteristics and include key aspects of the customers' consumption profile such as peak demand, demand variation or average load. They concluded that developing an automated and robust expert system for the detection of NTL is an urgent task. de Souza et al. (2020) presented a new system for identifying fraudulent consumers and detecting energy theft in advanced metering infrastructures. The authors combined the data captured by smart meters with databases for obtaining a best performance.

Another topic within this sub-section is the detection of abnormal energy consumption. Regarding the abnormal energy consumption detection by using AIoT systems, the main challenge is the lack of ground truth references about abnormal and normal consumptions (Himeur et al. 2020). To solve this issue, 2-stages models are employed. First, an unsupervised algorithm could be used in labeling the energy consumption data from the IoT system into two categories: normal consumption or abnormal peak. Then, supervised algorithms are applied for detecting anomalous consumptions (Lim et al. 2022). Himeur et al. (2021) reviewed the existing literature on abnormalities detection by applying AI algorithms. Excessive consumptions were studied and characterized by energy consumptions and occupancy data captured by sensors. The authors recommend the use of other data sources different than the traditional ones (energy consumption measurements) such as meteorological data and characteristics of household appliances. The authors pointed out the deep anomaly detection on the edge as the future trend in AIoT systems. Hurst et al. (2020a, b) employed density-based classifiers for estimating the number of outliers (which refers to high periods of anomalous energy consumption for example) and modelling trends in households. For detecting infrequent energy consumption density-based spatial clustering methodologies were applied among occurring groupings of people that have similar traits. Depending on the algorithm applied, they came to detect 53-218 outliers on a dataset comprised of 1,058,534 readings from 1,026 homes.

It was identified that the future trend in AIoT systems includes deep anomaly detection at the edge. NTL is associated with unauthorized connections, billing errors, meter manipulation, and unpaid bills. Fraudulent consumer identification and energy theft detection utilize smart meter data and databases. Density-based algorithms and spatial clustering are used for detecting periods of anomalous energy consumption.

3.3 Poor Energy Efficiency

Buildings are responsible for up to 40% of the world's primary energy consumption and 30% of its greenhouse gas emissions. Heating, ventilation, and air conditioning (HVAC) systems are among the main sources of primary energy consumption and carbon dioxide emissions worldwide (Kim et al. 2022). Research based on AIoT for inefficient energy buildings has been undertaken, notably for building performance (European Commission 2018, 2022). A vast number of research studies on building energy efficiency focus on the application of AIoT to identify building energy usage trends and management (Arivukkody et al. 2022; Das et al. 2021). Another use of AIoT in this area was the study of building occupancy and person behaviors (Ngarambe et al. 2019).

One of the challenges identified after the review of works focused on the study of the energy efficiency of buildings to combat energy poverty is the lack of real data. To solve this problem, on many occasions, he makes use of data from simulations. Al-Obaidi et al. (2022) reviewed the application of the IoT to energy efficiency in buildings. The authors found that IoT integration in building and city contexts had a positive impact on energy conservation. However, the widespread adoption of IoT-based technology has revealed weaknesses and limitations that are still hampered by a variety of challenges when implemented into the built environment such as insufficient comprehension of technologies and their applied methods. As a result, the study presents an overview of the main issues in this field and proposes viable paths for built environment professionals to take.

It was identified that AIoT enhances building energy efficiency, combating energy poverty by identifying trends, optimizing HVAC systems, and managing consumption. Buildings contribute to global energy consumption and emissions. Challenges include limited real data, reliance on simulations. IoT integration benefits energy conservation but faces comprehension and implementation obstacles. Solution: address challenges, improve efficiency in construction industry.

4 AIoT Approaches for Thermal Comfort Characterization

Because one of the most common definitions of EP is "the inability to afford adequate warmth in the home," thermal comfort is an important consideration. Traditionally, the concept focused on the health risks associated with low-income households experiencing low temperatures. However, in recent years, particularly since the summer 2003 heat wave that killed 35,000 people across Europe, research on the health risks associated with high temperatures has emerged (Ascione et al. 2017). Recently many works have pointed out the importance of the application of the AIoT in the context of thermal comfort and this interest has been transformed into the increase of works dedicated to this topic.

Regarding the AIoT-based systems for predicting thermal comfort, the most used algorithms were neural networks and decision trees. Somu et al. (2021) predicting thermal comfort in buildings by applying hybrid deep transfer learning strategy. For thermal comfort modeling, a controlled environment is chosen as the data source, equipping the building/zone under study with the necessary sensors and collecting the relevant data at regular intervals. The Synthetic Minority Oversampling Method was used to address the absence of adequate samples across all temperature settings in the existing thermal comfort datasets. The potential of convolutional neural networks to achieve an accuracy of >55% with little data in target buildings was demonstrated through experiments with two source datasets. Ramadan et al. (2021) compared various machine learning (ML) algorithms and the thermal gray box model to forecast the indoor temperature of a closed room. An IoT-based monitoring system was developed using sensors, an open hardware board and wireless communications. The outcome demonstrated that the thermal gray box model underperformed and that the best prediction was made using the extra trees regressor (ET) and ANN approaches. Focused on control applications, Zhao et al. (2020) demonstrated that the performance of AIoT applications for comfort controlling is superior to traditional control on energy-saving and comfort. Their system automatically completed a series of operations through IoT hardware devices distributed throughout the building. 1,700 data sets from simulation were used for training and then, the output predicted values were obtained and compared with the real figure.

Wang et al. (2022) carried out an analysis on the challenges of the AIoT. According to the study's findings, "lack of infrastructure," "insufficient funding," "cybersecurity issues," and "lack of trust in IoT and AI" are the main reasons that are holding back a greater expansion of AIoT. Focused on the specific case of the application of AIoT systems to alleviate EP by characterizing thermal comfort, the main shortcoming is the digital divide in vulnerable population (Eyrich et al. 2021) that impede the deployment of the AIoT applications. Research suggests that attempts to reach a population vulnerable to EP (older people, migrants, etc.) informed about the use of the Internet and the adoption of new technologies should consider aspects such as the socioeconomic situation and the access points available (Alliance for Affordable Internet 2021), requiring a greater effort.

After reviewing the works based on AIoT in the context of thermal comfort, it was verified that most of the works are dedicated to the prediction of thermal comfort and the control of thermal comfort systems using AI algorithms on data collected by IoT systems. It was identified that neural networks and decision trees were the most popular algorithms for characterizing thermal comfort.

5 The Future of the AIoT for Eradicating Energy Poverty

The future of AIoT is described as a combination of a few essential features after evaluating the existing situation and the difficulties in using AIoT to eradicate EP. Future challenges for AIoT deployment were identified and they include lack of infrastructure, insufficient funding, cybersecurity issues, and lack of trust in IoT and AI (among other). The digital divide among vulnerable populations may also impede the adoption of AIoT applications. Until now, AIoT has not relieved EP as much as it could have owing to a lack of sensing among the most vulnerable homes (who are the most likely to suffer from energy poverty). Sensorization of the most vulnerable people would allow for a more precise evaluation of the situation as well as the discovery of a greater number of the hidden energy poverty situations.

The review of research focused on AIoT-based systems applied to socioeconomical aspects (Sect. 3.1) has revealed a lack of usage of explainable methods in AI algorithms used. In the future, adding explainability to AIoT applications in this area will be critical, particularly for decision-making systems. More work focused on AIoT applications to alleviate EP should be done developing edge intelligence (Corchado Rodríguez 2021). Because the IoT network is dependent on a central server, a server failure, which would be imminent if overburdened with data, would result in a stop in the operation of the smart service for which the IoT network was implemented. As a result, decentralizing operations becomes a critical component of AIoT for alleviating EP. This is accomplished using the Edge Computing concept, which moves data processing to the network's edge. Artificial intelligence is present at the network's edge, where data may be processed, filtered, and evaluated. It is also feasible to give the network's edge the power to make judgments by implementing AI techniques. Because critical choices may be made more quickly at the network's edge, numerous social, environmental, industrial, and administrative processes can be streamlined. Since AIoT deals with extremely sensitive personally identifiable information that may be exploited for other purposes, improving cybersecurity is another of the key issues raised by its adoption to AIoT to alleviate energy poverty.

6 Conclusions

The use of AIoT has the ability to undertake EP and hence function as a driver for the achievement of Sustainable Development Goal 7. The application of AIoT can have a positive impact on reducing energy poverty by improving thermal comfort in homes. This can contribute to achieving Sustainable Development Goal 11, which aims to make cities and human settlements inclusive, safe, resilient, and sustainable. AIoT can help optimize energy consumption and reduce energy waste, leading to more efficient use of resources. It can also contribute to mitigating the effects of climate change by reducing carbon emissions. The main benefit of employing AIoT in the context of EP is that it allows for the development of realistic models using disaggregated data, characterizing EP in a most adjusted manner, and allowing the identification of hidden EP.

There have been few research focusing on the AIoT application for tackling EP (considering EP a multifaceted phenomenon). The most often employed AI techniques in the field of EP relief were decision trees and neural network-based algorithms. It was determined that one of the major flaws is the lack of true data acquired by smart meter non-electric sensors. Due to the lack of real-time and remote EP monitoring, there is a significant paucity of genuine data in this sector, hence many studies get data through simulations (Bienvenido-Huertas et al. 2023) or surveys. Some studies employ data from IoT devices, but only from a subset of EP, indicating a scarcity of works that adequately represent EP as a multidimensional phenomenon.

There has been little research focusing on AIoT to address EP (see Sect. 2). In recent years, a significant number of AIoT deployments have been documented, with a focus on partial aspects of EP or challenges closely related to EP that allow for effective problem characterization. After the review of the study of the AIoT to the socioeconomic situation, it has been verified that the most frequent is the use of images by satellite combined with algorithms based on convolutional networks for the study of poverty. The application of the AIot to the study of the "high energy bills" driver has been divided into two: energy consumption and unpaid bills. The energy cost calculation component has been left out of the study, because although there are many AI algorithms that are applied to them, no IoT applications have been found in this field. Regarding the AIoT application to energy consumption, the most utilized AI approach was neural networks-based algorithms, while factors such as prediction lead time or application field may create variances; in addition, the most usual is to make forecasts 24 h in advance. When using AIoT in "Anomalies in energy billing and unpaid fuel bills," it is usual to combine data from sensors with data from databases. As for the IoT, the measurement of electricity is extended. However, remote and real-time monitoring of other crucial aspects for calculating energy poverty is not well developed; this is especially significant when studying the poor energy efficiency of buildings. Thus, because of the lack of real-time and remote EP monitoring, there is a significant scarcity of real data in this sector, which implies that many studies collect data through simulations.

The concept of EP includes the inability to afford adequate warmth in the home, and thermal comfort is an important consideration. While previous research has focused on the health risks associated with low temperatures, recent studies have also highlighted the risks of high temperatures. There is growing interest in the application of AIoT in the context of thermal comfort, with most works dedicated to predicting and controlling thermal comfort systems using AI algorithms and data collected by IoT systems. Neural networks and decision trees are the most used algorithms for predicting thermal comfort.

The main limitation of this work is the reduced number of works that apply AIoT. The future of AIoT for alleviating energy poverty confronts obstacles such a digital gap among disadvantaged groups, a lack of infrastructure, finance, and cybersecurity problems. The ability of AIoT to relieve EP has been hampered by the lack of sensors in susceptible households. Decision-making systems in socioeconomical AIoT applications require AI algorithms that can be explained. By developing edge intelligence, activities may be decentralized, and critical actions can be made more rapidly. Because of the sensitive personally identifiable information involved, cybersecurity is another important concern for AIoT adoption in reducing EP.

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AIoT-Enabled Smart Grids: Advancing Energy Efficiency and Renewable Energy Integration

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Abstract The SDGs cover a wide range of issues, including poverty eradication, hunger, health, education, gender equality, clean water and sanitation, affordable and clean energy, decent work, industry and innovation, climate action, life below water, life on land, peace, and justice, and strong institutions, among others. Each goal has specific targets and indicators to track progress. Integrating AI (AI) and the Internet of Things (IoT) has revolutionized various industries, including the energy sector. This chapter explores the potential of AIoT-enabled smart grids in enhancing energy efficiency and integrating renewable energy sources. The synergy of AI and IoT technologies enables smart grids to dynamically adapt to changing energy demands and optimize energy distribution, contributing to a more sustainable and resilient energy landscape. The chapter presents a conceptual framework for AIoT-enabled smart grids, detailing components and design considerations for integrating AI algorithms with IoT devices in energy management. AIoT can advance energy efficiency through demand response, load management, and real-time data analysis. It also discusses integrating renewable energy sources, enabling accurate forecasting, optimization of renewable energy generation, and smart grid control to maintain grid stability. The chapter also addresses challenges and security concerns associated with AIoT in the

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energy sector, including technical challenges, data privacy, and cybersecurity considerations. Mitigation strategies and best practices for ensuring reliable operations are presented. Future trends and innovations in AI algorithms, edge computing, and the potential impact of 5G on AIoT-enabled smart grids are also discussed. Policy implications and regulatory frameworks are also discussed, emphasizing the need for a conducive environment to foster AIoT adoption in smart grids. In conclusion, this chapter highlights the significance of AIoT in transforming the energy sector and achieving energy efficiency and renewable energy integration goals. By harnessing the power of AI and IoT technologies, smart grids can pave the way for a sustainable and greener future. Recommendations for further research and implementation are provided, encouraging stakeholders to embrace AIoT as a key enabler for sustainable energy solutions.

Keywords AIoT · Smart grids · Energy efficiency · Renewable energy integration · Sustainable energy solutions

1 Introduction

The IoT has recently received much interest because of its ability to link and interoperate with many types of physical objects (Moradi et al. 2019b). This would make data transfer and automation much simpler. The technology behind AI has made major strides forward in recent years, allowing computers to learn, reason, and make choices independently of human input (Bhattacharya et al. 2021). The confluence of AI and the IoT, also known as AIoT, has arisen as a force transforming several sectors, notably smart grids. Consumers and the grid can engage in a two-way flow of energy and information with the help of these grids, which represent an evolution in the conventional power distribution systems that have been in use for decades. These grids include modern communication and control technology (Weissler et al. 2021). The IoT allows smart grids to dynamically adapt to changing energy needs, maximize energy distribution, and proactively react to shifting environmental circumstances. This synergy tackles important difficulties that conventional power grids face, such as inefficient energy utilization, excessive energy loss during transmission, and a lack of flexibility in accepting renewable energy sources (Varsha et al. 2021).

Sustainable development requires cooperation between governments, corporations, civic society, and people. The SDGs seek to abolish poverty, hunger, inequality, decent education and healthcare, sustainable economic development, climate change, and biodiversity by 2030 (Onkila & Sarna 2022). The SDGs need political will, enough resources, and effective policies. Governments define priorities, connect policies with SDGs, and raise funds. Sustainable business methods, innovation, and goal attainment are promoted. In conclusion, the SDGs provide a worldwide plan to end poverty, inequality, and environmental degradation. We must work together to achieve the SDGs (Murtazova & Khadisov 2022).

This research aims to investigate the applicability of AIoT in smart grids and determine its role in increasing energy efficiency and integrating renewable energy sources. It will look at previous studies and implementations that have already taken place in the real world, emphasizing the technical elements of integrating AIoT, the influence on energy efficiency, and the facilitation of integrating renewable energy (Bhattacharya et al. 2021). The research will also evaluate the policy ramifications and regulatory frameworks required to facilitate the implementation of IoT technologies in smart grids. The study will focus on the architectural framework, the integration of AI algorithms with IoT devices for energy management, and the role of AIoT in advancing energy efficiency and renewable energy integration. The scope of the study will include an extensive literature review of existing research and case studies on AIoT in smart grids, as illustrated in Fig. 1.

Smart grids change energy efficiency, renewable energy integration, and environmental sustainability. Smart grids help solve global energy problems by intelligently and efficiently managing energy supplies (Dibia & Nwaigwe 2017). Smart grids will help us reach our energy objectives and leave a better world for future generations. This will determine the field's current state (Ali et al. 2022; Dada et al. 2021). The study will also explore future tendencies and breakthroughs, such as improvements in AI algorithm development and the possible influence of 5G and edge computing on AIoT applications in agricultural environments. The importance of AI and the IoT in attaining sustainable agriculture and food security will be the primary focus of the research, with a particular emphasis on precision agriculture, remote sensing, monitoring, and weather forecasting. In addition, it will examine the deployment of smart irrigation and water management methods, livestock management, health monitoring, early disease diagnosis, IoT-enabled smart logistics, and supply chain tracking. The study results and suggestions will be useful tools for policymakers, energy sector stakeholders, and academics working on sustainable energy solutions.

This chapter is arranged into nine (9) different sections. Section 2 discusses the evolution of AIoT, and its application in energy systems are discussed in detail. The literature review is presented in detail in Sect. 3. Section 4 provides a discussion on AIoT-enabled Smart Grids: Concepts and Framework. Section 5 provides the advancing energy efficiency through AIoT in smart grids. Section 6 discusses the renewable energy integration in AIoT-enabled Smart Grids. Section 7 addresses challenges and security concerns, future trends, and innovations in Sect. 8. And finally, Sect. 9 concludes the study.

2 Evolution of AIoT and Its Application in Energy Systems

The expansion of the world's population, urbanization, and industrialization have all contributed to the rapid ascent of the demand for energy worldwide. On the other hand, traditional energy systems primarily dependent on fossil fuels have led to the destruction of the environment and climate change (Giuffrida et al. 2022). The notion of smart grids has evolved as a potentially game-changing approach

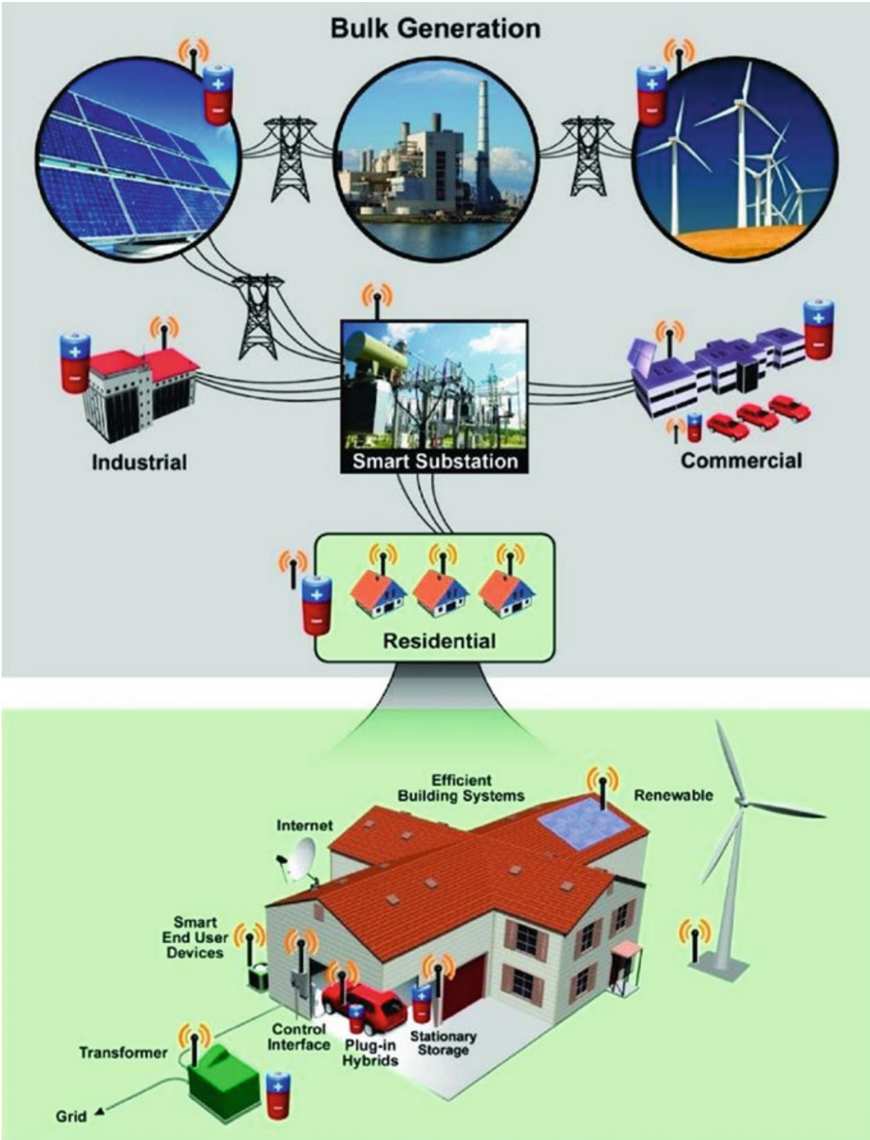

Fig. 1 Overview of AIoT-enabled smart grids (Torres et al. 2021)

to solving these difficulties. Smart grids bring together various forms of modern technology with energy distribution networks. Smart grids are playing a vital role in the advancement of energy efficiency as well as the seamless integration of renewable energy sources, paving the way for a more sustainable and greener energy future (Kumar et al. 2020). The IoT and AI have independently revolutionized many sectors, and merging AIoT is short for the "IoT," and it refers to a strong mix of cognitive data analytics and real-time connection that enables smart objects to communicate with one another, learn, and adapt on their own (Opoku et al. 2022). This chapter examines the development of AIoT and its important applications in energy systems, especially in the context of making strides toward increasing energy efficiency and integrating renewable energy sources. IoT's development, which led to the evolution of AIoT. The development of internet-capable smart gadgets and the ability to link such devices to the Internet gave rise to the idea of the IoT in the early 2000s (Shahinzadeh 2020). Because of this connectedness, huge amounts of data could be collected, and remote monitoring could be carried out. Developments in AI, in particular machine learning and deep learning algorithms, have made it possible for computers to analyze data, recognize patterns, and make judgments without the assistance of a human being. The combination of IoT and AI led to the emergence of AIoT, a concept in which connected devices may analyze data locally or in the cloud, learn from it, and optimize their operations (Salami et al. 2022).

AIoT allows accurate forecasting of energy needs based on historical data, weather patterns, and consumer behavior. Energy Demand Prediction AIoT enables precise forecasting of energy demands. Because of this, energy suppliers can optimise energy production and delivery to meet shifting consumer needs successfully (Nasrabadi et al. 2022). The IoT makes real-time monitoring and control of smart grids possible, improving the grid's stability and efficiency. It enables dynamic energy routing, load balancing, and demand response, ensuring that grid management is carried out effectively. AIoT devices may learn the energy consumption habits of users and offer energy-saving practices, which promote efficient energy use in both residential and business environments (Polleux et al. 2022). The IoT facilitates smoothly incorporating renewable energy sources into the power grid. It helps predict solar and wind energy availability, enabling utilities to plan energy storage and distribution according to those predictions (Yang et al. 2022). AIoT optimizes energy storage devices, such as batteries and energy storage units, by anticipating energy supply and demand and ensuring that energy is stored and released effectively. Depending on occupancy patterns, weather conditions, and energy prices, AIoT-based energy management systems may control building heating, cooling, and lighting (Wang & Tester 2023). This can result in considerable savings on energy use, as illustrated in Fig. 2.

3 Literature Review

Numerous studies (Lin et al. 2022; Nozari et al. 2022; Sahmim et al. 2019) have shown the potential advantages of AIoT-enabled smart grids and energy management, demonstrating the technology's ability to alter the energy landscape radically. Demand response, load forecasting, and energy routing are just some smart grid features that have benefited from using AIoT. Using machine learning algorithms, scientists have been able to forecast energy consumption trends and optimise energy

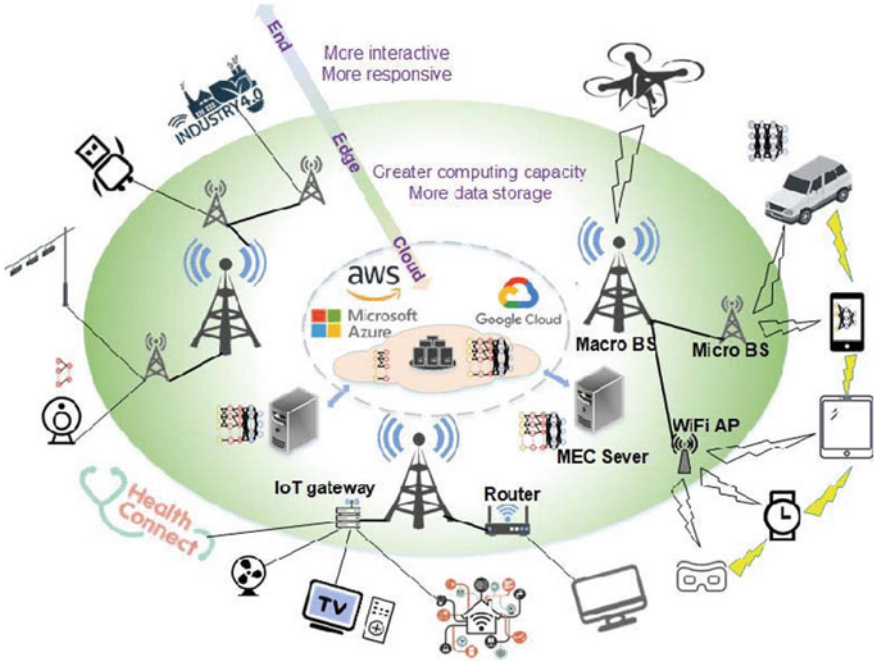

Fig. 2 AIoT and its application in energy systems (Çetin et al. 2021)

distribution appropriately and reliably (Chiu et al. 2022). These optimization methods help lessen the burden on the power grid and make smart grid operations more reliable. To achieve sustainability and lower carbon emissions, it is essential to include renewable energy sources like solar and wind in smart networks. Regarding maintaining a healthy energy supply and demand balance, AIoT is an indispensable tool (Rusch et al. 2022). Researchers such as (Chatterjee et al. 2018; Chen et al. 2018) have increased the stability and productivity of electricity production from renewable sources by using AIoT. Building energy efficiency is important for sustainable practices since buildings utilize a disproportionate amount of energy relative to their size. Bhattacharya et al. (2021) note that AIoT has been used in building management systems for smarter temperature, humidity, and lighting regulation. AI algorithms may reduce energy costs by adapting use to the demands of occupants based on data from IoT sensors.

When optimizing energy storage systems and demand-side management, AIoT is crucial. Weissler et al. (2021) note that AIoT algorithms can effectively operate energy storage devices to balance the grid, making them an important tool for regulating the intermittent nature of renewable energy production. Additionally, different demand-side resources may be more responsive using AIoT-enabled demand-side management, improving grid reliability. Data security and privacy are still major concerns as AIoT devices collect and analyze massive volumes of data from many different sources. Cybersecurity risks are exacerbated in smart grids because of the proliferation of IoT devices (de-Lima-Santos et al. 2022). Protecting sensitive energy-connected information requires addressing data security problems and adopting strong encryption and authentication mechanisms. Standardized protocols and frameworks are necessary to interoperability of various IoT devices and platforms in smart grids. Problems with interoperability might develop if multiple devices and systems use distinct communication protocols (Fedorchenko et al. 2022). To guarantee compatibility across particular AIoT devices, it is essential to develop common standards and protocols. Scalability and latency issues may occur as the scope and complexity of AIoT systems expand. To sustain effective energy management, large-scale smart grid rollouts need real-time data processing and decision-making (Meneses Silva et al. 2021). Research should be directed toward improving AIoT algorithms' scalability and reducing latency so that smart grids can operate effectively. While the IoT holds great potential for reducing overall energy usage, it is important not to lose sight of the energy used by IoT devices. AI algorithms that need a lot of processing power and frequent data transfer might raise the energy requirements of IoT gadgets (Varma et al. 2021). Sustainable AIoT deployment requires the creation of energy-efficient devices and the optimization of efficient algorithms.

Existing studies of AIoT-enabled smart grids and energy management show the technology's great promise in boosting energy efficiency and facilitating the incorporation of renewable energy sources. Some of the most potential uses of AIoT in energy systems include optimizing smart grid operations, integrating renewable energy efficiently, and enhancing building energy efficiency. Widespread adoption of AIoT is hindered by data security, interoperability, scalability, and energy efficiency issues. To fully realize the promise of AIoT in attaining sustainable energy practices and accelerating the worldwide shift to cleaner, more efficient energy systems, these challenges must be overcome.

4 AIoT-Enabled Smart Grids: Concepts and Framework

AIoT is a synergistic mix of IoT with AI that improves the functionality of IoT gadgets and infrastructure. Energy efficiency, renewable energy integration, and AIoT are three primary areas of concentration. Smart grids rely heavily on the IoT to collect and disseminate data on energy use, grid performance, weather, and renewable energy output (Badr et al. 2023). AI systems like machine learning and deep learning analyze massive volumes of data, making data collecting and aggregation vital procedures. Energy optimization, load balancing, and demand-response systems, all of which improve grid efficiency and dependability, need real-time decision-making (Moradi et al. 2019b). Autonomous control is another benefit of AIoT; it paves the way for AI algorithms to govern energy supply and demand, grid frequency, and storage system management. Reduced downtime and operating expenses are two key benefits of predictive maintenance. AIoT's ability to analyze user behaviour and environmental conditions improves energy efficiency and the incorporation of renewables (Shahinzadeh 2020). Together, the intelligence of AI and the massive amounts of data produced by IoT devices pave the way for smart grids to become more efficient, sustainable, and resilient. This method may achieve a cleaner, more sustainable energy future worldwide (Ali & Choi 2020).

AIoT-enabled smart grid architecture and design are critical for realizing the full potential of this new technology. A good strategy provides seamless integration, fast data processing, and intelligent decision-making, which leads to better energy management and grid efficiency (Sung et al. 2022). Edge computing, scalability and flexibility, data security and privacy, interoperability, and standardization, data analytics and AI integration, redundancy and reliability, real-time monitoring and control, and integration of renewable energy sources are all important considerations in designing AIoT-enabled smart grid architecture. Edge computing minimizes latency and assures real-time decision-making while reducing data volume transported over the network (Bano et al. 2020). Scalability and flexibility are required to accommodate the expanding number of IoT devices and the growing amount of data produced by these devices (Das 2022). Data security and privacy are critical, and encryption, authentication, and access control techniques that include encryption, authentication, and access control mechanisms are required. Interoperability and standardization encourage a vendor-neutral approach and help to prevent vendor lock-in (Aliahmadi et al. 2022a, b). Data analytics and AI integration are critical for energy optimization and demand forecasting. Incorporating AI algorithms into the design may enable intelligent decision-making and autonomous control. Redundancy and reliability mechanisms should be built into the design to guarantee continuous operation and minimize system failure risks (Nozari et al. 2022). Real-time monitoring and management of grid components are critical for operators to react quickly to changing grid conditions, optimize energy use, and handle any problems that may develop.

Ultimately, AIoT-enabled smart grid architecture and design considerations are critical for realizing the full potential of this disruptive technology. Smart grids may become more robust, sustainable, and capable of handling the challenges of the current energy environment by adding sophisticated analytics and AI algorithms (Kumar 2022). With the advent of energy management systems incorporating AI algorithms with IoT devices, power consumption, distribution, and optimization are all about to shift radically. Energy managers may balance loads, reduce energy waste, and streamline incorporating renewable energy sources using AI algorithms' real-time data analysis and prediction skills (Pise et al. 2022). The result is an energy ecosystem that is more robust, environmentally friendly, and cost-effective, all contributing to the worldwide push for a low-carbon, sustainable future. Intelligent IoT devices powered by AI can dynamically balance grid energy demands, increasing efficiency and reliability. Because of this, we can reduce our energy use and improve our productivity significantly (Mishra & Shrivastava 2021). To lessen our dependency on fossil fuels and reduce carbon emissions, AI-driven IoT devices

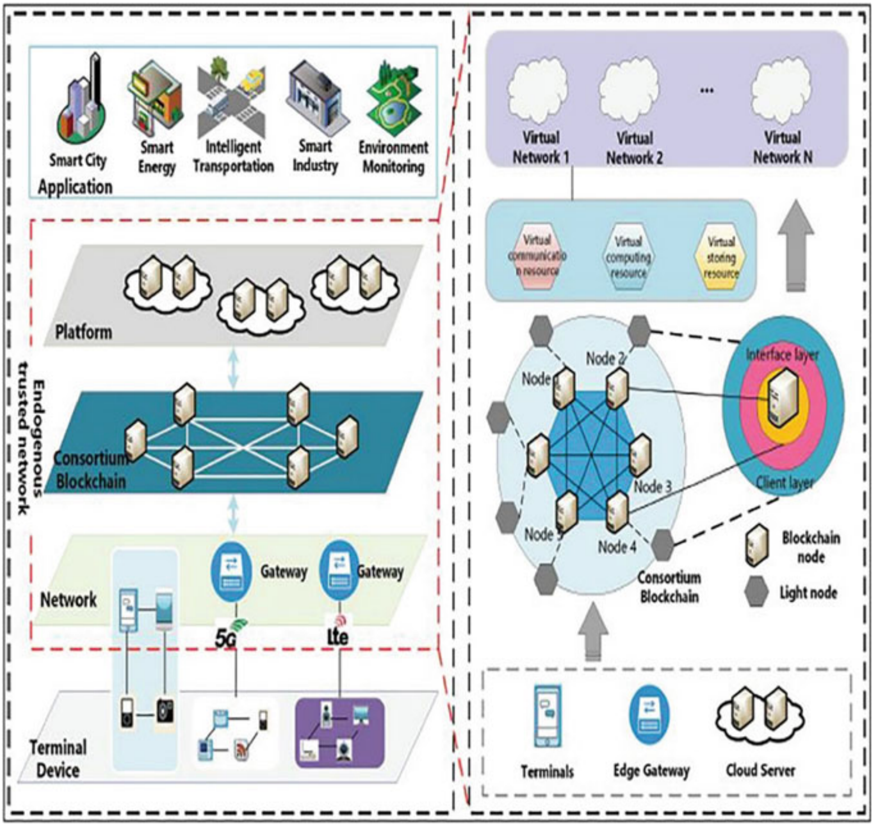

Fig. 3 The AIoT-enabled smart grids framework (Kumar 2022)

may analyze meteorological data and renewable energy production trends to coordinate the most efficient use of clean energy. IoT devices powered by AI also provide consumers with granular data on their energy use and expenses, so they can make educated choices to reduce their carbon footprint (Aliahmadi et al. 2022a, b). Thus, the AIoT-enabled smart grid framework is provided in Fig. 3.

5 Advancing Energy Efficiency Through AIoT in Smart Grids

Energy efficiency has come to the forefront of the conversation in recent years due to expanding worldwide demand for energy, environmental concerns, and the need for sustainable energy solutions. There is tremendous potential for improving energy efficiency and radically altering energy management practices via AI in smart grids

(Moradi et al. 2019b). Focusing on demand response and load management, predictive analytics and energy consumption optimization, and smart metering and real-time data analysis for energy conservation, this chapter examines the role of AIoT in promoting energy efficiency in smart grids (Torres et al. 2021). Efficient energy management relies on demand response and load control, which may benefit from using AI and other IoT technologies. With the help of AIoT, utilities may dynamically alter energy use in response to demand changes thanks to real-time monitoring of energy consumption and demand trends. Automating demand response programs requires combining AI algorithms with IoT devices like smart thermostats and appliances (Wahab Ahmed et al. 2017). By moving less important loads to off-peak times, AIoT may ease grid pressure and reduce unnecessary energy waste during peak times. AI's predictive analytics skills are essential to optimizing energy use. AIoT can forecast future energy demand and consumption patterns by analyzing past data and weather patterns (Badr et al. 2023). Using this information, utilities and customers may better manage energy consumption, allocate resources efficiently, and reduce energy prices. Predictive analytics also allows preventative maintenance and prevents downtime by predicting possible grid faults or disturbances (Dalipi & Yayilgan 2016).

An integral part of AIoT-enabled smart grids, smart metering offers real-time data on energy use at the individual consumer level, which may be analyzed for conservation purposes. AI systems process this information to provide targeted advice on reducing energy use (Ali & Choi 2020). AIoT promotes energy saving and behavior modification by providing users with real-time data. Informed consumers may make better choices about energy usage, resulting in cost savings and a more environmentally friendly lifestyle. Smart grids rely heavily on AIoT to facilitate the incorporation of renewable energy sources like solar and wind (Moradi et al. 2019a). AI systems can anticipate the availability of renewable energy based on meteorological conditions, allowing for modifying energy consumption habits. This synchronization facilitates the shift towards a more sustainable energy environment by maximizing the use of renewable power and decreasing dependency on fossil fuels (Cliff et al. 2023). Smart grids may optimize energy distribution and identify defects or abnormalities with the help of AIoT's real-time data analysis and automation (Saad et al. 2023). By rerouting energy flow and balancing demands, AI algorithms can keep the grid stable and supplies going without interruption. This capacity to repair itself is a boon to the efficiency and dependability of the power grid as a whole (Cliff et al. 2023).

To summarise, AIoT is a game changer in promoting energy efficiency in smart grids. Automation of demand response and load control, optimization of energy use via predictive analytics, and consumer education about energy saving are all possible thanks to AI and IoT (Luzolo & Tchappi 2023). Sustainable and efficient energy systems are further improved by the role of AIoT in integrating renewable energy sources and providing grid optimization and self-healing capabilities. AIoT provides a viable route towards a greener and more energy-efficient future as the globe strives to solve energy consumption concerns and environmental sustainability (Saad et al. 2023).

6 Renewable Energy Integration in AIoT-Enabled Smart Grids

The increasing need for eco-friendly power options has spotlighted renewables, including solar, wind, and hydro. Smart grids powered by AI have the potential to dramatically alter the energy environment in favor of a greener, more sustainable future (Shahinzadeh 2020). AIoT is crucial in finding solutions to the problems associated with incorporating renewable energy sources by optimizing generation, transmission, and consumption in real time. Smart grids can predict the availability of renewable energy, balance energy supply and demand, and maximize the use of clean energy by using AI algorithms. This integration results from improved grid stability, lower carbon emissions, and the beginnings of a sustainable energy environment (Ning 2021).

Applications of AIoT in integrating renewable energy span various capabilities, from forecasting and predictive analytics to management of energy storage and demand response and demand-side management to grid optimization and flexibility to decentralised energy production (Gawusu et al. 2022). Clean and sustainable energy, grid resilience and dependability, cost savings, and decentralised energy production are just a few advantages of incorporating renewable energy into AIoT-enabled smart networks. Data privacy, cyber security, and scalability are just some of the obstacles that must be overcome (Salami et al. 2022). Standardized protocols, data security, and removing technological impediments all need cooperation between governments, companies, and academic institutions. Sustainable energy and combating climate change, in conclusion, need the widespread use of smart grids that the AI of the IoT enables (Governance & Management 2019). Using AI to improve renewable energy utilisation, grid stability, and clean energy consumption via forecasting, energy storage management, demand response, and grid optimisation. The transition to a sustainable and resilient energy future may be hastened by overcoming obstacles and tapping into the promise of AIoT (Moradi et al. 2019b).

6.1 AIoT for Forecasting and Optimizing Renewable Energy Generation

In order to battle climate change and make progress towards sustainable development objectives, there must be a worldwide transition towards the use of renewable energy sources (Badr et al. 2023). Incorporating AIoT technology into renewable energy systems has emerged as a viable option to overcome the issues posed by the fluctuating energy production that occurs when using renewable sources (Torres et al. 2021). Combining the capabilities of AI with those of the IoT and data analytics, AIoT provides a potent toolkit for predicting and optimizing renewable energy production in real-time. Using historical data, weather patterns, and other pertinent criteria, AI techniques, such as machine learning and deep learning, allow reliable forecasting of renewable energy output (Ali & Choi 2020). The optimisation of renewable energy generation using IoT-based AI entails making real-time adjustments to the amount of energy produced in response to shifting needs for energy and conditions on the grid. AI algorithms can analyze real-time data from IoT sensors to optimize energy dispatch (Ali & Choi 2020; Moradi et al. 2019b). This ensures that produced renewable energy is used effectively, and there is no waste. Enhanced energy efficiency, grid stability and dependability, cost savings, scalability, and flexibility are some advantages that may realize through using AIoT to produce renewable energy (Dalipi & Yayilgan 2016). Accelerating the transformation of energy systems worldwide to clean, sustainable, and resilient ones depend on the effective integration of AIoT for producing renewable energy. It is anticipated that the combination of AI and IoT technologies will play a major role in determining the future of renewable energy integration and the fight against climate change as these technologies continue to improve (Kariuki 2021). Figure 4 shows AIoT for forecasting and optimizing renewable energy generation.

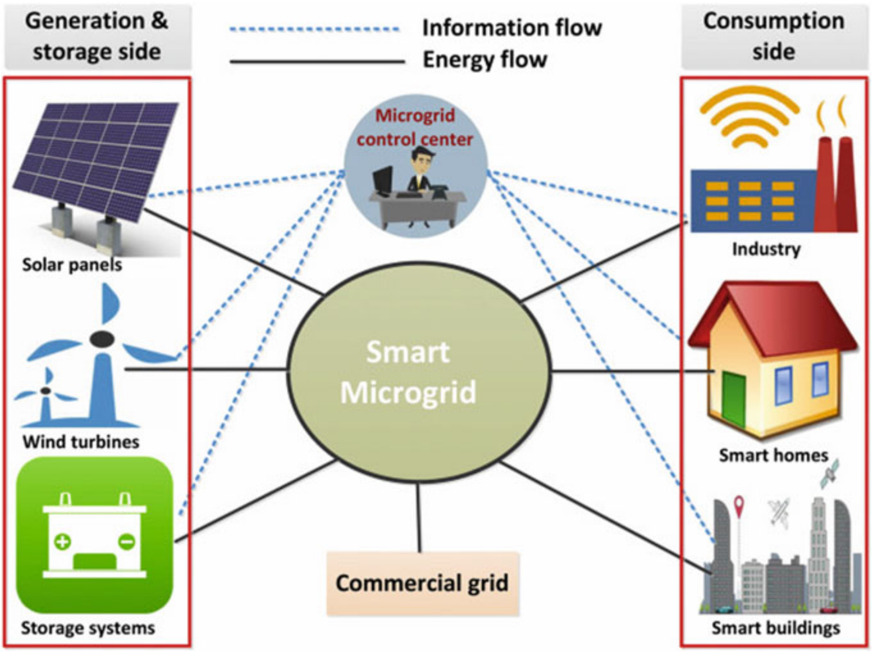

Fig. 4 AIoT for forecasting and optimizing renewable energy generation (Haseeb et al. 2019)

6.2 Smart Grid Control for Grid Stability with High Renewables

Due to the intermittent nature of renewables like solar and wind, maintaining grid stability has become a significant concern as they have been integrated into electricity systems. Controlling the power grid using cutting-edge technology like AI and the IoT is essential for maintaining grid reliability and maximizing renewable energy sources (Dixit 2018). AI and IoT technologies play critical roles in smart grid control, maintaining grid stability and dependability by facilitating real-time monitoring, management, and coordination of distributed energy resources to balance supply and demand (Lu 2018). Energy storage integration maximizes energy storage devices like batteries, while demand response programs motivate customers to alter their power use in response to grid circumstances. Accurate predictions of renewable energy supply and demand patterns are now possible with AI-based predictive analytics, enabling grid operators to anticipate swings and take preventative actions to maintain system stability (Das et al. 2022). Decentralized grid management, in which renewable energy supplies are controlled locally, decreases reliance on long-distance transmission while increasing system resilience by enabling each local grid to function autonomously in the event of grid interruptions (Heydari et al. 2019).

When many renewables are connected to the grid, stability is essential, and here is where AI and IoT come in. Optimization of renewable energy resource utilization and grid stability is achieved via smart grid control's combination of demand response, energy storage integration, predictive analytics, and decentralized grid management. Since renewables are expected to be increasingly important in the global energy transition, adopting smart grid control technologies is crucial to ensuring a secure and sustainable energy future (Lin et al. 2018). Thus, Fig. 5 illustrates smart grid control for grid stability with high renewables.

7 Addressing Challenges and Security Concerns

The digital age presents numerous challenges and security concerns for businesses and organizations. Cybersecurity threats, data privacy, and regulation compliance are crucial for organizations to thrive. To address these challenges, organizations should implement robust cybersecurity measures, conduct regular security audits, and implement transparent data handling policies (Orabi et al. 2020). AI and ethics concerns arise from the growing integration of AI technologies, which require ethical guidelines and human oversight. Cloud security is essential for scalability and cost-effectiveness but also introduces security challenges like data breaches and unauthorized access (Meneghello et al. 2019).

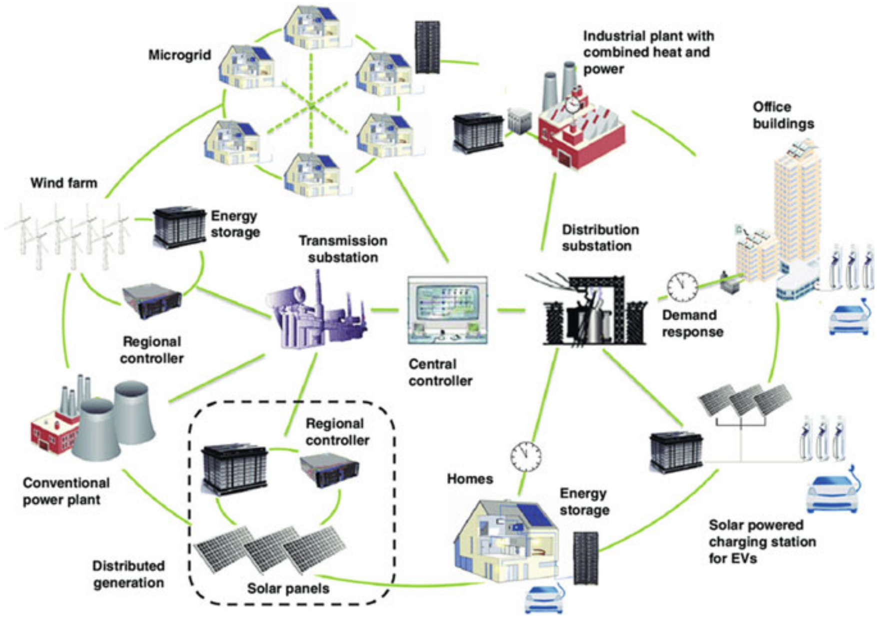

Fig. 5 Smart grid control for grid stability with high renewables

7.1 Technical Challenges in AIoT Implementation for Smart Grids

The energy industry benefits greatly from smart grids that use AIoT to improve grid efficiency, optimise energy usage, and smooth the way for incorporating renewable energy sources. However, there are a number of technological hurdles that must be overcome before AIoT can be successfully used in smart grids (Das 2022). Due to the massive amount of data created by IoT devices and sensors, data management and processing pose substantial hurdles in AIoT adoption for smart grids. Edge computing, cloud-based solutions, interoperability, standards, security, privacy, energy efficiency and power consumption, real-time decision making, and high-performance computing are all possible approaches (Nozari et al. 2022). The use of industry standards, open application programming interfaces, and energy-aware algorithms may facilitate the smooth flow of information between various parts. Protection against unauthorised access and continued confidence in the reliability of the smart grid infrastructure may be achieved via the use of robust encryption mechanisms and secure authentication techniques (Hiou 2022). It is a considerable problem to balance energy efficiency and the reliable functioning of AIoT components. Another technological obstacle to using AIoT for smart grids is making real-time decisions. AIoT edge analytics may decrease latency, and high-performance computing capabilities can allow for real-time data processing and analysis (Aliahmadi et al. 2022a, b). These obstacles may be surmounted, and the full potential of AIoT for smart grids can be realized if the energy sector adopts creative solutions and works with industry stakeholders. This will pave the way for a more efficient, dependable, and sustainable energy future.

7.2 Mitigating Risks and Ensuring Reliable Operations

Choose reputable cloud service providers with robust security measures and compliance certifications, and ensure data encryption before storing data in the cloud (Wu et al. 2022). IoT vulnerabilities arise from the proliferation of IoT devices, which can lead to disruptions in critical infrastructure sectors. Addressing these challenges requires ongoing vigilance, collaboration with industry peers, and adherence to best practices to avoid emerging threats and ensure a safe and secure digital future.

There are several advantages to incorporating AIoT into energy systems, including better efficiency, optimized energy usage, and better grid management. Nonetheless, major concerns over data privacy and cyber security are being raised in response to this expanding interconnectedness (Oyebode 2022). Strong safeguards are required to prevent data breaches and guarantee customer privacy due to the sensitive nature of energy data and the risk of cyberattacks. Real-time energy usage, user behaviour, and personal information are just some of the types of data that AIoT-enabled energy systems create (Zhu et al. 2015). Solutions may include data encryption, anonymization, frequent security audits, software patching, secure communication protocols, and mutual authentication to preserve customer confidence and meet data protection standards. Inadequate cyber defenses leave our nation's power grid vulnerable to hacking, data tampering, and outages. Vulnerabilities may be found and patched ahead of time if security checks and updates are performed routinely (Çetin et al. 2021).

When it comes to data privacy and cybersecurity, insider threats are a major concern. Role-based access control, training of staff, and data retention and deletion rules are all vital in reducing these dangers. When data is no longer required, it should be deleted securely and permanently following established data retention regulations and by other means of secure elimination (González et al. 2021). Finally, AIoT-enabled energy systems have enormous prospects for energy efficiency and sustainable management but also create cybersecurity and data privacy issues. A holistic strategy is necessary to reap the advantages of AIoT in energy systems while minimizing hazards (Ranjbari et al. 2022). For AIoT-enabled energy systems to have secure data storage and communication, collaboration between industry stakeholders, legislators, and technical experts is essential (Ochieng et al. 2022).

8 Future Trends and Innovations

A more sustainable and efficient energy future is possible by using AIoT in smart grids. AIoT leverages AI and IoT connectivity to improve electricity production, transmission, and consumption (Das 2022). Machine learning for predictive maintenance, edge computing for real-time decision-making, and swarm intelligence for grid optimization are just a few examples of the latest and greatest in AI algorithms and edge computing for smart grid applications (Muhammed et al. 2022). Microgrids may use AIoT to facilitate decentralized energy management and achieve dynamic local load balancing. Blockchain technology can revolutionize energy trade by reducing direct peer-to-peer transactions between energy prosumers, leading to greater energy efficiency and sustainability (Muhammed et al. 2022; Tham et al. 2023). Real-time data interchange is crucial for grid optimization, and the combination of 5G and AIoT in energy management will make that possible (Tham et al. 2023). Decisions powered by AI may be made in real-time at the network's edge, thanks to edge intelligence and 5G edge cloud computing. Improvements in AIoT technologies are important to the development of future smart grids (Al-Anbagi et al. 2013; Torres et al. 2021). Future smart grids will be more effective, dependable, and environmentally friendly because of the development and refinement of AI algorithms, edge computing, swarm intelligence, and the advent of 5G networks.

Adopting these emerging practises and technologies can hasten the shift to a cleaner, more resilient energy environment, bringing the world one step closer to its sustainability objectives. The full potential of AIoT in defining future smart grids will need concerted efforts by academics, policymakers, and industry stakeholders working together.

9 Conclusion

In this chapter, we have discussed the concepts of smart grids enabled by the IoT and how they may be used to improve energy efficiency and incorporate renewable energy sources. We addressed how AIoT has developed through time and how it may play a part in making energy systems more sustainable. Our research reveals that AIoT has considerable promise in optimising energy usage, demand response, and renewable energy source integration into the grid. Improved energy efficiency and responsiveness may be achieved via AI and IoT devices in energy management, which allows for real-time data analysis and predictive analytics. To help achieve the larger objective of sustainable energy systems, AIoT is being used to improve the manufacturing process's predictability and efficiency of renewable energy. Further, by effectively regulating the fluctuation of renewable energy sources, grid stability is maintained via AIoT in smart grid management in the presence of high renewables. Smart meters and real-time data analysis are further areas where AIoT proves its worth, empowering customers to make more sustainable energy selections. Smart grids enabled by the IoT need further study and deployment as we go ahead. Prospects for the future include developments in AI algorithms and edge computing, which may improve the responsiveness and efficiency of smart grids via improved decision-making.

Microgrids and peer-to-peer energy trading provide another promising avenue for the IoT to play a significant role in optimising energy distribution within local communities, hence fostering greater energy independence and efficiency. Finally, we need to investigate how the combination of 5G and AIoT could alter the face of energy management. The total efficiency of smart grids may be increased due to 5G networks' high bandwidth and low latency, facilitating better communication and coordination amongst IoT devices. It is essential to resolve the difficulties and security issues associated with integrating AIoT into power grids to achieve these goals. Safeguarding sensitive data and ensuring the safe functioning of smart grids necessitates paying attention to data privacy and cybersecurity concerns.

In conclusion, AIoT has the potential to significantly improve smart grids' energy efficiency and enable the integration of renewable energy sources. AI and the IoT can help us build cleaner, more reliable energy infrastructure. To make the transition to clean and sustainable energy systems a reality, more study, cooperation, and use of AIoT are required.

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Achieving SDGs Using AI Techniques and Digital Twins for Nuclear Power Plants: A Review

Kousik Barik, Sanjay Misra, and Harald P.-J. Thunem

Abstract With the rapid growth of digitization, the potential usefulness of Artificial Intelligence (AI) and Digital Twins (DTs) in Nuclear Power Plants (NPPs) are being explored. The Sustainable Development Goals (SDGs) conform as an exhaustive framework tracing methods for attaining stability and prosperity for society and the atmosphere, both in the current and extended term. This chapter explores the specific activity of DTs in NPPs and AI tools employed in NPPs for decision-making, simulations, optimization, and operations. The chapter discusses the goals of the SDGs that can be attained by implementing DTs. The chapter emphasized the challenges of utilizing AI techniques in NPPs, the open issues of integrating AI and DTs, and future study direction.

Keywords Digital twin · Artificial intelligence · SDGs · Nuclear Power Plant

1 Introduction

Countries worldwide are increasingly endorsing low-carbon policies in reaction to the swift expansion of multinational economizing. These approaches aim to lessen the use of high-carbon aids and greenhouse gas emissions by altering the energy composition. Sustainable economic development aims to prioritize environmental safety (Badruddin 2023). They are renewable, which makes wind power, solar energy, and other non-fossil energy sources competitive. Nonetheless, the persistent issue of energy supply instability caused by these energy sources' volatility, intermittency,

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and additional limitations endure until energy repository techniques are sufficiently grown (Schär et al. 2023). Given these occurrences, nuclear energy can be a dependable and sustainable source of energy that provides consistent electricity, making it a valuable strategic choice (Imran et al. 2023). Nuclear power plants must demonstrate economic efficiency and ensure safety, reliability, and sustainability to be more competitive and integrated within contemporary energy systems (Hrinchenko et al. 2023). Emerging technologies are increasingly being integrated into enterprises in recent years.

The emergence of digitalization has stimulated diverse industries to create systems that support them throughout their projects (Boukhatmi et al. 2023). The merging of the physical and virtual worlds is increasingly recognized as a significant factor in innovation, commonly called digitalization. Digital solutions provide significant value for institutions. The concept of DT represents a specific manifestation of creating digital solutions (Menon et al. 2023). The term digital twin can have various interpretations contingent upon the context employed. The fundamental concept is a comprehensive system simulation incorporating various physical models, sensors, and historical data from a fleet to accurately replicate the system's behavior (Glaessgen and Stargel 2012). Virtual replication of physical reality, encompassing objects, resources, or processes, is an alternative definition. This replication can range from simple to complex. The efficacy of this technology has been evaluated in diverse contexts, encompassing aviation, industrial applications, and facility management (Lukaj et al. 2023). In recent years, digital twins have garnered significant attention in academic and industrial domains, encompassing various related concepts, publications, advantages, and methodologies (Zhu et al. 2023). The concept of the digital twin of the customer (DToC) was introduced in Gartner's 2022 Report. The DToC refers to an active virtual replica of a consumer that can simulate, learn, emulate, and anticipate behaviour (Pinnock et al. 2023). A significant challenge in digital twin technology involves maintaining the accuracy of models in the face of system modifications (Chen et al. 2023). Therefore, it is imperative to regularly update the digital twin to ensure an accurate representation of the system's behaviour (Overbeck et al. 2023).

AI has rapidly been deployed in high-tech sectors, reducing costs, improving profit margins, and increasing industrial competitiveness (Zheng and Fen 2023). The nuclear energy sector has significant potential for contemporary AI technology due to the substantial underutilized data amassed by numerous nuclear power plants over the past few decades. In the present era, several nuclear scientists are exploring combining the nuclear industry with AI. However, it is worth noting that most AI applications aimed at enhancing the capabilities of the nuclear drive are still in the preliminary exploratory phase (Sethu et al. 2023). The implementation of these solutions in practical contexts is hindered by inherent challenges, including but not limited to algorithmic robustness. Therefore, studying AI technology's appropriate, effective, and thorough utilization will be vital for advancing sustainable innovation in nuclear power reactor research. Various stages, such as design, construction, operation, maintenance and decommissioning, are involved in the life cycle of a nuclear plant. Given the prevalence of existing studies, the importance of AI research in

Table 1 Research questions

Numbers	Research questions
RQ1	Which methods for which specific activity purposes of DT in NPP?
RQ2	What AI/ML tools are used in NPP for decision-making and simulations?
RQ3	What AI/ML tools are used in NPP for optimization and operations?
RQ4	How can the goals of SDGs be attained by implementing DT in NPP?
RQ5	What are the open issues and challenges of implementing DT and AI in NPP?

nuclear reactors using digital twins is analyzed in the current study. This paper aims to address the research questions as presented in Table 1.

The remaining chapter is formatted as follows. Section 2 illustrates the NPP overview, digital twins' capabilities, and various methods and activity purposes in NPPs. The application of AI in NPPs for decision-making, simulations, optimization, and operations maintenance is presented in Sect. 3. The attainable goals of SDGs by implementing DTs in NPPs are presented in Sect. 4. The open issues, challenges, and future study direction in implementing AI in NPPs are described in Sect. 5. Section 6 concludes the chapter.

2 Overview of NPP, Stages, and Usage of DT for SDGs

Nuclear Power Plant (NPP) systems provide thermal power via fission, compelled by the interchange of neutrons. The preceding aspect of fission in retail power exhibits is uranium (Kochunas and Huan 2021). State-of-the-art nuclear plants operate commercially and may utilize other power transformation processes. These elements need to be digitized and supported to create a DT. However, nuclear power designs can have many additional elements (Cramer et al. 2022). The power transformation methods for nuclear power are identical to those employed in the fossil enterprise; there is significant overlap in the elements needed for digitization to create a DT. The descriptive element of nuclear energy methods is the nuclear substance. However, certain alternate systems and elements operate admirably with technical elements, yet they are the radiological impact on fresh-water caused by highly intense radiation environments (Wada et al. 2016).

Some earlier U.S. Government study agendas also employed physical twin aids to produce reactor systems (Repacholi and Greenebaum 1999). Since then, there has been little invention or refinement in DT. Consequential advancements have been completed in the technological underreach of the different elements, design, and linked measurement measures. Still, there has yet to be much in envisioning the physical techniques and twins or usage (Kablov 2020). Figure 1 demonstrates a high-level concept of DTs used in NPPs. The process flow for Physical Twin is demonstrated, i.e., application and functionality, operations, and maintenance. Based on the prediction, it learns, simulates, analyzes, and predicts. The Virtual and Physical Twin are updated continuously.

DTs can be used in different enterprises such as production, agribusiness, instruction, structure, pharmaceutical, and commerce (Singh et al. 2022). DTs can employ/use ML methods, SVD, auto encoders, and generalized latent assimilation.

It is essential to handle two overarching technological requirements: (1) modelling and simulation and (2) data governance (Yadav et al. 2021). The components encompassed by DTs in the context of M&S consist of various elements: data analytics, AI

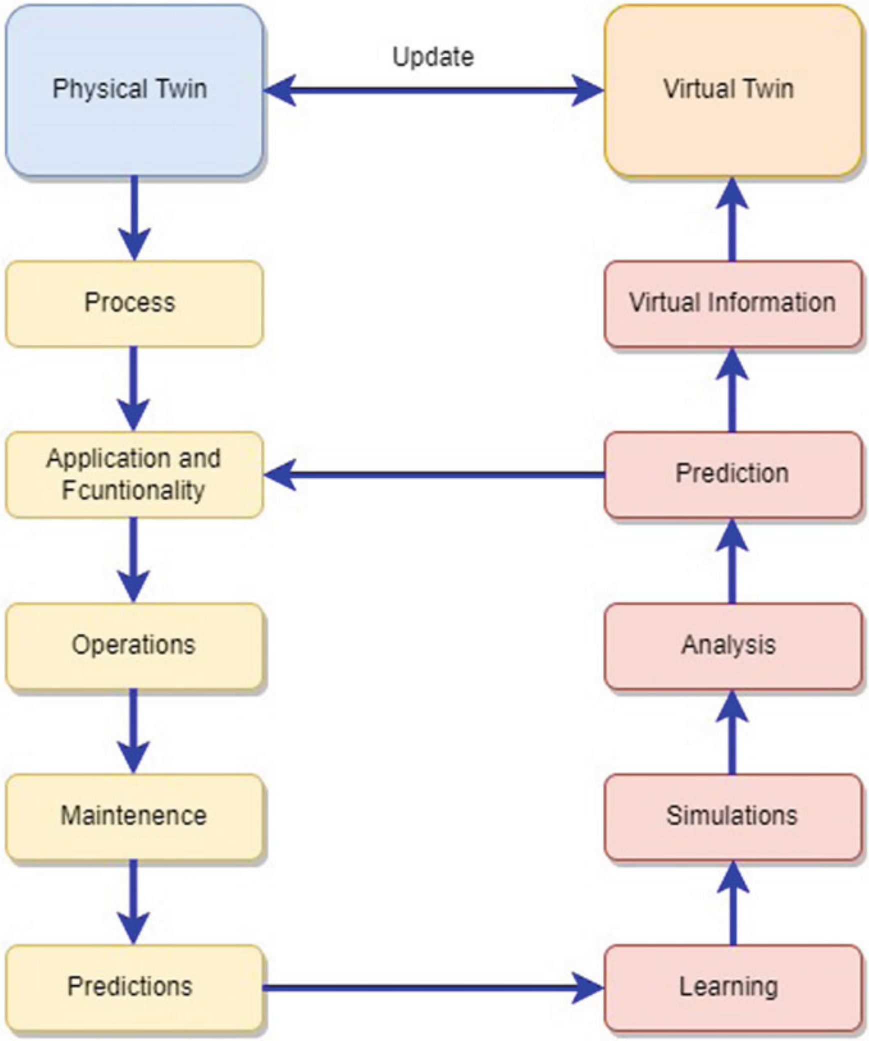

Fig. 1 High-level concept of DT

and ML, physics-based models, data-informed models, and others. These components are utilized to estimate the current and prospective requirements of the physical twin. Data and information administration concerns the structure of a framework for organizing, processing and transmitting data. This framework must adhere to applicable rules and current data for individuals and user applications in a coherent, assimilable method capable of being authenticated for accuracy and reliability (Yadav et al. 2021). This method encompasses various information repository methods, including local storage, data infrastructure, and cloud-based repositories. It also includes software solutions that facilitate the smooth integration of diverse factory information, continuous information accessibility, and instantaneous interchange across DT instances and data repositories. It also confines interfaces outside the primary command center, such as a plant monitoring and diagnostic command, a modelling and simulation interface, and handheld digital devices (Zhang et al. 2022). The availability of data regarding the plant and its subsystems, physical phenomena, processes and activities, and instrumentation information is crucial in facilitating a digital twin's sustained, accurate, reliable, and efficient operation (Yadav et al. 2021). Asset information encompasses various aspects, including dimensions, geometries, topologies, materials, chemical compositions, and other relevant factors. These attributes are contingent upon factors such as the type or function of the asset and the specific requirements for its digital representation. The primary purpose of realtime data acquisition in NPPs is to support the information displayed in the NPP command space.

Running a DT approach offers activities and guidance facilitating a system's secure, trustworthy, and effective function. The activities and advice of DTs have been categorized into the following groups: diagnostics, maintenance recommendation, and independent functions and management (Yadav et al. 2021). The acquisition and utilization of knowledge serve as the fundamental basis for all other capabilities within the data technology field. DTs can offer novel and substantially enhanced potential data that is reliable, up-to-date, readily accessible, accurate, and comprehensive. The agreement and awareness of the state facilitate this capability. In addition to the passive functions of receiving and transferring information, digital technology should possess the active capabilities of keeping, sharing, and organizing data (Yassin et al. 2023). These functionalities are crucial in enabling the information to support and enhance other important capabilities. The different stages of DTs in NPP applications are presented in Fig. 2.

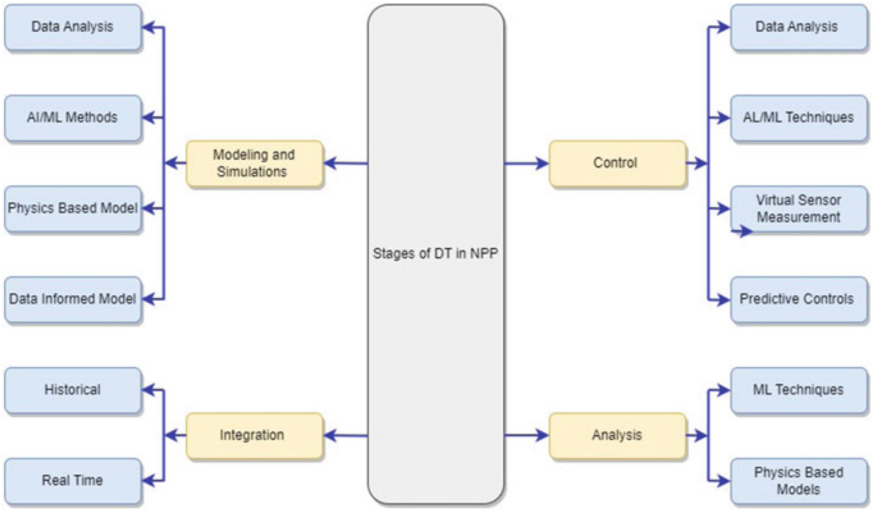

Fig. 2 Stages of DT in NPP

3 AI Tools for NPP

3.1 AI Tools for NPP Decision-Making and Simulations

This section discusses using AI tools in NPP for decision-making, simulations, optimization, and operations. The utilization of artificial intelligence (AI) applications carries great promise in generating substantial problem-solving value through the implementation of more advanced and smart solutions. Numerous AI techniques have been suggested in the existing academic publications about the energy sector and aid within power methods (Feng et al. 2021). System-level programs encompass various aspects, such as incorporating varying energy resources and designing and planning microgrids on reliability (Aizpurua et al. 2017). As elucidated in the subsequent subsection, various learning techniques and AI functionalities are utilized to implement these applications. Enthusiastic individuals may desire a more comprehensive and in-depth analysis of the field of AI (Ramachandran et al. 2022). An independent calibration technique is presented for NPPs to reimburse for the computing preference of low-accuracy prototypes (Song et al. 2022). ML/AI is essential to enable DT technologies, which can be utilized to construct strategies, processes, or supervision findings (Gunasegaram et al. 2021).

AI techniques offer diverse functionalities that align with the advancement and deployment of intelligent applications to resolve power system challenges. AI can emulate human intellect, empowering decision-making processes autonomously (Jarrahi 2018). The roles of AI in decision-making can be categorized into two primary classifications. The initial aspect involves furnishing corroborative data to aid individuals in making more precise decisions. Within this particular domain, it is the human species that continues to exercise authority over the process of resolving problems (Kurt 2014). The second role involves substituting human agents with automated systems, improving operating efficiency. AI-driven decision-making involves extracting valuable features from gathered data to determine and execute the appropriate movement (El-Sefy et al. 2021).

The presence of uncertainty and time-varying characteristics poses a challenge for a static AI model that solely captures the past states of a given system (Hua et al. 2023). Online learning has the potential to address the issues of low efficiency and limited scalability that are often associated with traditional batch learning methods. This is achieved through the ability to update the learning model with new data samples promptly (Boger 2002). Fresh data samples are collected from existing systems, accurately representing their most recent state. This allows for the simultaneous updating of the model alongside any changes made to the system. The ANN model can be used as a decision-making tool that learns from past behaviour in NPPs (Xie et al. 2023). Feature extraction refers to reducing the dimensionality of raw data while retaining essential and pertinent information. The fault localization strategy in multilevel converters involves extracting features from neighboring sliding-time windows. Feature extraction techniques are implemented to discern the spatial pattern and point data to calculate solar radiation. The different AI/ML tools used in NPPs for decision-making and simulation are demonstrated in this section (RQ2) as outlined in Table 2.

3.2 AI Tools for NPP Optimization and Operations

Montes et al. (2011) presented an ant colony algorithm to optimize the design of water reactor radial energy lattices. De Oliveira and Schirru (2011) proposed the artificial bee colony technique to address the combinatorial challenges of optimizing in-core fuel management. This method exhibits a notable characteristic of reducing the computational cost by utilizing a substantially reduced number of control parameters, resulting in enhanced performance. Radaideh et al. (2021) effectively employed reinforcement learning techniques to optimize fuel assemblies to satisfy predetermined conditions. Radaideh and Shirvan (2021) proposed a new rule-based hybrid reinforcement learning (RL) framework incorporating evolutionary computing techniques. The primary objective of this framework was to enhance optimization performance while reducing computational time. Ma et al. (2017) employed back-propagation networks to ascertain the heat transfer coefficient within the range of supercritical water pressure. Gao et al. (2021) presented an innovative soft measuring approach using convolutional neural networks (CNN) to predict void particles in two-phase gushes. Expandable AI (XAI) can be used in the energy sector (Machlev et al. 2022).

ML/AI technologies can utilize data-driven practical measures to perform complex analyses and develop projections (Ghenai et al. 2022). This permits ML/AI techniques to perform assignments, namely computing operating effectiveness,

Table 2 Summaries of existing studies in decision-making and simulations

References	Description	Tools
Franki et al. (2023)	Analysis of existing AI techniques in the power sector	Machine learning, Artificial Neural Networks, Multi-agent systems
Feng et al. (2021)	Review of recent AI applications in the power sector	ANN, SVM, Ensemble Learning, LSTM, KNN, MLP, ELM
Song et al. (2022)	Trend of AI and DT in NPP	AI-based dataset testing, enactment of fault diagnostics, lifespan prediction, predictive control, and time scale
Kurt (2014)	Integram algorithm for decision making in NPP	fuzzy TOPSIS. Choquet fuzzy
El-Sefy et al. (2021)	Predicting dynamic behaviors in NPP	Data-driven models, ANN
Hua et al. (2023)	Time varying problem solving on model structures	Dynamic neural networks
Boger (2002)	Deep learning method as a decision making and simulations in NPP	ANN
Xie et al. (2023)	Deep enforcement learning for power grid systems	Multi-agent deep reinforcement learning

seeing interpretation abnormalities, autonomously applying or suggesting mitigation measures when issues arise, or confirming that the maintenance operations are optimized across the energy factory. ML/AI techniques can be useful at any phase of the factory life stage (Kobayashi et al. 2022). The most problematic aspect of building ML/AI techniques is selecting the optimum quantity of grade data that is suitable, expected, and finished to deliver trustworthy outcomes. Due to the plurality of analog detectors and instrumentation, developed reactors require operational data (Lin et al. 2022). Data from computational instances can influence the input information for ML/AI techniques within DTs. The execution of DTs necessitates selecting the best data to train, test, and validate ML/AI models. Limited data, such as the absence of failure scenarios due to the recent adoption of digital detectors, can hinder the initial performance of ML/AI in nuclear applications (Muhlheim et al. 2022). It is essential to receive responses to the following queries: (1) the data size of training and testing, (2) features for input data sets, (3) the optimum sampling frequency, (4) classification techniques, (5) the complexity of the algorithms, (6) computational resources, (7) infrastructure. The processes and tools for employing data at an NPP must satisfy varying conditions, especially their closeness to security procedures and baselines (Edwards et al. 2023). Satisfactory, supported records of security methods and processes should be studied, endorsed, and archived as per regulatory provisions or advice and executed through mandated procedures (Sleiti et al. 2022). Various new technologies underlying the usefulness of DTs in different enterprises can be

Table 3 Summaries of existing studies in optimization and operations

References	Description	Tools
Montes et al. (2011)	Water reactor radial fuel lattice design	An ant-colony approach
De Oliveira and Schirru (2011)	AI techniques in fuel management optimization in NPP	Artificial Bee Colony with Random Keys (ABCRK), Genetic Algorithms (GA), Particle Swarm Optimization (PSO)
Radaideh and Shirvan (2021)	Nuclear assembly optimization using reinforcement learning	Reinforcement learning
Radaideh and Shirvan (2021)	Rule-based reinforcement learning for constrained optimization	Reinforcement Learning, GA, SA, PSO
Ma et al. (2017)	Water heat transfer analysis	BP Neural Network
Machlev et al. (2022)	Usage of AT techniques in power system operations	Explainable Artificial Intelligence (XAI)
Sleiti et al. (2022)	Usage of DT in complex NPP environment	Deep Learning, ADL

straight or readily transferrable to protect nuclear applications (Gong et al. 2023). Acclimating these measures to developing technology is critical in decreasing the obstacles to accessing these advancements. The different AI/ML tools applicable for optimization and operations in NPPs (RQ3) are summarized in Table 3.

4 Achieving SDGs by the Implementation of DTs

The United Nations Sustainable Development Goals (SDGs) outline 17 essential study areas of activity that international economizing should reach via their suitable strategic objectives by 2030 (Chong et al. 2022). The SDGs, which seek a coordinated collaboration among all nations and stakeholders, should be the foremost objective of a contemporary global evolution approach to determining the unidirectionality of the standard method. Digital conversion accelerates sustainable expansion, and circumstances vary at all levels using rising digital technologies, namely digital twins, the Artificial Intelligence of Things (AIoT), and AI in NPPs. It presents accomplishing the SDGs by enhancing the grade, applicability, effectiveness, reusability, safety, and influence of the UN Development Program (UNDP) via more useful information use, prediction, and communication (Oberoi et al. 2021). The widespread appeal of DTs is emerging from the increase in digital conversion. Figure 3 presents worldwide Google trends for SDGs and DTs since 2021.

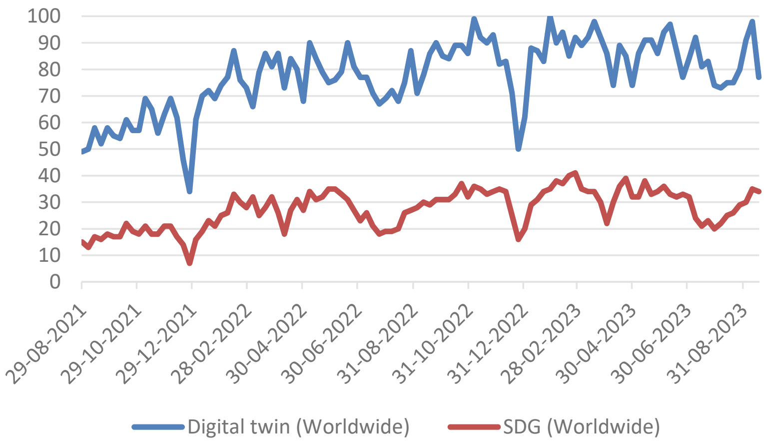

Fig. 3 Google trends worldwide for SDGs and DT since 2021

DT systems can be used in NPPs to enhance the methods for maintaining plants; troubleshooting works tools, and the parameter tuning of automated controllers (Wang et al. 2017). DTs can facilitate the monitoring, interpreting, and enacting of all human performance and provide enduring healthiness understanding to enhance the quality of energy and well-being. Simulations permit the analysis of several scenarios, and the innovation and research processes shrink, making prototyping quick. DTs can be utilized in various phases of the development strategy (Tao et al. 2018). DTs can decrease working expenses and lengthen the life of tools and support once enforced (Bellavista et al. 2023). They can further predict faults and impairments in the manufacturing design and thus can organize the supervision of the development in advancement. DTs can provide the most suitable explanation or supervision system by affecting further procedures. In expansion, the continuous feedback between DTs and their physical replication can be utilized (Jafari et al. 2023). The physical instrument can be managed and observed remotely utilizing DTs. DTs can be remotely controlled and supervised (Benhamaid et al. 2022). AIoT allows new digital development components. DT aids create the needed technological interfaces to integrate with AIoT (Singampalli and Pise 2023). This section discusses the SDGs as goals that can be attained by implementing DTs (RQ4), illustrated in Fig. 4.

5 Discussion, Open Challenges, and Future Research

This section discusses the open issues of employing AI methods in NPPs and recommends directions for future studies. Although nuclear energy can produce electricity without harmful side effect, it must establish its trustworthiness, ecological responsibility, and economic viability to compete with renewable energy sources effectively.

Fig. 4 Goal of SDGs achieved using DT

Developing cost-effective designs with secure functional and predictive capacities is crucial as nuclear reactors aspire to license regenerations and more contemporary cutting-edge reactor strategies emerge in demand. The nuclear sector has witnessed the emergence of various applications of AI, such as structure optimization, predictive supervision, flaw identification, and progressive management approaches. Using sensor information obtained from reactors and associated approaches, in conjunction with ML and DT methodologies, may facilitate the development and implementation of digital twins. Nevertheless, using AI to create advanced digital replicas and frameworks for evaluating conditions may encounter various obstacles. These challenges encompass the acquisition and management of data, which necessitates computational resources and incurs expenses, as well as the vulnerability to cyber-attacks and concerns regarding security (Kim et al. 2023). Further exploration is necessary to establish responsibility in utilizing data-driven ML methods and enhance their accessibility for a resilient framework.

5.1 *Challenges in Data Availability and Analysis*

The level of proficiency exhibited by AI-driven methods can exhibit considerable variation contingent upon the data accessible for its training and testing phases. The augmentation of data can be employed to expand the size of a database, which in turn can be utilized for training the machine learning framework. However, further investigation is needed to examine the grade validation process of data enlargement techniques. The efficacy of many AI methods is contingent upon the quantity and caliber of training data that is accessible (Sethu et al. 2023). Existing sensor data and historical records about functional abnormalities in nuclear energy generation establishments are not publicly accessible. Possessing the appropriate security permission and obtaining primary permissions from the competent authority is necessary to acquire such information.

5.2 Challenges in Computational Overhead

AI techniques, specifically those utilized in deep learning, necessitate substantial computational resources, including many cores, Graphical Processing Units (GPUs), Random Access Memory (RAM), and other similar components, to evaluate the condition of systems within strict time constraints effectively. Nevertheless, the implementation and upkeep of such tools can incur significant costs (Sandhu et al. 2023). Prospective research in machine learning algorithm design for system condition assessment should focus on reducing computational complexity through data preprocessing, exploration of data diffusion methods, execution of sensitivity analysis, and evaluation of energy usage.

5.3 Challenges in Data Security

Using AI techniques to deliver dependable and economically efficient software solutions for the nuclear energy industry carries the potential risk of unauthorized access by malicious actors, such as cybercriminals, to compromise sensitive data about nuclear facilities. The continuous updating of malware through the utilization of AI serves as a means to evade detection by online security platforms (Park et al. 2022). The manipulation of data is a primary objective of cyber-attacks, wherein the occurrence of false positives can initiate incorrect actions and result in significant repercussions within a nuclear power facility. Software bugs can impede the enactment of AI in DTs and their position estimation models.

5.4 Challenges in ML and AI

Choosing the proper nuclear DT techniques relies on several significant elements. The training and testing data volume can affect classifier choice and minimal information availability in both the training and testing phases (Turabieh et al. 2019). The designated algorithm should be capable of acclimating to climbing up further elements, adding input and output parameters, incorporating datasets, and climbing up from the testing environment. The final prototype should be capable of handling deployment and use cases. The importance of explainability of AI techniques, actions, and suggestions in nuclear must be emphasized. This section addresses the open issues and challenges of implementing AI/ML techniques in NPPs (RQ5). Based on the study, the challenges in using AI/ML techniques in NPPs are indicated in Fig. 5.

Figure 6 illustrates the existing issues and challenges while integrating AI and DTs in NPPs towards SDGs.

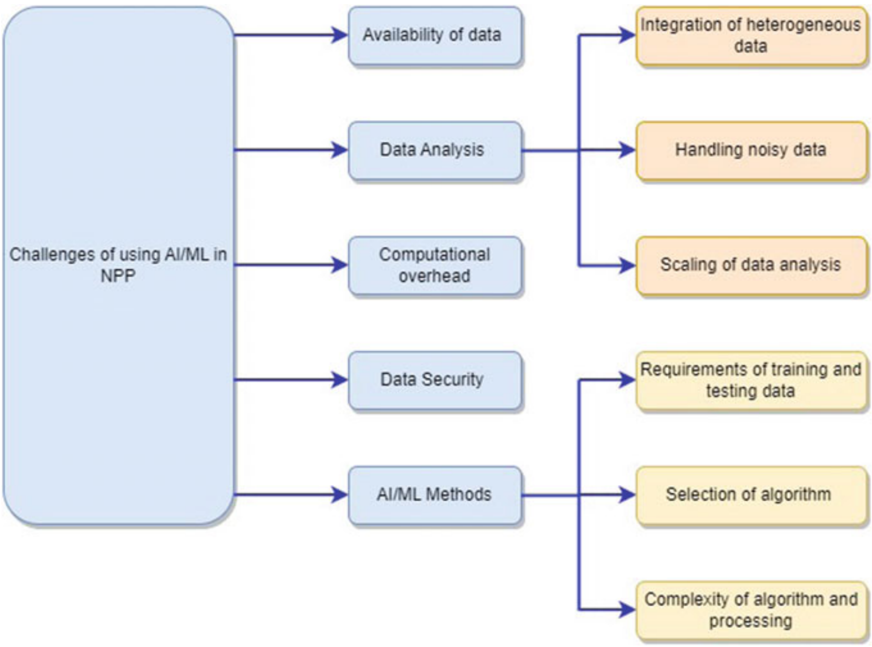

Fig. 5 Challenges in using AI/ML techniques in NPP

5.5 Future Study Recommendations

Further research and analysis are needed before providing AI techniques for enactment in existing and future nuclear sectors. Some of the suggestions for future studies are as follows.

1. Data management, encompassing its accession repository, poses significant challenges in the context of self-supported methods. Properly storing and managing continuous data streams from nuclear power plants is imperative. The demonstration should utilize cloud-based techniques and proficient data analytical techniques.
2. Further research is required to explore the impact of limited data availability on the predictive efficacy of a machine-learning method. Potential strategies for addressing the issue include the analysis of processes such as data enlargement and acute feature engineering.
3. Implementing mechanization within the nuclear sector aims to mitigate process, optimization operations, and maintenance expenses. Nevertheless, executing AI can result in significant computational expenses. It is imperative to comprehensively assess the overall energy consumption associated with different AI techniques and the computational outlay involved in their enactment and utilization. A comparative analysis would provide the nuclear endeavor with the necessary

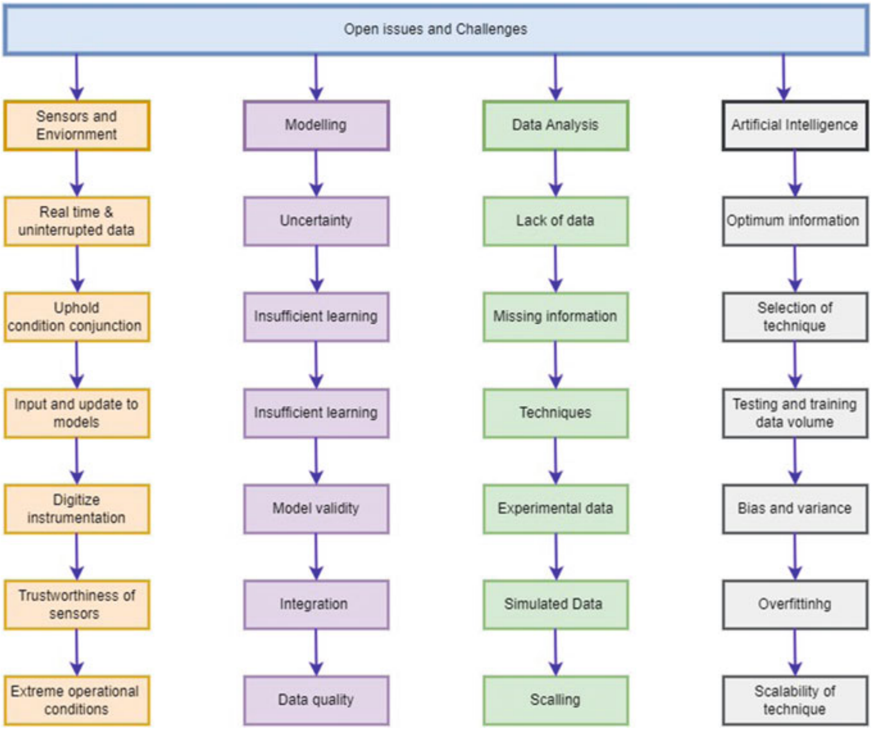

Fig. 6 Open challenges in integrating AI. DT in NPP towards SDGs

information to construct conclusions regarding AI-driven solutions' effectiveness concerning the associated costs.

4. Researching cyber-safety mechanization venues is imperative in protecting the public and the nation. There is a need to develop designs that exhibit robustness in the face of breaches and unauthorized access to data by cyber-criminals.
5. The reliability of the situation estimation method in a nuclear establishment ensures safety. Using an interpretable ML method can improve this trustworthiness. Certain ML algorithms, namely random forests, decision trees, etc., are known for their superior interpretability compared to deep learning techniques like neural networks. Nevertheless, it needs the exploration of intricate algorithms, such as Artificial Neural Networks and Convolutional Neural Networks, which have the potential to surpass that of other more easily interpretable models. It is imperative to analyze the equilibrium between the explainability and accuracy of diverse AI algorithms for potential applications in the nuclear sector.

6 Conclusion

A comprehensive study of the existing literature on using AI in the decision-making, simulations, optimization, and operation of nuclear reactors is conducted. The impact of SDGs by implementing DTs in NPPs is presented. The majority of these studies have exhibited excellent outcomes when applied to datasets of restricted scope. To enhance the application of AI technologies in managing practical challenges in nuclear reactors, specifically in protection advancement, prospective AI solutions designed for organization use must possess enhanced interpretability, data security, computational overhead, data availability, classification technique, and the complexity of algorithms.

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Carbon and Decarbonization Disclosure: Role of Responsible Innovation in Adoption of Artificial Intelligence of Things Towards SDGs

Assunta Di Vaio, Anum Zaffar, and Daniel Balsalobre-Lorente

Abstract This chapter relates carbon disclosure and performance in three different levels i.e., financial performance by incorporating financial reporting, operational performance by incorporating operational reporting and sustainability performance by incorporating sustainability reporting with decarbonization practices supporting by the institutional, legitimacy and stakeholder theories. It further discusses the relation of digital technologies, especially Artificial Intelligence (AI) and Internet of Things (IoT) in decarbonization processes as the worldwide use of technology gives a solution to maintain development without harming the nature. This chapter focuses on these technologies to understand the role of digital transformation in decarbonizing processes and the challenges for the non-financial disclosure on the decarbonization practices adopted by the enterprises. The enterprises are engaged in the "accountable" behaviors and "transparent" sustainability disclosure to demonstrate their governance model based on Responsible Innovation (RI) for the Artificial Intelligence of Things (AIoT) adoption in the decarbonization practices to meet Sustainable Development Goals (SDGs) especially SDG 5. This sustainable goal purposes to achieve gender equality as strategic resource for business success, which often treated as "victim" of technological innovations adoption. The analysis based on literature and international organizations' reports is developed regarding carbon disclosure and decarbonization practices which adopt AIoT and its implementation with respect to RI to meet SDG 5 adopted by UN 2030 Agenda.

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Keywords Artificial Intelligence of Things (AIoT) · Carbon Disclosure · Decarbonization Practices · Sustainable Development Goals (SDGs) · Responsible Innovation (RI) · SDG 5

1 Introduction

Climate change puts pressure on firms by demanding their carbon disclosure. The many other non-financial stakeholder groups i.e., governments, press and media, customers, general public and employees, and other financial groups, demand relevant information from firms' activities on what they are doing to mitigate risks of climate change (Guenther et al. 2015). Moreover, increased attention is given even by employees and customers to disclose firms' carbon performance for better decision-making of firms regarding their environmental stability. Therefore, stakeholders pressure them to be informed about firms' performance and other related activities to disclose such information (Clarkson 1995). It is a two-way relationship. The carbon performance positively impacts carbon disclosure, and when the carbon performance of a firm improves, it will improve its carbon disclosure too. This link plays a vital role in conceptualizing the corporate social responsibility of firms (Siddique et al. 2021). It is found in the literature that the link between carbon disclosure and carbon performance may have different results according to different theories, i.e., legitimacy theory and stakeholder theory act as two main theoretical frameworks to predict their relationship (Luo 2019). The legitimacy theory depicts that firms with less carbon performance can make soft qualitative disclosure about their performance to satisfy their different groups of stakeholders. However, when the legitimacy of an organization is at high risk, stakeholders might consider the firm's performance non-sustainable (Hummel and Schlick 2016). The legitimacy theory further represents that firms should run their activities with societal boundaries to sustain in the environment. In simple words, it can be said that legitimacy is the contract between societal values and firms to disclose the relevant information to meet stakeholders' expectations (Siddique et al. 2021).

The literature states that the primary cause of global warming is carbon emission which is a red signal for the survival of different species on Earth (Romar 2009). In this regard, there are many internal and external factors which exert pressures on enterprises to define better their public policies related to carbon emission. Moreover, the performance of enterprises can be measured by focusing on carbon emissions intensity which is the main goal and measurable outcome of enterprises. In addition, the enterprises seek and represent their actual carbon performance through direct voluntary disclosure that cannot be easily simulated by poor environmental performers (Datt et al. 2018). Also, the enterprises react actively to disclose information on greenhouse gas (GHG) emissions on volunteer basis (Romar 2009) because, in literature, the studies revealed that with the help of signaling theory, there is a positive relationship between carbon performance and voluntary disclosure (Datt et al.

2018). In this regard, the carbon disclosure project (CDP) is a not-for-profit organization created in 2000 focusing on enterprises incorporating information related to carbon emissions in their activities (Depoers et al. 2014).

The previous studies focused the relationship between environmental disclosure and its performance by arguing that financial reporting does not represent different aspects of current corporate value properly, whereas, on the other hand, some research results depict that both of these variables have no association and the firms represent specific information that has limited access to managers (Simnett et al. 2009; Ball et al. 2012). The environmental disclosures are also divided into two types, i.e., soft and hard and on the basis of this division, the stakeholders analyze how firms react differently to achieve their goals (Clarkson et al. 2008). By achieving and trying to achieve goals, the enterprises represent their contribution towards sustainability through digital technology adoption that inspires the markets to produce innovation in the long-term (Di Vaio et al. 2022b).

Modern digital technologies enable enterprises to collect and analyze the data, and this development led investigators to resist that this is a skillful technique for analysis to perform better. However, to move from the current phase to the adoption of digital technologies phase, the management should amend the overall decision-making process by incorporating artificial intelligence (AI) into organizational strategies (Borges et al. 2022). Digital technologies are modernizing the life in every field, and depending on these technologies; it is considered that the adoption of decarbonization practices would help firms to reduce carbon emissions (Agarwala et al. 2021). The human defines the guidelines to direct AI for their decisions, and as a result, modern digital technologies promote in-depth interaction, specifically across distances, between workforces and enterprises (Di Vaio et al. 2021a). To achieve all these goals like adoption of green technologies has become much crucial for firms as they have to face extreme pressure from internal and external stakeholders, so they have to design such strategies through which they can sustain their position in the market.

Meanwhile, they have to meet the sustainable development goals (SDGs) adopted by the United Nation (UN) through the UN 2030 Agenda by focusing specifically the participation of women in management (Pelle and Reber 2015) as women play a vital role in any country to make its economy strong. Hence, their participation in every sector is necessary to meet SDGs. Past studies explains that institutional theory motivates gender integration by introducing some innovative systems, i.e., AI and internet of things (IoT), to reshape the organizational and managerial culture due to internal and external pressure factors (Hew et al. 2020; Kummer et al. 2020). Moreover, the use of digital technologies and decarbonization practices help effectively achieve SDGs; for example, in the cruise industry their sustainability reporting highlights that they invest more in technologies to minimize the environmental effects of their routine activities (Di Vaio et al. 2022b).

After reviewing the relevant literature, this chapter aims to link carbon disclosure with carbon performance by incorporating non-financial reporting with decarbonization practices through institutional, legitimacy and stakeholder theories. The chapter further focuses on the relation of digital technologies, specifically AI and

IoT, in decarbonization processes to understand the role of digital transformation and the challenges enterprises face regarding non-financial disclosure. The chapter is composed of an analysis based on literature and international organizations' reports regarding carbon disclosure and decarbonization practices which adopt AIoT and its implementation for Responsible Innovation (RI) to meet SDG 5 adopted by the UN 2030 Agenda.

This chapter is structured as follows. Section 2 briefly conceptualizes carbon disclosure with different levels of performance paradigm, i.e., financial, operational and sustainable. Section 3 introduces the concept of carbon disclosure under the lens of institutional, legitimacy and stakeholder theories. Section 4 describes Artificial Intelligence of Things (AIoT) in decarbonization practices. Section 5 explains the relationship between RI and AIoT towards Sustainable Development Goal (SDG) 5, i.e., gender equality, and Sect. 6 presents a conceptual framework of carbon disclosure and decarbonization practices with the perspective of SDGs. Finally, Sect. 7 depends upon a detailed conclusion with some limitations of the study and directions for future research.

2 Carbon Disclosure: A Conceptualization Within the Performance Paradigm

GHG emissions have become one of the main red signals that threatening the survival of life on Earth. The increase in GHG emissions will lead the atmosphere of Earth's atmosphere to undesirable situations by producing global warming (Liu et al. 2015). One of the most critical environmental issues, i.e., climate change, can be the reason of many upcoming problems, which is why firms are more concerned about their activities regarding corporate social responsibility (Clarkson et al. 2008) as enterprises play an important role to create this global warming as they are the biggest GHG emitters, which is why the financial and non-financial stakeholders exert pressure on them to decrease this emission that is risky for the healthy environment (Heede 2014; Comyns 2016; Helfaya et al. 2019). As a result, the organizations are trying to reduce their GHG emissions and contribute towards the sustainable green environment (Luo 2019).

Carbon disclosure is an important platform where enterprises can operate effectively and be accountable to their investors. The climate governance strengthens the link between carbon disclosure and its performance, but the relationship is complex and dependent on multiple factors (Hollindale et al. 2019). Carbon disclosure is also a measure that help internal and external stakeholders to monitor the firm's performance and to regulate their GHG emissions. The firms that have improved carbon performance may result in good firms' financial performance (Shen et al. 2019). The enterprises dealing with high emissions, i.e., those operating in the energy sector, can produce high emissions continuously because of the nature of their main business activities. However, as enterprises must prove their responsibility to investors, they can select to merely increase the disclosure of soft information to clarify their initiatives for carbon reduction without demonstrating the information with rugged gauges of definite carbon mitigation (Garcia-Meca and Sanchez-Ballesta 2010). While doing so, enterprises can represent themselves as responsible actors playing well to save environment by focusing their emissions-intensive actions. In rare cases, disclosure can be used to defend or hide increased levels of carbon emissions, thereby negotiating pressures exerted by the public and understanding the issues related to climate change (De Villiers and Van Staden 2006).

The regulations regarding climate change, for example, emissions schemes, may result increase in carbon emission disclosure for both voluntary and regulated disclosure systems. The management of enterprises always faces pressure to minimize the negative impact of their activities on environment by initiating some specific enticements to clearly state all the required information to stakeholders (Clarkson et al. 2008).

2.1 Carbon Disclosure and Financial Performance

The carbon performance of firms impacts carbon disclosure, and carbon disclosure affects the financial performance of firms. The firms which are causing high GHG emissions are considered as socially irresponsible (Luo 2019). The regulatory bodies might penalize such firms for causing such irresponsible behavior and do not adopt the strategies to avoid climate change (Siddique et al. 2021). The firms with excellent performance disclose even their non-financial information on a volunteer basis to better explain their performance (Clarkson et al. 2008) and the firms with excellent carbon performance are assumed to have lower cost of capital so as a result, they attract more investors and can upgrade their market value (De Villiers and Marques 2016). Another dimension is also found in literature that the firms only disclose favorable information for themselves and avoid disclosing such information that can show their low performance (Hummel and Schlick 2016).

The CDP is a widely used disclosure mode in climate change that works with different financial and non-financial stakeholders to disclose their information regarding GHG emissions (Guenther et al. 2015). The relationship between carbon disclosure and corporate environmental performance varies in firms' financial reports as the high-achieving firms convey their best carbon emission performance to prove themselves as excellent and responsible market players. In contrast, firms with poor performance are not good indicators of their proper performance. The firms with good indicators of carbon performance intend to motivate their stakeholders that they are performing their best and report on carbon disclosure on a volunteer basis to achieve their goals (Clarkson et al. 2008).

2.2 Carbon Disclosure and Operational Performance

For the firms, it is essential to be accountable to their stakeholders whose resources they are using to run their daily activities and to continue this relationship in future also (Schaltegger and Burritt 2000). The result of past research claim that the climate governance minimizes managerial discretion on carbon disclosure, specifically in over-acclaiming of their excellent performance through general disclosure and trying to hide their poor performance through minimal disclosure. Therefore, the climate governance is crucial factor in enabling carbon disclosure to represent carbon performance in valid terms (Bui et al. 2019). Internal and external factors are essential to firms' performance and carbon disclosure. If any organization fails to justify its running operations by reporting its carbon disclosure and carbon performance, many communities can request to cancel its license to run its activities in future (Guenther et al. 2015).

Moreover, environmental issues are increasing because of instant industrialization and more energy consumption, specifically in developing countries (Usman et al. 2022). The signaling theory prefers that the enterprises with excellent carbon performance are likelier to present their good performance to their stakeholders and extensively report climate change issues in return, they receive high financial benefits such as market value and low cost of capital for their routine activities (Luo and Tang 2014).

2.3 Carbon Disclosure and Sustainable Performance

Sustainability reporting is a fundamental component of business requirements as the stakeholders demand the firms to be more accountable and transparent to fulfill their social responsibility (Corporate Register 2008). It is an effective tool the management uses to measure their environmental performance because sustainability reporting lead towards higher information asymmetry between the stakeholders and the management (Sarkis et al. 2011).

The idea of sustainable performance emphasizes that the enterprises should focus on the accomplishment of environmental and social goals as well as their regular economic performance (Bombiak and Marciniuk-Kluska 2018; Seles et al. 2018; Yusliza et al. 2020). In literature, studies have different results of negative, positive, and sometimes insignificant between sustainable performance and carbon disclosure. Enterprises which have poor carbon performance do not prefer to disclose their carbon disclosure if they are operating in such countries where strong GHG regulations are practiced (Guenther et al. 2015). The CDP is a widely used mean for firms to disclose their relevant information and keep their stakeholders aware of their efforts to minimize GHG emissions to respond to climate change. It targets climate change which depicts an explicit restriction on carbon-intensive industries by providing an opportunity for the renewable energy sector in the perspective of sustainable performance (Guenther et al. 2015).

The enterprises are not only considered to be more accountable for financial performance but also their social performance as well. There is a debate in literature on the developing non-financial reporting, explicitly focusing on sustainability and integrated reporting (Bebbington and Larrinaga 2014; Al-Shaer and Zaman 2018). To respond to the pressure exercised by investors, the enterprises try to report a complete picture of GHG emissions in their annual sustainability reports (European Commission 2010). The guidelines of Global Reporting Initiative (GRI) help firms to report the disclosures publically to respond certified environmental management system (Rankin et al. 2011).

3 Contribution of the Theories to the Carbon Disclosure Concept

The concept of carbon disclosure varies depending on different contexts. For example, some studies found that enterprises disclose only the most minor necessary information to respond to social and environmental potentials (Stanny 2013). Some other studies conclude that carbon disclosure is a technique to meet the demands of stakeholders for the valuation of climate risk and the suitability of climate policies as stakeholder theory explains the multi-accountability of management to numerous stakeholders with contradictory interests and clarifies voluntary carbon disclosure (Liao et al. 2015). Some studies also conclude that voluntary carbon disclosure is a method that enterprises incorporate when the benefits compensate for its costs (Griffin and Sun 2013). On the other hand, other scholars relate the concept with social movement theory to uncover new visions about the complex strategies regarding carbon disclosure and its relationships between enterprises, regulatory bodies and advocates (Reid and Toffel 2009).

As climate change management tools, carbon performance and disclosure are important in today's stakeholder relationships. As its standard definition, carbon performance explains the quantitative GHG emissions of climate change and the measures and procedures for its reduction from the environment (Hoffmann and Busch 2008). Carbon emissions play an essential character in global warming and climate change. The advanced and sustainable business models represent a modern type of management thinking and seeing the business as part of responsible society (Marousek et al. 2019). This new decarbonization technologies adoption can strengthen the United Nations (UN) Sustainable Development Goals and the Paris Agreement (Velte et al. 2020).

The link between carbon disclosure and the performance due to the adoption of decarbonization practices is highly complex and reacts differently when addressed under different theories. There is a need to indicate enterprises' accountability as opposed to hiding the poor performance of enterprises as well as governance mechanisms can affect the link between carbon disclosure and carbon performance (Bui et al. 2019).

3.1 Carbon Disclosure Under Institutional Theory

To respond to the global challenge of climate change, the firms started disclosing their information regarding sustainability in the form of their sustainability reporting. However, these reports may vary due to pressures exerted by stakeholders. In literature, it is seen that institutional theory influences the institutional logics by solving the complexity of different stakeholders (Herold 2018). The company's management holds all the information and control the flow of information to disclose the selective one for their stakeholders, and due to this, it is challenging to get information for the stakeholders about the company's activities. In this regard, sustainability reporting is considered an essential tool for firms to be accountable in the eye of their stakeholders (Kolk et al. 2008). The institutional theory is not mainly focused on maximizing the profits of organizations but also affected by different institutions, i.e., regulatory bodies and institutional investors. These factors influence the organizations to run their activities accordingly (Meyer and Rowan 1977).

The institutional theory responds the external pressures by adopting specific organizational practices that influence their behavior. Their behavior is also influenced by other institutions that have some social interaction with them (Scott 1995). Simply put, it can be said that the pressures exerted by institutions and the social interaction of firms with other characters in society have influenced the organizations' daily activities. For example, to respond the external pressure, enterprises react by adopting sustainability logic to disclose their sustainability information, and the sustainability logic becomes a critical mode for the implementation of sustainability disclosure as it focuses on the sustainable values for stakeholders (DiMaggio and Powell 1983).

3.2 Carbon Disclosure Under Legitimacy Theory

Legitimacy can be explained as a universal view to focus the activities of organizations that are appropriate, suitable, and applicable within the social norms, values, beliefs, and definitions (Suchman 1995). This theory suggests that organizations are anticipated to work within the boundaries of social values. Otherwise, they will face hurdles to continue their existence. The results of studies conclude that there should be a strong connection between organizations and society. This connection should lead to the best level of disclosure of all relevant information to fulfil the expectations of stakeholders and other relevant societal groups (Solomon and Lewis 2002; Cormier et al. 2005; Luo 2019) as the CO_2 is the main component of GHG emission that is ultimately the primary reason of climate change (IPCC 2007). Hence, the stakeholders demand that enterprises control their carbon emissions (Matsumura et al. 2014). For this purpose, the regulatory bodies are designing policies that inspire reducing GHG emissions to prevent climate change (Stern 2007). To achieve social approval, enterprises should have social norms and can meet the expectations of society (Bui et al. 2019). There is a link between regulatory bodies and enterprises' decision-making process because the enterprises should mold their decisions according to policies, so the legitimacy theory helps by sending honest signals to improve the reputation of enterprises (Connelly et al. 2011). The legitimacy theory also suggests that the level of disclosure depends upon the pressure exerted by the stakeholder groups. Otherwise, firms withhold such information to avoid an inverse relationship between disclosure and performance (Peters and Romi 2013). The theory can be considered as the motivation for sustainability reporting because it details the factors that motivate sustainability reporting (Suchman 1995).

3.3 Carbon Disclosure Under Stakeholders Theory

The stakeholder theory is considered vital in environmental disclosure, but in research, the role played by stakeholders in a firm's disclosure is still touched little. Stakeholders and investors demand the enterprises' social and environmental information for their investment decision, and in response, the regulatory bodies focus on some specific information disclosures for reporting. This issue can only be handled under stakeholder theory (Perkins et al. 2022). With the help of stakeholder theory, the management provides relevant information based on environmental factors in response to the pressure exerted by stakeholders. The CDP is considered one of the standard responses to answer investors' pressure and help the management with little flexible space (Depoers et al. 2014).

Stakeholder theory, as a flexible concept, has numerous interpretations by differentiating legal and managerial regulations and ethical perspectives. Regarding the managerial perspective, organizations must create links between groups that hold a stake in their routine activities that are essential for business because business is all about how the stakeholders interact and create value for the firms (Freeman et al. 2007). By interpreting carbon disclosure, the firms can satisfy their stakeholders by adopting a managerial approach to respond multidimensional environment and can enable themselves to fulfill the social needs. There are various internal and external factors, i.e., public, government, and media exert pressure to reduce emissions and to report their carbon performance. Many other private parties and non-governmental organizations are interested in carbon performance of firms and can pressurize regulatory bodies to introduce such regulations for firms to disclose their carbon performance (Jenkins and Yakovleva 2006).

The stakeholder theory can act as moderator in the relationship between carbon disclosure and carbon performance because it can strengthen their relationship by focusing on the interest of stakeholders who have a direct and indirect effect on organizations' reporting behavior about carbon disclosure (Guenther et al. 2015). In literature, it can also be seen that firm specifically focused on carbon performance can better explain carbon disclosure. Moreover, firms operating with strong GHG politics can have a strong relationship between carbon disclosure and carbon performance (Baird et al. 2012).

4 Artificial Intelligence of Things in the Decarbonization Practices

AI can be defined as the ability of a system to perform intelligently and interpret external data to achieve definite goals in a corrective way (Kaplan and Haenlein 2019). The concept of AI is somehow different from IoT as IoT helps enterprises to get external data and allows them to use it as input for AI (Di Vaio et al. 2020). As the digital technologies, i.e., big data, IoT and AI are getting attention increasingly because they can help to implement decarbonization practices and can enhance the efficiency of enterprises because, with the help of these new technologies, the enterprises can make their economic side more feasible and can have a positive impact on the environment (Inderwildi et al. 2020). IoT is considered a revolution to bring innovation in every field of human life by upgrading renewable energy resources to minimize the negative impacts of technological advancements on the environment (Maksimovic 2017). Because of their importance, emerging technologies have gained societal acceptance for successful sustainable transitions (Mishra et al. 2022).

Furthermore, IoT and AIoT are highly encouraged by various industries to decarbonize their operations through reduced costs and increased efficiency (Bin et al. 2022). Past studies examine that the enterprises which have specific environmental committees to respond environmental and social issues have a positive effect on sustainability disclosure (Peters and Romi 2014; Liao et al. 2015). So, enterprises should incorporate carbon oversight in their board structures to improve their carbon performance and tend to highlight their accountability to investors, creating a link between carbon disclosure and carbon performance, climate governance is considered an essential factor because it reduces over-acclaiming of excellent performance through broad level of disclosure (Bui et al. 2019).

4.1 Artificial Intelligence to Climate Change in the Decarbonization Practices: Performance and Non-financial Disclosure

People are getting aware of climate change, so they are giving preferences to emissions trading schemes as monitoring procedures to address these issues by understanding the policies, rules, and regulations which firms should adopt (Bui and Fowler 2019). The new sustainable business models and AI technologies unwrapped the advanced levels of flexibility towards firms' performance. Among all the other advanced technologies, AI has achieved the maximum adoption percentage and has shown the best results as it improves the efficiency of different sectors. AI has three main applications of forecasting, optimization, and services (Viskovic et al. 2022). Where the adoption of AI is significant, meanwhile, the reporting on corporate social responsibility can help a lot while addressing stakeholders' demands and achieving legitimacy (Rosati and Faria 2018). The firms should not only depend on AI to compute and use the information for decision-making but also get an advantage in designing such business strategies from a sustainable and societal acceptance perspective (D'Amore et al. 2022). The advent of AI determines its evaluation of sustainable growth because enterprises are continuously facing challenges to improve the innovation side to preserve the integrity of the environment and natural resources (Di Vaio et al. 2020). To align themselves with the changing environment, enterprises should adopt the main drivers of modern performance reporting, which will be helpful for them in terms of financial benefits and shareholder value (Bronner et al. 2021). The AI and solutions enable other analytical tools, such as simulations and optimizations-based techniques, to work together to respond to climate change because AI can decide which product should offer to which customer; in short, this technology can be used to optimize the processes and decisions of enterprises (Boza and Evgeniou 2021).

4.2 Internet of Things to Climate Change in the Decarbonization Practices: Performance and Non-financial Disclosure

To decrease the GHG emissions approximately from every segment of the whole economy is essential because these emissions are the major source of global warming. There is a need to introduce some modern technologies and new operational approaches that should be cost-effective and compatible with a pathway to decarbonization (Rissman et al. 2020). With this respect, the IoT combines our everyday objects collectively with universal intelligence (Xia et al. 2012). When there is a dire need for digitalization, the IoT leads the basics of Industry 4.0, the development of smart cities and sustainability, including many other important areas (Zanella et al. 2014). Both the induction of IoT-based products in firms' daily operations and building the sustainable business models with the alignment of decarbonization practices affect the enterprises' performance, and the performance will lead to the non-financial disclosure of firms to justify the requirements of stakeholders (Palmaccio et al. 2020). IoT is not only important for firms' performance, but it also provides a highly distributed network of communication between humans and beyond this, it is also a fact that adoption of IoT is affecting the wealth production of firms (International Data Corporation 2014).

4.3 Artificial Intelligence of Things Framework to Sustainable Development Goals-UN 2030 Agenda

Modern technologies are not the best solution of this problem until proper policy guidelines and suitable investments are not introduced in the sector to save the whole economy and achieve SDGs (Rissman et al. 2020). Moreover, adapting sustainable and technological business models might be inspired by unique competitive factors and align with rules and regulations (Elliot 2013). As, AIoT hit the market sector, there is a rise seen in sustainable business models because it provides a solution to many complex problems by offering extraordinary insights into cooperating with the environment (Saarikko et al. 2017). AIoT technologies must be rooted in the firms' culture dedicated to their implementation (Hussain 2017). AIoT is increasingly used to chase SDGs and sustainable development research (Vinuesa and Sirmacek 2021). There has been much research in past decades on sustainability development, but now AIoT can play an essential role in achieving these agendas (Filho et al. 2022). Sustainable development is a detailed vision to pursue SDGs by addressing universal issues i.e., gender equality, environmental degradation, values and justice and related to decarbonization (Fuso Nerini et al. 2018). The advancements while using AIoT provide a reasonable response to the socio-economic and environmental sustainability challenges as it is becoming the most critical factor in many fields such as business, education, health, and life standards (Goralski and Tan 2020). AI has vast potential to enable devices to work intelligently in IoT, referred to as AIoT (Bronner et al. 2021). Because AIoT also has other capabilities to reduce hurdles towards sustainability innovation and risk-related barriers, it has the flexibility to cope with environmental challenges (John et al. 2022). As AIoT enables enterprises to create sustainable business models to build strong relationships with their customers and stakeholders also by improving their market value. Moreover, AIoT enables them to perform routine functions more effectively (Bronner et al. 2021).

5 Responsible Innovation from Artificial Intelligence of Things Towards Sustainable Development Goal 5 (SDG 5)

Today, AIoT is an essential tool for achieving SDGs as they can respond to environmental challenges (Obracht-Prondzynska et al. 2022). A few of the technologies, i.e., IoT and AI, when combined, form the fourth industrial revolution, commonly known as Industry 4.0. In the academic and practical fields, enterprises and research institutions tried to classify the technologies of Industry 4.0. The Boston Consulting Group (BCG) is its famous example which classified nine technologies as the nine pillars of Industry 4.0. The pillars comprise the industrial IoT, big data and analytics, and later AI and machine learning methods are included (Hansen and Bogh 2020).

The RI is considered a solution to cope with innovation progress towards universal sustainability challenges to meet SDGs. Moreover, the RI may be treated as a governance model where many societal actors interact with each other responsibly with the perspective of moral and ethical values (Di Vaio et al. 2022a). AIoT is also treated significantly to deal with all SDGs and especially SDG 5, and it focuses on equal rights for women in almost every field of life (Filho et al. 2022).

5.1 Responsible Innovation from Artificial Intelligence Adoption in the Decarbonization Practices to SDG-5

As the industrial sector is moving towards green technologies to avoid global warming and to respond to climate change, renewable energy resources are gaining much attention (Rissman et al. 2020). In this regard, the AI helps digital transformation by providing solutions based on the data available, but still, the capabilities of AI have not been used at their best to take full advantage of them (Papagiannidis et al. 2022). AI can challenge competition through the assessment of various disciplines, such as psychology, sciences, values, and ethics, that are raised from RI (Zamponi and Barbierato 2022). In this regard, gender equality is the main area to focus on when AI is in practice because the firms which take responsibility for societal values must treat the issue of gender equality that all genders should have equal rights, responsibilities, and opportunities when it is about community or society (Frennert 2021). In the era of digitalization, while adopting decarbonization practices, gender norms and expectations cannot be ignored. These things can be adequately implemented if they result in equal rights without discrimination (Cazzola 2018). In recent years, as technology is getting much awareness, gender equality is also capturing the attention by elaborating EDI as equity, diversity, and inclusion. The focus of EDI is to eliminate any discrimination under legal rights as EDI is a fundamental human right, so the area of energy and AI are facing many challenges today to be responsible and to achieve maximum societal concerns (Frennert 2021).

5.2 Responsible Innovation from Internet of Things Adoption in the Decarbonization Practice to SDG-5

Some scholars found that technological innovation is an essential pillar in achieving sustainable business models as these tools are very efficient in improving transparency and accountability for sustainable economy (Di Vaio et al. 2022b). IoT application is introduced as a new standard to run firms' functions efficiently, so the involvement of women in the usage of modern technologies is crucial. The IoT services should work independently and be free from race, gender, age, and so forth (Cassioli et al. 2020). The IoT is not just a revolution, but it is also changing the environment, and it is a critical aspect as there is a clear vision of technology usage and the objectives for the firms to achieve while adopting decarbonization practices, therefore, to empower the women in technological skills and enable them to enjoy the technology field by providing them equal chance of employment opportunities. Technological changes such as digitalization and decarbonization practices promote entrepreneurship opportunities. However, women face hurdles as they have less developed social networks, specifically in developing countries but the share of women in entrepreneurial activities is relatively high in developed countries. For this purpose, regulatory and government bodies and non-governmental organizations are taking different measures to promote the digital inclusion of women around the world (Women20 Study, 2017). The Women20 Study, 2017 further elaborates following initiatives to reduce this gender gap by monitoring their policies:

- Community and network building to support and advice each other.
- To offer trainings to improve some specific knowledge to handle digital technologies.
- Capacity building to develop skills to successfully operate the digital technologies and to implement decarbonization practices.
- To develop infrastructure that involves easy access for women to digital technologies.
- To advocate such activities which aims to influence the decisions on political, social, and economic levels.
- To raise awareness regarding the problems of women.

The involvement of females in the usage of advanced AIoT technologies can open excellent views in the context of enterprises' financial benefits and the development of new technological skills (Cassioli et al. 2020).

5.3 Responsible Innovation from Artificial Intelligence of Things in the Non-financial Disclosure

The idea of modern technology to meet all societal interest is not new, but RI further elaborates its new directions to focus strictly on new technologies to fulfill all the ethical, legal, and social concerns of society (Pelle and Reber 2015). While investigating the adaptation of current sustainability guidelines and practices, the influence of internal factors of organizations is considered a black box (Faria and Andersen 2017). The societal acceptance of RI can be enhanced by depending upon different factors as proposed and promoted by European Commission:

- The participation of the public in research and innovation
- Education related to science and technology
- Gender equality
- Easy access to scientific information and data
- RI governance

Firms, if adopt modern technologies with all these key factors, they can satisfy their internal and external stakeholders by disclosing all the relevant information (EC 2013). The RI is a framework that depends on corporate social responsibility because approaches are aligned with the processes of societal needs and interests. Therefore, the RI allows the firms to shape their processes according to ethical and social constraints and desirability (Pelle and Reber 2015).

The previous studies present that firms cannot achieve SDGs and sustainable performance without innovation, which is why the adoption of modern technologies, i.e., AI and IoT, can solve complex problems and also meet UN-2030 Agenda (D'Amore et al. 2022). Some researchers conclude that sustainability can be achieved precisely by developing business models with the help of digital technologies (Di Vaio et al. 2022b). Climate commitment and increasing sustainable awareness are critical to achieving SDGs; digital technologies are also necessary. Therefore, with this respect, the interest of stakeholders towards sustainability, enterprises should legitimize their behaviors to enable technologies towards SDGs (Sanches et al. 2020; Di Vaio et al. 2021b).

6 Conceptual Framework of Carbon Disclosure and Decarbonization Practices with Perspective of Sustainable Development Goals

The United Nations World Commission on Environment and Development (WCED) emphasized the significance of sustainability around thirty years before to meet the needs of current generation's needs without negotiating the capability of coming generations to meet their requirements (WCED 1987). In response, many enterprises have unified sustainability considerations into their daily operations, particularly the executives, analysts, investors, and other business stakeholders have showed their interest in environmental, social, and governance (ESG) indicators based on which they can compare the performance of different organizations for their smooth decision-making process regarding investments (Crace and Gehman 2023). Moreover, in this regard, digital and innovative technologies play an important role in economic growth and reducing GHG emissions as they are accommodating in understand how renewable energy resources can be used and consumed (Ye, 2021). This is the time when new technological solutions i.e., big data, IoT, blockchain technology, cloud computing, and AI, move ahead regarding environmental concerns of different groups, specifically the AI system is beneficial to bring change in the environment as it has the characteristics of generalization, adaptability, prompt decision making and constant execution time (Viskovic et al. 2022). With this respect, when the enterprises are moving from their current phase to the innovative phase of new technology adoption, the CDP disclosure must have all the features of CSR (Grauel and Gotthardt 2016). The enterprises which adopt the feature of reporting to CDP express their responsibility for carbon emissions by incorporating such policies and gaining the attributes and incentives for reporting to meet the expectations of their investors (Matten and Moon 2008). The application and implementation of digital technologies such as AI, analytics, big data, networked devices, and cloud data storage allow systems-based methodologies to reduce carbon emissions across the globe to make the economy strong and also to accelerate the decarbonization in almost every sector i.e., construction, energy, transportation, manufacturing and agricultural sectors (Ye 2021). These system-based approaches deliberate the collaboration of several types of equipment, their control and working to enhance the overall collective performance of enterprises, i.e., financial, operational and sustainable. The purpose of digitalization is to collect maximum and higher quality data regarding the physical world by using different sensors and analyzing that data with AIoT, and to manipulate that information into actions that can help enterprises to increase their efficiency (Ye 2021). Digital technologies, particularly AIoT, have an insightful impact on the future of all the sectors, but it's a bitter reality that it costs a lot to invest in these technologies, which can be difficult for many enterprises but it means a lot in the terms of money in the long run (Bello 2021). The conceptual framework of carbon disclosure and decarbonization practices with perspective of SDGs is shown in Fig. 1.

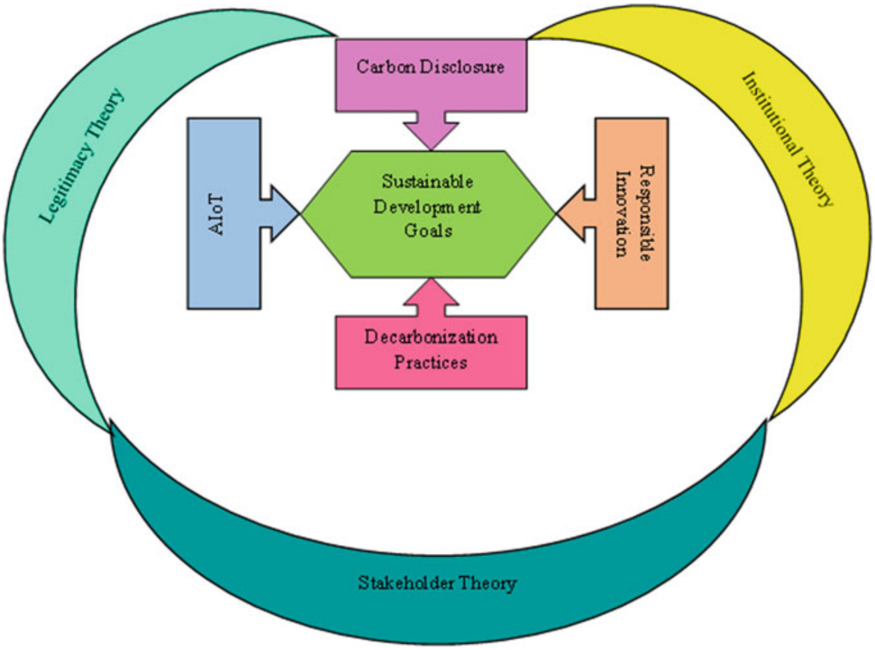

Fig. 1 Conceptual framework of carbon disclosure and decarbonization practices with perspective of SDGs

7 Conclusion

Firms have to respond to the pressure exerted by societal groups to report their sustainable results (Perello-Marin et al. 2022). The growing awareness of society towards environmental problems has raised concern regarding the adoption of green technologies (UN 2015). The development of digital green technologies is directly linked with the possible solutions to climate change (Dwivedi et al. 2022). For this purpose, enterprises are using digital technologies, i.e., AI and IoT, that are the system-based approaches and can be used to reduce energy and carbon emissions across the globe, including every sector of the economy. AI, IoT and AIoT support enterprises to play their role significantly regarding improvement in quality of life, economic growth and environment (Maksimovic 2017). Digitalization is about easy access and analyzing higher quality data about the whole world using a variety of sensors to get best results which are more productive and efficient (Ye 2021). Digitalization also helps to communicate between different stakeholders and consumers for the implementation of modern strategies that can enhance the potential of renewable energy resources.

Moreover, this technological transformation can bring various advantages that include customer and stakeholder satisfaction, maximized profits and an eco-friendly environment (Maksimovic 2017). Once, the firms adopt modern technologies, they must have transparent disclosure about global warming effects and GHG emissions. Where the adoption of digital technologies is vital for enterprises; meanwhile, carbon disclosure has a positive impact on the carbon performance of enterprises (Qian and Schaltegger 2017). These steps will lead them to achieve SDGs that are the most important goals for which every firm has designed their strategies and to sustain their position in market and specially the participation of women is encouraged to meet stakeholders' demands for the keen interest of the public in sustainable reporting (Ben-Amar et al. 2017).

7.1 Limitations of the Study

The chapter is focused on carbon and decarbonization disclosures and carbon performance. Despite growing concerns about performance and disclosures, less evidence is found in the literature related to actions taken by enterprises (Qian and Schaltegger 2017). Adopting decarbonization practices is essential for enterprises. Meanwhile, it is challenging. Moreover, the adoption of technology is not cost-effective for all enterprises; meanwhile, the training of employees is required to run new processes. Hence, regulatory bodies should introduce more flexible strategies that make this adoption possible for all enterprises in this competitive era.

7.2 *Directions for Future Research*

This chapter opens new ways for scholars to focus on different performance levels by stressing other theories, i.e., resource-based view and agency theories. The new research can be more focused on CDP and carbon accounting tools to reduce carbon emissions and can specify one sector only to present a clear picture of decarbonization challenges. Also, renewable resources are typically considered economical, technological and social, but for future research, it is crucial to decarbonize industry or transport as they face more difficulties in this shift. Environmental policies should be strictly stressed in terms of carbon emissions.

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Artificial Intelligence of Things (AIoT) Solutions for Sustainable Agriculture and Food Security

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Abstract The United Nations established the Sustainable Development Goals (SDGs) in 2015 to address worldwide social, economic, and environmental challenges. This study examines the significance of the Artificial Intelligence of Things (AIoT) in sustainable agriculture and food security. Innovative and effective agriculture practices are needed more than ever due to population growth and environmental issues. Real-time data and analytics from AIoT enable farmers and stakeholders to make smart choices and optimize resource use. AIoT's role in food security and sustainable agriculture is introduced in the study. It discusses AIoT in precision agriculture, smart irrigation, animal management, and supply chain efficiency. Case studies and real-world deployments evaluate successful AIoT systems in diverse areas, including lessons learned and best practices. The study also examines AIoT developments, AI and machine learning integration, 5G and edge computing, and agricultural AIoT applications. It highlights technical, data security, and financial issues with AIoT adoption and offers solutions. The results emphasize AIoT role in sustainable agriculture and food security. AIoT and multinational cooperation may make agriculture more resilient, resource-efficient, and transparent. The chapter concludes with a call for further research and implementation, highlighting the need for interdisciplinary cooperation to maximize the potential of AIoT in agriculture.

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1 Introduction

Food security is a crucial global problem affecting billions of people worldwide. Food security is defined by the Food and Agriculture Organisation of the United Nations (FAO) as "when all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (Cudjoe et al. 2021). Despite tremendous improvements in recent decades, food security remains a key concern, especially in developing nations and among vulnerable people (Keesstra et al. 2016). The world's population continues to rise, placing enormous strain on agricultural systems to produce enough food to feed everyone effectively. Weather patterns that are erratic, severe occurrences, and changing climatic circumstances significantly influence agricultural production, resulting in crop failures, lower yields, and food shortages (Nathan and Joel Uche 2023; Oseni and Masarirambi 2011). Soil erosion, deforestation, and degradation of arable land endanger agricultural production and restrict cultivable land availability. Water shortage in many locations impedes irrigation and farming practices, resulting in water stress and lower crop yields. Much of the world's food supply is lost or squandered at different points throughout the supply chain, from production to consumption, aggravating food poverty (Khanna, 2018).

Sustainable agriculture is an important strategy for addressing global food security concerns while minimizing negative environmental consequences. Sustainable agriculture seeks to increase production, protect natural resources, promote ecological balance, and assure farmers' economic viability (Herzberg et al. 2022). It entails putting practices that promote long-term food production in place while neither depleting resources nor damaging the environment (Abubakar 2021). The AIoT has emerged as a disruptive technology with enormous promise to revolutionise the agriculture industry in recent years. The AIoT is a network of networked devices with sensors, software, and data analytics capabilities that gather and share data via the Internet. AIoT may be used in agriculture to monitor and manage different elements of farming, such as crop health, irrigation, pest control, and animal management (Saad et al. 2023). Furthermore, recision farming is made possible by AIoT-enabled sensors and data analytics, which allow farmers to monitor and optimise inputs such as water, fertilizer, and pesticides, resulting in higher efficiency and decreased resource waste (Giuffrida et al. 2022). Weather forecasting and monitoring powered by AIoT assist farmers in adapting to changing weather patterns, mitigating risks, and making educated crop management choices. AIoT enables farmers to monitor their crops and animals from afar remotely, increasing output and minimising the requirement for personal presence (Kemmoe et al. 2022). AIoT applications in the food supply chain increase traceability, minimize food loss, and improve overall supply chain efficiency. AIoT technologies improve efficiency and solve problems in agriculture and food supply systems. Food security and sustainable agriculture need precision farming, smart irrigation, livestock monitoring, supply chain traceability, climate resilience, data-driven decision-making, and sustainable resource management (Kazmi and Sodangi 2022).

The United Nations established the Sustainable Development Goals (SDGs) in 2015 to address worldwide social, economic, and environmental challenges. These 17 global objectives provide a comprehensive framework for promoting sustainable development and improving people's well-being. They cover various issues such as poverty eradication, hunger, health, education, gender equality, clean water, sanitation, affordable energy, decent work, industry, innovation, climate action, life below water, life on land, peace and justice, and strong institutions (Kalu et al. 2021). The SDGs emphasize collaboration among governments, businesses, civil society, and individuals to achieve sustainable development. By 2030, the SDGs aim to end poverty, hunger, inequality, access to quality education and healthcare, promote sustainable economic growth, combat climate change, and protect biodiversity (Erin and Bamigboye 2022). Implementing the SDGs requires political commitment, adequate resources, and effective policies. Governments play a crucial role in setting national priorities, aligning policies with the SDGs, and mobilizing financial resources. Businesses are encouraged to adopt sustainable practices, invest in innovation, and contribute to the achievement of the goals (Khan et al. 2022). In conclusion, the SDGs represent a global roadmap for creating a more sustainable and equitable future for all, addressing the root causes of poverty, inequality, and environmental degradation. Achieving the SDGs requires collective efforts and a shared commitment to leaving no one behind.

The study's research goal is to look at the role of AIoT in promoting sustainable agriculture and tackling food security issues. The research will examine the possible advantages and drawbacks of AIoT applications in agriculture, such as crop management, water conservation, animal monitoring, and supply chain management. The study will thoroughly examine current literature, case studies, and real-world deployments of AIoT solutions in agriculture. It will concentrate on the influence of AIoT on agricultural production, resource efficiency, and climate change resistance. In addition, the research will look at the problems and hurdles to AIoT adoption in agriculture, policy implications, and future trends. Overall, this study aims to improve knowledge of how AIoT may play an important role in promoting sustainable agriculture and maintaining food security in a fast-changing world. The study seeks to give significant insights for policymakers, academics, and stakeholders to make informed choices and build strategies for sustainable agricultural growth by highlighting the prospects and difficulties of AIoT adoption in agriculture.

This chapter is arranged into nine different sections. In Sect. 2, the related works are discussed in detail. The research on AIoT applications in sustainable agriculture is presented in detail in Sect. 3. Section 4 provides a discussion on AIoT in food supply chain management. Section 5 provides the challenges and barriers. Section 6 discusses the policy and regulatory considerations. Section 7 provides the

Case Studies and real-world implementations as well as future trends and innovations are provided in Sect. 8. Finally, Sect. 9 concludes the study.

2 Literature Review

Climate change, water shortages, and the need for effective resource management are just a few of the many obstacles that agriculture must overcome to ensure the world's food supply. The AIoT has emerged as a potent tool to overcome these obstacles and improve agriculture's long-term viability (Praveen et al. 2021). AIoT systems use sensors, data analytics, and real-time connectivity to monitor and optimize agricultural operations for higher yields, lower resource waste, and safer food supplies (Nwankwoala and Okujagu 2021). This section examines current AIoT technologies for sustainable agriculture and food security. Using sensors to monitor soil moisture, temperature, nutrient levels, and crop health is at the heart of precision farming, a prominent use in agriculture. More informed choices about watering, fertilizing, and controlling pests may be made by farmers thanks to this information (Sohel et al. 2022). With real-time data from weather stations and soil moisture sensors, AIoT-enabled smart irrigation systems can fine-tune watering schedules to meet the precise needs of individual crops. These methods help farmers save water and irrigate their crops more efficiently, especially in arid areas (Farooq et al. 2022).

AIoT devices with sensors and GPS may track cattle and monitor their well-being and habits. Better livestock management and greater food production result from using livestock monitoring tools that assist farmers in identifying health problems early, optimizing feeding patterns and enhancing breeding practices (Eze et al. 2022). Due to AIoT-based supply chain traceability systems, food goods may be tracked and monitored in real-time through the supply chain. These methods improve visibility and tracking, safeguarding against food fraud and keeping consumers secure (Farooq et al. 2022; Kazmi and Sodangi 2022). Weather patterns, temperature, and humidity data are gathered via AIoT-based weather stations and environmental sensors, which are then used for climate monitoring and prediction (Al-otaibi 2022). This information is utilized to foresee the effects of climate change and harsh weather on crops, allowing farmers to make necessary preparations in advance. To keep tabs on pest populations in farms, AIoT systems have integrated pest monitoring sensors and data analytics. As stated by (Zhao et al. 2022), pests may be managed more sustainably and with less reliance on chemical pesticides if their presence is identified sufficiently soon.

Automated and optimized nutrition and water management is achieved via integrating AIoT technology into aquaponics and hydroponics systems. These methods allow for year-round farming, reduce water use, and boost the long-term viability of fish and vegetable harvests (Yoon 2020). Data on crop health and stress may be gathered in real-time via remote sensing technologies like satellites and drones fitted with AIoT sensors. This data aids farmers in making early diagnoses of disease and nutritional deficits, which leads to more focused treatments and fewer crop failures (Abdullahi et al. 2022). AIoT technologies use automated traps, drones, and AI for smart pest control (Shahinzadeh et al. 2019). This allows for precise monitoring and managing of pest populations without harming the ecosystem. Indicators of soil health, such as pH, nutrient content, and organic matter, are tracked using AIoT sensors and devices. Producing crops sustainably and effectively requires this information to implement precision agricultural practices and enhance soil fertility (Mishra and Pandya 2021). As a result of optimizing resource utilization, increasing productivity, and raising the efficiency of food supply chains, AIoT technologies have the potential to revolutionize agriculture and solve food security concerns. Current AIoT solutions show how important technology is to attaining sustainable agriculture and meeting the needs of a rising global population.

3 AIoT Applications in Sustainable Agriculture

Global food security depends on agriculture, yet climate change, water shortages, and resource management pose concerns. The AIoT can solve these problems and improve agriculture's sustainability. AIoT systems monitor and optimize agricultural processes using sensors, data analytics, and real-time connectivity, improving productivity, resource efficiency, and food security (Dibia and Nwaigwe 2017; Herzberg et al. 2022). For precision farming, AIoT sensors capture soil moisture, temperature, nutrient levels, and crop health data. This data may help farmers optimize irrigation, fertilization, and insect management for better resource utilization and crop yields. Smart irrigation systems optimize watering schedules based on crop water needs using real-time data from weather stations and soil moisture sensors (Ambayea et al. 2022). Livestock monitoring systems enhance livestock management and food production by detecting health concerns early, optimizing feeding patterns, and improving breeding practices. Supply chain traceability systems reduce food fraud and ensure food safety by tracking and monitoring food goods in real-time (Oberlack et al. 2021). Farmers can modify their practices and safeguard their from bad weather using AIoT-based weather stations and environmental sensors. Data analytics and integrated pest monitoring devices reduce the demand for chemical pesticides and promote eco-friendly pest control (Awofeso and Odeyemi 2021). Aquaponics and hydroponics systems automate and optimise nutrition and water management, allowing year-round growing, decreased water use, and sustainable fish and vegetable production. Farmers need remote sensing for crop health and stress to identify illnesses and nutrient shortages early and cure them for maximum development and output (Norton 2016). Farmers may plan planting, irrigation, and pest management using weather forecasts and predictive analytics. Smart farming and precision agriculture improve crop quality, food safety, efficiency, sustainability, data-driven decision-making, labour, and time (Ambayea et al. 2022; Voora et al. 2022). However, early investment expenditures, data privacy and security issues, and farmers' technical knowledge are obstacles. Smart farming may be vital to global food

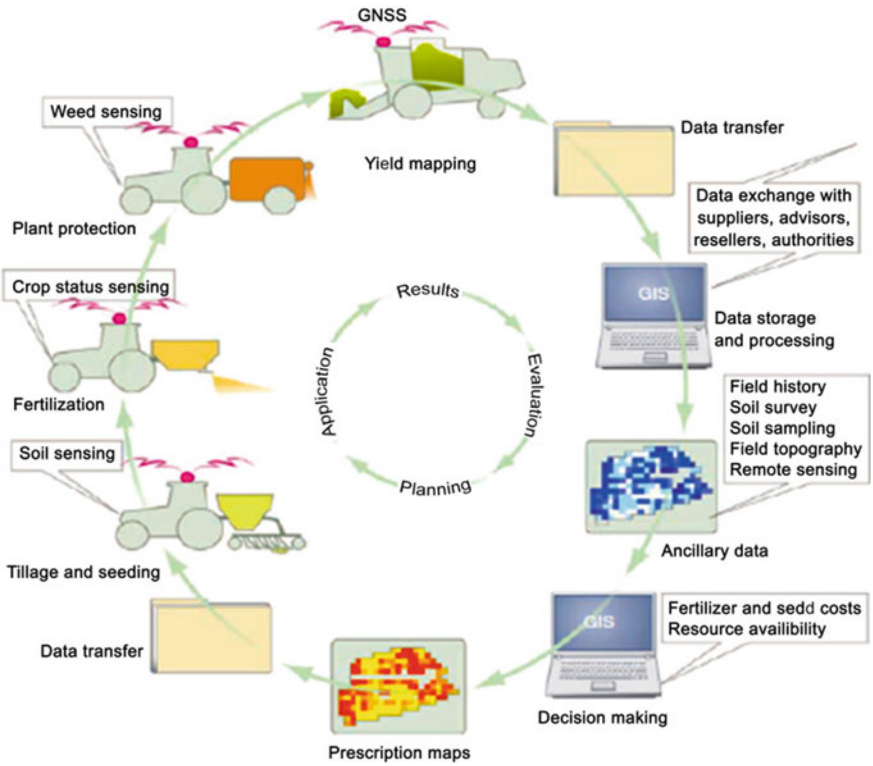

Fig. 1 The components of precision agriculture (Herzberg et al. 2022)

security and environmental sustainability as technology advances. Thus, components of precision agriculture are illustrated in Fig. 1.

3.1 Smart Irrigation and Water Management

Smart irrigation is a cutting-edge technique for managing water in agriculture. It allows farmers to save water without sacrificing yield. Smart irrigation systems reduce water waste while supplying water reliably to crops depending on individual demands, local weather, and other data collected from various sensors and AIoT devices (Raghuvanshi et al. 2022). Agriculture uses a lot of water, so finding ways to save and reuse that water is essential. Smart irrigation systems determine when and how much water should be supplied to crops by monitoring soil moisture and evapotranspiration rates (Zhang, Xu et al. 2022b). Smart agricultural practices, such as drip irrigation and controlled watering systems, are increasingly used to reduce water waste from evaporation and runoff. This technology allows farmers to minimize labor by remotely controlling irrigation cycles and maintaining a steady water supply. Smart irrigation helps conserve water, grow crops with the same amount of water, save money, be more eco-friendly, and be less vulnerable to climate change (Neupane et al. 2022; Ning and Liu 2015). However, barriers to wider adoption exist, including the need for costly upfront investments, specialized knowledge, and consistent access to the Internet (Arubayi 2023). Finally, smart irrigation and water management provide a game-changing strategy for environmentally responsible farming by helping farmers reduce water waste, maximize crop output, and safeguard natural resources. Farmers can help ensure food security in the face of climate change by adopting smart irrigation practices like drip irrigation and automated watering systems (Merem et al. 2018). Smart irrigation in agriculture is predicted to play a crucial role in attaining sustainable water management and guaranteeing the resilience of agricultural systems as technology develops.

3.2 Livestock Management and Health Monitoring

Livestock management is an important part of contemporary agriculture since it ensures the health and production of livestock animals (Ali and Choi 2020). AIoT technology is helping to improve livestock management and health monitoring. Farmers may monitor their animals' health, behaviour, and position in real-time by employing wearable sensors and tracking devices, allowing for early diagnosis of health concerns or irregularities (Okonofua et al. 2021). AIoT-enabled monitoring devices give significant data into cattle movement and behaviour, assisting farmers in managing grazing patterns and preventing straying. Behavioral monitoring may detect indicators of discomfort or changes in eating patterns, resulting in better animal welfare (Kochovski and Stankovski 2018). One of the most important advantages of AIoT in livestock management is illness diagnosis and prevention facilitated by AIoT. AIoT devices may notify farmers of any sickness or stress symptoms by monitoring vital signs and physiological factors, limiting disease transmission and significant economic losses (Khan and Ahmad 2022).

Furthermore, AIoT-based data analytics may aid in identifying illness patterns and trends, hence contributing to the creation of effective disease preventive programmes. AIoT technology increases animal welfare, productivity, labour costs, resource management efficiency, illness control, and biosecurity. However, there are hurdles to using AIoT in livestock management, such as initial expenses for AIoT devices and infrastructure, dependable connection in remote locations, and data privacy and security issues (Abdullahi et al. 2022). Finally, AIoT technology has revolutionized livestock management and health monitoring in agriculture, allowing farmers to carefully monitor the health and behavior of their animals, resulting in enhanced animal welfare and production. AIoT-enabled early disease detection and prevention improve biosecurity measures and minimize illness-related economic losses (Mishra and Pandya 2021; Shahinzadeh et al. 2019). To ensure the well-being of animals and

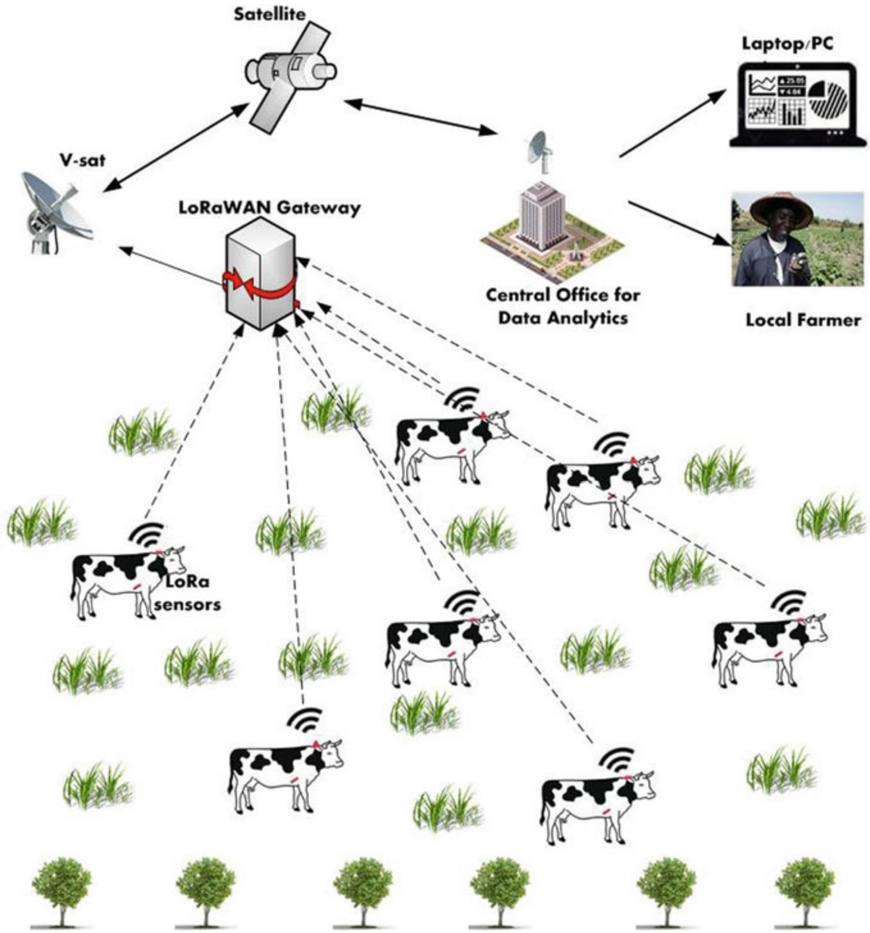

Fig. 2 Livestock management and health monitoring (Darem et al. 2022)

farmers, the AIoT integration in livestock management will be crucial as technology develops, as illustrated in Fig. 2.

4 AIoT in Food Supply Chain Management

The AIoT has changed the logistics and supply chain management industries by enabling real-time monitoring and tracing of items in transit. Sensors and gadgets enabled by the are built into things, containers, and vehicles to track and record data such as location, temperature, and humidity (Praveen et al. 2021). This real-time information allows businesses to streamline their supply chains and reduce wasted time and money. Due to AIoT-enabled smart logistics, companies can improve inventory management, save operating costs, and boost customer satisfaction with on-time, precise delivery (Kamble et al. 2019). Perishable items' quality and safety, including fresh fruit, medicines, and vaccinations, depend on effective cold chain management and food preservation (Zhong et al. 2015). Cold chain management powered by the helps keep goods fresh and secure across the supply chain, which helps cut down on food waste and boosts food security. Assuring the quality and security of goods via sensors and monitoring is crucial. Sensors enabled by the can check food for pH, moisture, and pollutants to ensure it's safe and up to standards (Nozari et al. 2022; Rehman Khan et al. 2022).

The AIoT makes supply chain visibility, transparency, efficiency, cost savings, product quality and safety improvements, sustainability, and environmental impact possible (Ezenwa 2019). Data privacy and security, standardization and interoperability of AIoT systems, and dependable and continuous connection are just a few hurdles that need to be cleared before widespread adoption can occur in supply chain and food management (Bertin et al. 2022). AIoT-enabled smart logistics and supply chain monitoring, cold chain management, and quality and safety assurance are revolutionizing how organizations operate and ensuring that supply chain operations are efficient and sustainable (Zakeri et al. 2022). Companies can improve logistics, protect the freshness of perishable items, and guarantee their products' safety by using real-time data and insights (Zhong et al. 2015). To keep up with the demands of the current business environment and ensure the delivery of high-quality goods to customers, supply chain management must increasingly use AIoT technologies, as illustrated in Fig. 3.

5 Challenges and Barriers

The technological difficulty of establishing and maintaining AIoT systems is a major obstacle to their widespread use in agriculture. Integrating sensors, devices, and networking technologies may be difficult, particularly for small-scale farmers in rural places with little infrastructure (Lu 2018). AIoT applications demand real-time data transfer, which might be difficult in rural areas. Data security and privacy are crucial as AIoT devices create massive volumes of data. Farmers must secure their crop production, soil health, and market data against unauthorized access and cyberattacks (Abdullahi et al. 2022). Data encryption, access limits, and secure communication protocols protect farmers' vital data. Small-scale farmers and underdeveloped areas may struggle to use AIoT technology due to their high upfront costs. AIoT devices, sensors, and connection solutions are costly, making it hard for resource-constrained farmers to use them (Zimba 2022). Technical support and maintenance may also strain finances. Lack of awareness and understanding of AIoT, limited access to technical competence, and cultural opposition to new technology may hinder small-scale farmers in developing nations. These areas may additionally struggle to embrace AIoT technologies due to language and digital literacy issues (Al Qartah 2020).

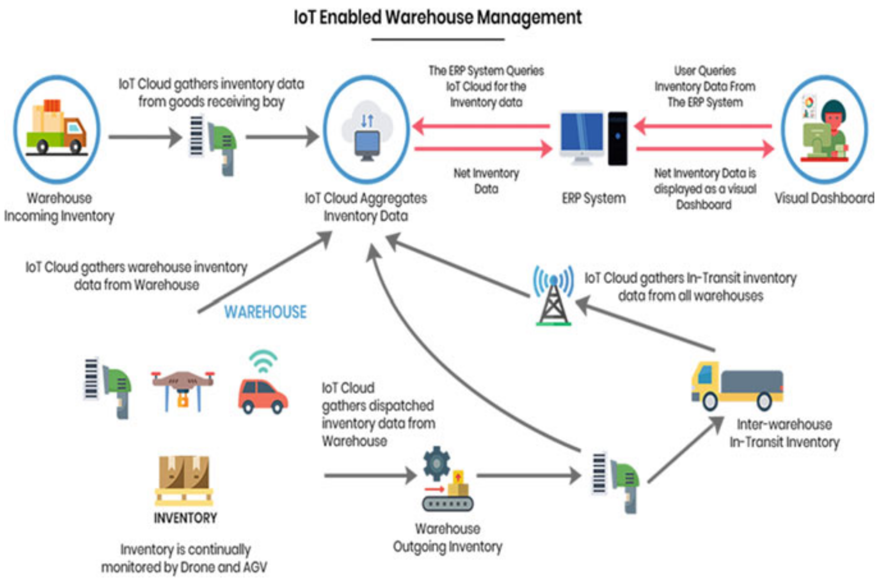

Fig. 3 AIoT in food supply chain management (Zhong et al. 2015)

5.1 Solution and Mitigation

Technical constraints, data security concerns, financial issues, and acceptance hurdles might prevent the broad adoption of AIoT in agriculture, especially in small farms and developing nations. Stakeholders, including governments, commercial enterprises, and non-profits, must work together to solve these problems (Hammi et al. 2022). By promoting accessible and user-friendly AIoT solutions, guaranteeing data security, giving financial incentives, and helping farmers with capacity development and training, the agricultural industry can maximize AIoT's potential for sustainable and efficient farming (Ouechtati et al. 2021).

Simplified and User-Friendly Solutions: Small-scale farmers may use AIoT solutions that are user-friendly and cost-effective. Plug-and-play AIoT devices and straightforward interfaces may help farmers set up and employ AIoT technology (Jayashankar et al. 2018).

Public–Private Partnerships: Government agencies, private firms, and NGOs may work together to deliver AIoT solutions in poor countries. Joint projects may overcome financial and technical constraints and give farmers with training and assistance (Hammi et al. 2022).

Data Security: Encryption and authentication help secure farmers' data from cyberattacks. To protect data privacy, farmers must be educated about data security (Bertin et al. 2022).

Subsidies and Incentives: Government subsidies or financial incentives for adopting AIoT technology might encourage small-scale farmers to invest in these solutions. Implementation costs may be reduced via cost-sharing and tax incentives. Training and capacity development may improve farmers' digital literacy and technical abilities. Extension programmes and training may assist farmers in grasping AIoT devices (Hammi et al. 2022).

6 Policy and Regulatory Considerations

Agriculture might become more sustainable, efficient, and productive using AIoT technology. Through different programmes, governments worldwide have supported AIoT adoption. These include financial support, research and development funding, capacity building and training, regulatory frameworks, public–private partnerships, testbeds and demonstration farms, digital infrastructure development, data analytics, and decision support, market linkages and e-commerce platforms, and policy advocacy (Lu 2018). These projects have helped farmers use AIoT to solve agricultural problems, boost production, and adopt sustainable and efficient farming methods. International partnerships and standards are critical to developing and accepting AIoT-based food security solutions since governments, organisations, and stakeholders must work together to solve the agricultural and food sectors' complex problems (Shahinzadeh et al. 2019).

The widespread use of AIoT technology in agriculture has led to sustainable, efficient, and more productive farming. Governments worldwide have been actively pushing and supporting the adoption of AIoT due to its critical importance (Fang et al. 2012). Governments provide financial assistance, grants, and subsidies to encourage farmers and agricultural enterprises to invest in AIoT technology. These rebates reduce the out-of-pocket expense of implementing an AIoT system or device, making them more feasible for farms of all sizes. Government funding for research and development (R&D) programs that provide specialized AIoT solutions for agriculture, such as precision agriculture, remote sensing, and livestock monitoring, has led to the developing cutting-edge tools and methods (Zhang, Li et al. 2022a). Governments host training programs and seminars to improve farmers' and agricultural employees' familiarity with digital literacy and technical abilities. They set up legislative frameworks that make it easier for farmers to use AIoT. Governments create standards for AIoT devices and data privacy rules to guarantee the safety of AIoT solutions and protect farmers' data. They work with businesses, universities, and NGOs to promote the use of AIoT in farming via public–private partnerships, resulting in increased opportunities for information exchange, access to cutting-edge technology, and the creation of industry-specific AIoT solutions (Kazmi and Sodangi 2022).

Governments also invest in constructing and updating digital infrastructure, such as high-speed internet access and mobile networks, to guarantee uninterrupted data transfer and communication between farm AIoT devices. They provide data analytics and decision support systems that use information gathered from AIoT devices to advise farmers on improving their operations (Yin et al. 2022). Governments also develop e-commerce platforms that link farmers with customers or purchasers, improving market connections and maintaining produce quality and traceability throughout the supply chain. Governments advocate for policies that encourage the use of AIoT in farming, such as lowering taxes, fostering cross-institutional research partnerships, and lobbying for more lenient rules (Godager et al. 2021). The extensive use of AIoT technology in agriculture can be attributed to various factors, including financial incentives, R&D funding, capacity building, regulatory frameworks, public–private partnerships, and the growth of digital infrastructure (Yang et al. 2021).

Sharing knowledge and best practices helps advance AIoT-based food security solutions. International cooperation and standards are essential for food security. Sharing knowledge, harmonizing standards, aggregating data, fostering research and development, aligning policies, pooling resources, and building capacities can help countries and organisations develop cutting-edge technologies and innovative solutions for the global agriculture and food sectors (Kumar et al. 2020). These agreements allow data exchange and aggregation, improving AIoT-based food security solutions. Cross-border research and development projects bring together professionals from various nations to solve food security issues, resulting in cutting-edge technology and novel solutions (Yin et al. 2022). Funding and resource allocation, capacity development and training, scaling up successful projects, and addressing data privacy and security issues are all examples of ways in which policy alignment and collaboration may be fostered. Thus, AIoT-based food security solutions can only be fully realised via international cooperation and standardization. Sharing information, harmonizing standards, gathering data, promoting research and development, aligning policies, pooling resources, and creating skills may help governments and organizations handle global food security issues. These combined efforts will lead to sustainable and resilient food systems for everybody (Chilaka and Chilaka 2019).

7 Case Studies and Real-World Implementations

The ability of AIoT solutions to tackle difficult problems and propel good change has been shown by their widespread adoption in some countries. AIoT technology may enhance productivity, sustainability, and resource management, as shown by the featured case studies in precision agriculture, fisheries management, and smart grids. Guidelines for future AIoT implementations may be derived from the lessons gained and best practices in interoperability, data security, user-centric design, and local context concerns (Yin et al. 2022). In order to create a more sustainable and interconnected society, AIoT solutions must continue to develop and cooperate. Many sectors, such as agriculture, healthcare, transportation, and more, have been radically altered by AIoT development. This section looks at real-world deployments of AIoT technologies in various areas to draw up lessons and best practices (Yin et al. 2022).

Some globally effective solutions are (Cliff et al. 2023; Godager et al. 2021).

Accurate farming methods in the USA: Precision farming has become more popular in the United States. Farmers use the devices like soil sensors, weather stations, and drones to monitor their crops and ensure everything is running well. Farmers may improve their irrigation, fertilization, and pest management methods with real-time data from these sensors. Sustainable agriculture has benefited from increased agricultural yields and more effective use of available resources.

Norwegian Smart Fishery Management: Norway has introduced -based solutions to encourage responsible fishing practices in its fisheries sector. AIoT technologies like GPS trackers and sensors are installed aboard fishing boats to keep tabs on catch rates, fish stocks, and environmental factors. By using this information, authorities can better enforce fishing limits, curb overfishing, and safeguard marine ecosystems, assuring the fishing industry's continued success.

South Korean smart grids: South Korea's energy industry has made great efforts towards implementing technology. (AIoT) sensors are used in smart grids for real-time monitoring of energy usage, distribution optimisation, and problem detection. Improved grid efficiency in South Korea has resulted in lower energy costs and greater sustainability through lowering energy waste and increasing energy dependability.

7.1 Best Practices and Real-World Lessons

The practices and real-world lessons include (Janabi and Kurnaz 2023):

Standardisation and Compatibility: Successful systems need standardized communication protocols and the ability to easily integrate new hardware and software. The easy sharing of data and compatibility across various AIoT components are made possible by establishing interoperability.

Data Privacy and Protection: Sensitive data must be collected and sent securely in AIoT implementations. To defend against cyber risks and preserve user privacy, implementers should prioritize data encryption, user authentication, and data access restrictions.

User-centered design: Users are the focus of good design. To increase user adoption and engagement, it is important to provide user-friendly interfaces, clear representations, and intuitive functionality.

Flexibility and scalability: The data volume and the number of connected devices are expected to grow over time. Therefore, AIoT implementations must be flexible. As a result of its adaptability, new technologies, and future growth may be easily included.

Consideration of the Local Context: Successful installations need adjustments for each unique situation. To provide successful solutions, it is essential to appreciate various geographical areas' specific difficulties, cultural subtleties, and infrastructural limitations.

Coordination and Cooperation: Governments, businesses, universities, and communities all have a stake in a successful rollout of the Partners may pool their knowledge, skills, and resources through collaboration to create long-lasting improvements.

Control and Assessment: To determine how successful an AIoT solution is and where it may be enhanced, constant monitoring and assessment are required. Insights derived from data analysis support continual optimization and enable evidence-based decision-making.

Instruction and Capacity Development: The knowledge and proficiency of end-users and implementers of AIoT technologies may be improved via training and capacity-building programs. Building people's abilities is crucial to ensuring that the solutions have the desired effect.

8 Future Trends and Innovations

The AIoT has advanced swiftly and is continuing to drive innovation. In the not-too-distant future, AIoT technologies will merge with AI and machine learning, resulting in unheard-of levels of efficiency and automation. The introduction of 5G technology and the development of edge computing will also usher in a new era of AIoT applications, particularly in the agricultural industry (Saad et al. 2023). Improvements in artificial intelligence, machine learning, 5G, and edge computing point to a bright future for AIoT in agriculture by fueling substantial gains in efficiency, sustainability, and production. 5G and edge computing will improve connection and data processing, and combining AI and machine learning with AIoT will allow for predictive analytics and autonomous systems. Precision farming, smart irrigation, remote monitoring, and evidence-based decision-making are just some ways the AIoT will revolutionise agriculture and strengthen the foundations of sustainable agriculture worldwide (Seyyedabbasi et al. 2023). The potential for innovation and beneficial influence on the agricultural business is limitless as these technologies continue to advance. The potential impact of 5G and edge computing on AIoT applications in agriculture and future trends and breakthroughs in AIoT are discussed.

8.1 Future Trends and Innovations in AIoT

Increasing connectivity among AIoT devices will provide simple two-way communication and data sharing. Because of this enhanced connectedness, data analysis and decision-making will become more holistic and integrated. Artificial intelligence (AI) and machine learning (ML) algorithms will be included into AIoT devices, allowing them to analyse and anticipate trends and patterns in real-time data (Garg and Goyal 2020). As a result of this capacity, procedures and resource allocation may be optimised for greater efficacy. With edge computing, processing may be done closer to the data source, which speeds up processing and decreases latency. Edge intelligence-equipped AIoT devices will be able to do sophisticated tasks locally, cutting down on demand for cloud computing. The AIoT, AI, and ML will merge to generate fully autonomous systems. As a result, production will rise, human errors will decrease, and efficiency will improve. AIoT will revolutionize urban planning and infrastructure management, leading to the construction of smart cities with linked transportation, electricity, waste management, and more systems (Mousavi et al. 2021).

8.2 Integration of AIoT, AI, and Machine Learning

AI and ML algorithms will analyze massive volumes of data the AIoT creates. This will allow for enhanced knowledge of agricultural procedures and more efficient use of available resources (Olan et al. 2022). Precision agriculture will become a reality in which farmers administer inputs like water and fertiliser with pinpoint accuracy using real-time data and analysis made possible by AI-driven AIoT apps. By taking this course of action, both yields and environmental impact may be improved. With AI, devices can anticipate when agricultural machinery and equipment need repair (Olan et al. 2022; Pan and Zhang 2021).

8.3 The Possible Effect of 5G and Edge Computing on Applications in Farming

With the increased bandwidth and decreased latency that 5G networks provide, the AIoT can communicate with one another in near real-time. With the help of 5G and edge computing, farmers can keep an eye on their crops and animals without leaving their homes (Rathod et al. 2023). Data-intensive AIoT applications, such as high-resolution image and video analytics, will be supported by 5G's fast data rates and the processing capabilities of edge computing, enhancing agricultural monitoring and analysis. AIoT-enabled irrigation systems with 5G connection and edge computing can optimize water consumption and save waste by adjusting the amount of water supplied depending on real-time data, soil moisture levels, and weather predictions (Varsha et al. 2021).

9 Conclusion

This chapter examines the potential to revolutionize agricultural practices via data-driven decision-making and precision agriculture on the path to sustainable agriculture and food security. Agricultural output, resource effectiveness, and supply chain management benefit greatly from AIoT-enabled systems. AIoT improves agricultural operations by helping farmers and stakeholders make better choices based on real-time data and analytics. Due to the AIoT, farmers can track and manage their crops with pinpoint accuracy, improving efficiency, lessening environmental damage, and boosting agricultural yields. By allowing farmers to adjust water distribution in response to current weather and crop circumstances, smart irrigation systems improve water efficiency while decreasing water waste. Better illness diagnosis, health assessment, and livestock management contribute to happier, healthier animals. A well-oiled supply chain guarantees that food is safe to eat, cuts down on post-harvest losses, and speeds up the delivery of crops to consumers. AIoT plays a crucial role in developing sustainable agriculture and attaining global food security by using real-time data and analytics and closing the information gap between farmers, agribusinesses, and consumers. With the ongoing development of AIoT, AI, and 5G technologies, the future of AIoT in agriculture seems bright. Data security, privacy issues, high implementation costs, and accessibility for small-scale farmers in underdeveloped countries are only some of the obstacles that must be overcome. Understanding AIoT's societal and economic effects on agriculture requires a study conducted by agronomists, environmentalists, and social scientists. Investing in AIoT-related research and development may lead to a future where agriculture is more sustainable, productive, and ecologically aware.

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AIoT-Enabled Precision Agriculture for Sustainable Crop Disease Management: Advancing SDGs Through Graph Attention Neural Networks

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Abstract By 2050, agricultural productivity must increase by 70% if food security is to be achieved throughout the world despite population expansion. For high-risk crops like wheat, rice, and maize in particular, crop diseases provide tremendous obstacles to food security which is a huge challenge towards achieving the Sustainable Development Goals (SDGs). Artificial intelligence (AI), especially deep learning, stands up as a possible answer in this endeavor. This research supports improved disease detection technologies using multi-object techniques based on Artificial Intelligence of Things (AIoT), including Graph Attention Networks (GATs), with an emphasis on wheat disease detection, which is crucial for diabetics globally. The literature review emphasizes the importance of AIoT and GATs in remote sensing, machine learning, gene editing, precision agriculture, and cost-effective crop monitoring systems. The suggested ensemble model, which combines Fast R-CNNs, Mask R-CNNs, and RetinaNet, distinguishes between healthy and Septoria/Stripe rust-infected wheat samples with good accuracy. GATs are useful in identifying patterns in complicated datasets, which improves efficiency. The success of this wheat disease classification technique is demonstrated by experimental validation, which shows an overall accuracy of 92%, precision of 89%, recall of 94%, and F1-score of 91% in disease classification. Early disease detection, enhanced crop management, and lower yield losses are all possible by integrating AI, AIoT, and SDGs-aligned solutions. This work demonstrates the potential of AIoT-driven initiatives to contribute to SDGs objectives for sustainable agriculture and global well-being.

Keywords Wheat Disease Detection · GATs · Multi-Object Techniques · AIoT · SDGs

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1 Introduction

The world's population is growing at an exponential rate, and global food security heavily relies on technological advancements. According to experts, agricultural production must increase by 70% by 2050 to provide sustainable food for the estimated 9 billion people on the planet. To overcome this daunting challenge, innovative technology-based solutions are imperative to revolutionize the agricultural landscape (Velickovic et al. 2017). Precision agriculture, smart irrigation, drones, and genetically modified crops are examples of modern technologies that can be used to increase food security (Kakulapati et al. 2020). Using artificial intelligence to automate and analyze data can efficiently optimize farming, resulting in higher output and decreased resource waste. Cooperation between technology companies, agricultural professionals, and policymakers is essential for the creation and execution of technological solutions worldwide. The advantages of technology must be harnessed to prepare for a future where we have enough healthy food for everyone, while also protecting our planet's well-being.

Even though this projection is very much achievable, crop diseases are one of the major factors that will be a great tall order to be achieved (Andrew et al. 2022). To achieve the projected growth, the agricultural value chain will encounter substantial challenges. Nevertheless, the use of artificial intelligence can help alleviate some of the pressure by providing accurate and efficient detection of crop diseases. The three major crops of the world, wheat, rice, and corn, (National Geographic 2022), need to contribute greatly to the 70% projected for the world to achieve future sufficiency, and these crops are among the major ones that are greatly affected by diseases which hinders improve production (Sahil Verma et al. 2023). Sustainable agricultural practices can regenerate the ecosystems and reduce future threats to human health and its effect on the environment ('FAO Publications Catalogue 2022' 2022) which further shows the importance of technology in advancing the Sustainable Development Goals (SDGs).

Many countries that contribute to the agricultural value chain of the world, need to step up in their capacity and ability to handle any hindrance to food security. Nigeria is one of the countries of the world that rely heavily on agriculture for its GDP (Oluwasani et al. 2021), and the world's three major food stables are the most produced by the country. Although climate change is one of the major reasons for low food production in the world, these greatly influenced the increase in crop diseases and thereby hinders the country's capacity to produce at its maximum abilities (Saleem et al. 2019). As a result, improve technological advancement can greatly improve the handling of crop diseases through the effective detection and classification of these diseases, and hopefully achieving improved food security (Bouguettaya et al. 2022). AI is increasingly being utilized in agriculture to increase crop yields, decrease pests and diseases, and optimize water usage. Deep learning and other AI-based approaches may identify agricultural diseases rapidly and correctly, even in their early stages (Sujatha et al. 2021). This has the potential to transform agriculture by lowering crop losses and increasing yields while also making agriculture more sustainable by minimizing the need for chemical pesticides.

The implementation of AI technology in agriculture has the potential to contribute significantly towards achieving several Sustainable Development Goals (SDGs) (Wakunuma et al. 2022). By improving crop health and increasing yields, it supports the goal of Zero Hunger. It also promotes sustainable farming practices and reduces the environmental impact of disease management, aligning with the goal of Life on Land. Furthermore, the use of AI can drive technological advancements and efficiency in the sector, supporting the goal of Industry, Innovation, and Infrastructure (Mhlanga 2021). Improving the livelihoods of farmers can also contribute to achieving the goals of No Poverty and Decent Work and Economic Growth (Cossy-Gantner et al. 2018). The power of AI in agriculture is undeniable, and its potential to create a more sustainable future is truly inspiring. With healthier food options and sustainable farming techniques, AI-powered agriculture can enhance diabetes patients' health status (Owoyemi et al. 2020). AI can also aid in the diagnosis of plant diseases, which benefits both agriculture and the environment.

1.1 Justification of the Research

The advancement in image research and processing through computer vision, machine learning, and emerging technologies has rapidly improved the world's ability to handle problems (Kusharki et al. 2022), including areas such as crop disease detection and classifications. These technologies, most especially deep learning methods, have helped greatly in solving complex image-related issues and thereby improving the world's security (Singh et al. 2020). Research such as (Andrew et al. 2022), where deep learning method techniques were used in detecting leaf diseases in the crop through the utilization of convolutional neural networks is valuable to practitioners in the field of agriculture. Although there are several pieces of research around wheat, rice, and corn, very little crop detection research is carried out in wheat production.

Wheat production is of particular interest to this research as the world population grabbles with the increase of diabetic patients to 700 million by 2045 (Li et al. 2021), whereas wheat is found to be key food in diabetes management as aptly captured in the work of (Mohammadi et al. 2022). According to (Mohammadi et al. 2022) research, eating wheat germ may improve mental health and BDNF levels in people with T2DM. A study of 60 people discovered that those who took wheat germ experienced significant improvements in depression, anxiety, stress, and BDNF levels. In this research, we attempted to answer some key questions: (1) what is the world wheat production needs for adequate food security? (2) Is wheat leaf disease crucial to production capacity and speed? (3) what is the efficiency of using multi–object techniques and graph attention neural networks in the fast and easy detection of these diseases? Our research has utilized a combination of multi-object techniques and GATs to accurately detect crop disease in wheat. Our ultimate goal is to improve food production and ensure food security, while also addressing the growing issue of diabetes worldwide.

In this section, we discussed the significance of food security and the consequences of crop diseases on food production. We investigate the use of artificial intelligence, namely deep learning algorithms, for identifying agricultural diseases. We reported a deep learning system used to identify wheat leaf diseases in Nigeria. The use of AI in agricultural disease detection supports SDG 2 (Zero Hunger) by boosting food security and sustainable agriculture. Also, by accelerating food production and reducing crop illnesses, this research indirectly helps to Goal 3 (Good Health and Well-being) by addressing the growing number of diabetes patients globally (Wakunuma et al. 2022). And the use of AI-powered solutions in agriculture helps to improve sustainable practices and supports Goal 9 (Industry, Innovation, and Infrastructure). By assisting farmers with disease detection and food production, AI technology can enhance their livelihoods and productivity, which can positively impact Goal 1 (No Poverty). This study emphasizes the significant impact of AI-driven solutions on several SDGs, such as food security, improved health, and sustainable agriculture.

2 Related Work

The purpose of attaining food security supply and ecological plant diversity is hinged on the need to have a very healthy society. As re-iterated, crop diseases are a major threat factor that affects food production the use of technology is essential, but these diseases are evolving frequently, and it is still challenging for existing advanced information and intelligence technologies. In this part, we review the relevant literature on multi–object techniques for plant diseases, the deployment of the graphical neural network on image processing as it affects crop diseases, as well literature that explained the use of computer vision in plant diseases.

2.1 Crop Diseases

Crop diseases are a major threat to food security. They can cause significant crop losses, which can lead to food shortages and price increases. In 2019, crop diseases caused an estimated $220 billion in losses worldwide (Kulkarni et al. 2021). And as the world's population rises, crop diseases represent a danger to food security worldwide (National Geographic 2022). Precision agriculture, gene editing, remote sensing, and machine learning are examples of cutting-edge technologies that offer promising solutions for disease identification and categorization, enabling precise predictions and effective control (Elaziz et al. 2021). Rice, wheat, and maize crop diseases may be identified and categorized using deep learning techniques on multi-label datasets (Li et al. 2020).

AI can be used to detect crop diseases with high accuracy. This can help farmers to identify and treat diseases early before they cause significant crop damage (Chen et al. 2021). AI can also be used to monitor crop health and predict the risk of disease outbreaks. This information can help farmers to take preventive measures to protect their crops. There are various ways in which using AI to identify agricultural diseases might enhance food security. It can be a first aid in lowering crop losses. Second, it may aid in enhancing agricultural production efficiency. Thirdly, it can help make crops more resistant to disease. Before the extensive use of AI to identify agricultural diseases, various issues must be solved. The requirement for big databases of tagged images presents a problem. The requirement to create AI models that are resilient to changes in lighting conditions presents another difficulty.

Although the use of AI in agricultural production is still in its infancy, it has the potential to completely alter how food is raised. The advantages of utilizing AI for agricultural disease detection are substantial notwithstanding these difficulties. Farmers may be able to produce more food more effectively and sustainably with the aid of AI. AI has the potential to improve the sustainability, efficiency, and climate change resistance of food production. The world's population's ability to access food might be significantly impacted by this. This could contribute to enhancing global food security.

2.2 Artificial Intelligence of Things (AIoT)

The use of AIoT in precision agriculture has the potential to revolutionize how major SDGs linked to crop disease control and food security are advanced. SDG 2, which aspires to eliminate hunger, benefits from AIoT-enabled agricultural disease monitoring, which enables early detection and response to plant health problems. Farmers can monitor agricultural conditions, detect disease outbreaks, and apply early preventative measures with AIoT sensors and devices, optimizing resource utilization and improving food output. Furthermore, SDG 3 coincides with AIoT-driven precision agriculture by lowering dependency on chemical pesticides, resulting in better and safer food items for customers, and so supporting enhanced public health and well-being.

The use of AIoT in precision agriculture also contributes to SDG 9, which emphasizes industry, innovation, and infrastructure. AIoT technologies enable smart and linked systems, automating tasks and optimizing resource allocation, increasing agricultural output, and supporting long-term infrastructure development in the agri-food industry. Also, AIoT promotes responsible consumption and production by enabling precise and focused intervention in agricultural disease control, avoiding resource waste, and minimizing environmental impact. More importantly, the climate-resilient feature of AIoT in agricultural disease detection aligns with the emphasis on climate action in SDG 13. AIoT helps farmers to implement adaptive methods by delivering real-time meteorological data and disease prevalence insights, boosting climate-smart agriculture, and increasing resistance to climate-related threats. AIoT lays the path for many SDGs in crop disease control, supporting sustainable agriculture practices, and ensuring a more food-secure and resilient future through these synergistic contributions.

2.3 Multi-Object Techniques

Crop image recognition and classification make extensive use of multi-object approaches, such as deep learning-based multi-object detection and multi-object classification (Ye and Wang 2021). In crop monitoring, assessing many crops in a single image might be a speedy and cost-effective option. While multi-object classification is a promising crop classification strategy, deep learning-based multi-object detection stands out in terms of accuracy. This technology is extremely accurate at detecting and categorizing crops, making it an excellent alternative for farmers and crop managers looking to expedite their monitoring process (Sakurada et al. 2019). The accuracy and efficiency of the detection and classification process are improved by methods like R-CNNs, quicker R-CNNs, Mask R-CNN, RetinaNet, and You Only Look Once (YOLO) (Singh et al. 2023). Utilizing multi-object approaches is a highly efficient method for accurately recognizing and categorizing crop images. This advanced technique can greatly improve crop monitoring, leading to a significant increase in productivity and efficiency.

2.4 Graph Attention Neural Networks (GATs)

GATs, or Graph Attention Networks, are a sort of Graph Neural Network (GNN) that is designed to analyze data in graph structures. They have shown to be quite effective at extracting significant information from various graphs, such as social networks, chemical compounds, and photographs (Kong et al. 2022). GATs' core strength is in their capacity to represent intricate connections between various items in multi-object scenarios, which makes them particularly useful for tasks like object recognition, tracking, and segmentation. By encoding leaf images as graphs, GATs have found major applications in agriculture for recognizing and classifying crop diseases (Velickovic et al. 2017). GATs can learn to effectively identify distinct states by examining the spectral features of neighboring pixels in a graph, allowing for reliable disease identification and categorization (Tang et al. 2015). Furthermore, GATs provide an adaptable and robust framework for analyzing multi-object techniques when working with graph-structured data, making them invaluable in a variety of domains, particularly agriculture, where their successful implementation has played a critical role in crop disease management.

2.5 Literature Review

The article by (Borhani et al. 2022) introduces a novel method for automated plant disease detection using a Vision Transformer (ViT) deep learning model. They demonstrate the high accuracy rates, up to 99.09%, achieved by the proposed approach in classifying plant diseases, surpassing other state-of-the-art models. While the research has practical implications for the agricultural industry, limitations include the use of a limited dataset, model interpretability, data bias, and computational intensiveness. In another research, (Andrew et al. 2022), a deep learning-based approach is proposed for detecting leaf diseases in tomato and potato crops. Their Convolutional Neural Network (CNN) model achieves high accuracy rates, up to 97.5%, in classifying leaf diseases, outperforming other state-of-the-art models. The study emphasizes the practical implications for crop management and provides a detailed methodology for crop disease detection using deep learning techniques. Limitations include the limited dataset, potential data bias, limited interpretability of the model, and high computational requirements.

A new approach by (Jin et al. 2020) presents a crop disease classification using graph convolutional networks (GCN) and hyperspectral images. The GCN-based approach improves classification accuracy by modeling the spatial relationships among different parts of the plant. Results show the approach outperforms several state-of-the-art methods, achieving an accuracy of over 98%. Limitations include the use of only one dataset, limiting generalizability, and a lack of in-depth analysis of the interpretability of the GCN-based approach. The research (Kong et al. 2022) introduces GHA-Net, a novel design that makes use of a graph-related high-order neural network to recognize plant diseases and pests. On two publicly accessible datasets, GHA-Net outperforms other approaches and effectively captures the graph-correlated representation of part-specific interrelationships. The authors suggest that more research might help the present architecture.

And the work of (Sakurada et al. 2019) proposes a CNN-based framework for multi-object detection and classification of crops using aerial images. The technique achieves good accuracy for both detection and classification tests, but limitations include the study's focus on a single crop type and the lack of thorough analysis of the interpretability of the CNN-based technique. Lastly, (Ahmed et al. 2020) introduce a novel method for scene classification based on multi-object categorization and logistic regression. The proposed method achieves higher accuracy than several state-of-the-art methods, demonstrating its effectiveness. Limitations include the lack of comparison with more recent state-of-the-art methods and the computational expense of object detection in large-scale scenes. To identify diseases, (Verma et al. 2023) used deep learning models based on convolutional neural networks. They developed a lightweight CNN model that can detect diseases in three important crops: corn, rice, and wheat. This model outperforms benchmark models with an accuracy of 84.4% while using only 387,340 parameters. Because of its practical design, it is a great instrument for real-time crop disease identification, especially in resource-limited contexts.

A new approach for multilabel classification using graph neural networks called Laplacian-based GNN is presented in (Ye and Wang 2021). This method constructs a Laplacian graph from data to capture label relationships, resulting in improved accuracy. The method outperformed other approaches on publicly available datasets, demonstrating its potential. Though the work could have included more details on implementation and limitations, it is still a valuable contribution to the field. According to (Knyazev et al. 2019) study, attention processes can significantly boost the performance of GNNs. GNNs were tested with and without attention on a simulated dataset with varied amounts of noise and node relevance. According to the results, the GNN with attention had an accuracy rate of 85%, which was higher than the former, which returned 70%. However, the study only looked at one sort of attention mechanism and used only synthetic data. More research is needed to determine the usefulness of this strategy on real-world data. To ensure that unconnected nodes did not alter the attention weights, the study used a self-attention layer with a masked SoftMax function.

Chen et al. (2019)'s work developed a novel approach for multi-label image recognition called GC-MLER. It constructs a graph from image data to capture relationships between pixels and uses a GCN to predict image labels. GC-MLER outperformed other methods on publicly available datasets. However, the authors could have provided more implementation details and analyzed limitations further. The paper of Chen et al. (2021) describes an innovative technique to multi-label recognition. The suggested method entails building a graph from multi-label data and training a Graph Convolutional Network (GCN) to learn a representation for each label in the graph. These label representations can subsequently be used to anticipate data labels. The method's accuracy ratings on the CIFAR-10 dataset were 85.7%, 93.1% on the STL-10 dataset, and 83.2% on the NUS-WIDE dataset. It should be emphasized that this strategy is suitable for multi-label recognition tasks and may not apply to other tasks. The research by Saberi Anari (2022), offers a hybrid model for classifying leaf diseases based on modified deep transfer learning and an ensemble method. On a test dataset of leaf photos, the model achieves a high accuracy of 96.7%. The research, however, does not address the question of scalability or the model's evaluation of a range of leaf diseases.

Another intriguing study is that of Cai et al. (2020) that suggests a fresh approach to classifying crop diseases. From the cropped photos, a graph is created, and a GCN is used to learn a representation for each pixel in the graph. The crop disease is then predicted using pixel representations. On the PlantVillage dataset, the approach had a 94.2% accuracy rate. As a limitation of this method, it should be noted that the classification technique employed is specifically designed for identifying and categorizing crop diseases. It is not suitable for addressing other issues requiring classification. Furthermore, a novel approach to overcoming the difficulty of image multi-label classification is presented in a recent research paper (Zhou et al. 2023). In the paper, a network structure is created from the image data using this technique, and GAT is then used to extract a specific representation for each pixel within the graph. The labels for the image are then predicted using these extracted representations. With 87.3% accuracy on the CIFAR-10 dataset, 94.1% accuracy on the STL-10 dataset, and 84.2% accuracy on the NUS-WIDE dataset, the proposed technique produced remarkable results. It should be noted that this method cannot be used for any other classification problem and is only intended for image multi-label classification task limitations.

The above pieces of literature reviewed the fact that crop disease detection received great attention but with limited use of multi–object techniques and GATs in wheat disease classification. The paper by Mohammadi et al. (2022) investigated the impact of wheat germ consumption on mental health and brain-derived neurotrophic factor (BDNF) levels in individuals with type 2 diabetes mellitus, where it employs a randomized, double-blind, placebo-controlled trial design to assess the effects of wheat germ on these variables, which show the importance of wheat in reducing the fast growth of the number of diabetic patients. By supporting sustainable agriculture and food security, our research can help achieve the Sustainable Development Goals (SDGs). We can decrease crop losses and boost yields by precisely recognizing and managing plant diseases, which will ultimately result in more effective and sustainable food production. This is in line with SDG 2: Zero Hunger, which aims to promote sustainable agriculture, achieve food security, and improve nutrition. By lowering the need for hazardous pesticides and fungicides, which can contribute to greenhouse gas emissions and environmental deterioration, this technology can also help SDG 13: Climate Action.

3 Methodology

In this research, we adopted a similar strategy to that of Jia et al. (2022) but with a lot of modifications. We obtained our data from a publicly available dataset on Kaggle (Anwar et al. 2021; Cai et al. 2019) and then used the method of data processing that involve image processing and augmentation as can be seen in Fig. 1 below.

We used ensemble multi-object approaches to improve our disease detection techniques by stacking Fast R-CNNs, Mask R-CNNs, and RetinaNet on our rigorously preprocessed datasets. This allowed us to analyze the preprocessed data thoroughly and correctly detect and segment wheat diseases based on the visual appearance of the leaves. As a result, our categorization method has become more robust and precise, enabling more accurate disease diagnosis (Zhang and Zhou 2014). Once the ensemble process was completed, several graphical representations were generated to showcase the outcomes. These graphical representations included scatter plots and line graphs, which highlighted the correlation between different variables in the model. The resulting graphs were then sent to the GATs for further analysis and classification. These tools were designed to scrutinize the graphs and identify any patterns or anomalies that may exist, giving valuable insights into the behavior of the model and the underlying data.

The ensemble method with Fast R-CNNs, Mask R-CNNs, and RetinaNet enables us to conduct a thorough analysis of the input image, capturing various characteristics of wheat diseases (Sun et al. 2020). By combining the predictions from Fast R-CNN,

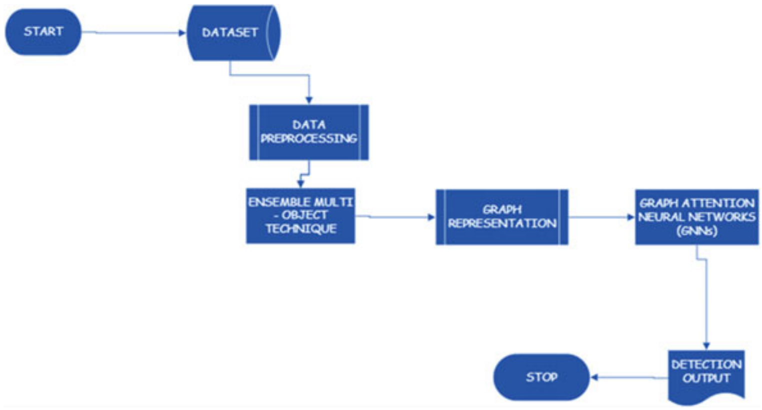

Fig. 1 The research methodology flowchart

Mask R-CNN, and RetinaNet models, we can achieve a more dependable and precise classification of wheat diseases depicted in the image. Each of these models analyzed the image and predicted the presence of wheat diseases (Chen et al. 2021). To generate a final output, the predictions from each model are combined by picking the most confident prediction among the three models. The ensemble technique tries to utilize the capabilities of each model and improve the overall accuracy and robustness of the classification by aggregating the outputs of the different models.

A graph representation is created from the outcomes of the ensemble multi-object procedure. In this instance, a graph depicts the connections between the various components of the discovered objects or regions of interest. Every component or area becomes a node in the graph, with the connections between them denoted by edges (Knyazev et al. 2019). GATs are designed to study the linkages and interactions between nodes in a graph since they are a sort of graph neural network that can operate on graph-structured data. As a result, the converted graph from the ensemble multi-object process is then fed into GATs for additional analysis and classification, and to extract significant features and patterns from the node interactions.

The technical schematic of GATs, which is shown in Fig. 2, highlights key elements of the model (Velickovic et al. 2017). Although the illustration in Fig. 2 is a simplified representation of GATs, it successfully communicates the key concepts behind GATs. In real-world applications, however, GATs frequently combine many layers and more complicated attention mechanisms to improve their effectiveness. The graph data is first received by the input layer, which is the first stage in the GAT model (Li et al. 2019). As a result, the attention layer is critical in digesting the graph input, using an attention method to train the neural network.

During the training process, the attention mechanism provides weights to the graph's edges, indicating the importance of the connections between various components. These weighted edges are subsequently provided as inputs to the output layer, yielding a unique graph representation (Cai et al. 2020). This freshly constructed

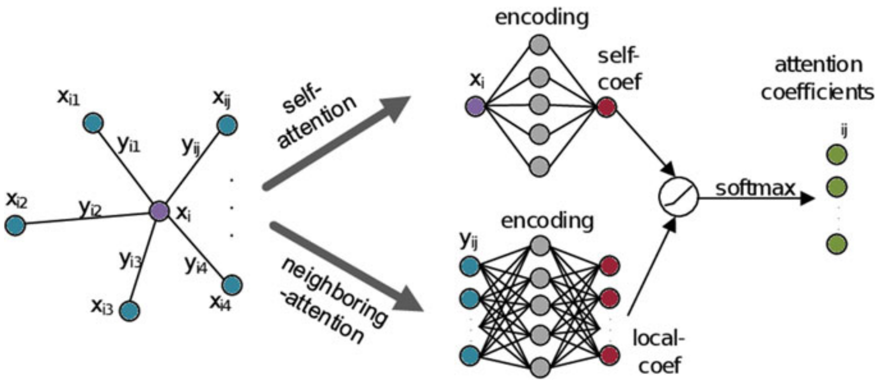

Fig. 2 GATs technical diagram (Velickovic et al. 2017)

representation serves as the GAT model's foundational output, incorporating critical information collected from the original graph data. GATs' use of multi-layer structures and elaborate attention processes highlights their sophisticated nature and ability to capture complex links within graph-structured data.

4 Experiment Comparison and Analysis

Before getting into the experimental results, it is vital to emphasize the critical role that data preparation plays in providing accurate and dependable results (Zhang and Zhou 2014). We obtained our wheat datasets for analysis from Kaggle and went through significant data preprocessing techniques. The wheat disease dataset, which included samples afflicted with Septoria and Stripe rust, underwent extensive data normalization and wrangling (Verma et al. 2023). This procedure attempted to normalize the dataset, remove biases, and improve its appropriateness for further research. Following that, images are preprocessed, which includes scaling, normalizing pixel values, and utilizing filters to improve image quality. Edge detection, color-based segmentation, and texture analysis are then used to extract the relevant characteristics from the wheat leaf images.

Following data preprocessing, three multi-object techniques: Fast R-CNNs, Mask R-CNNs, and RetinaNet—were used to accurately classify wheat diseases. These cutting-edge deep learning architectures were selected for their excellent accuracy in object detection and classification inside pictures. After preprocessing, the dataset was split into training, validation, and test sets. Using an ensemble technique, the models were trained on the training set. The ensemble strategy provided enhanced performance and robust classification results by using the outputs of the separate models. On the validation set, the models' performance was assessed using measures like accuracy, precision, recall, and F1 score. As shown in Table 1 below, the models

Table 1 Results of each method and the average results using voting ensemble

Model	Accuracy (%)	Recall (%)	F1—Score (%)
Fast R-CNNs	89	92	87
Mask R-CNNs	91	95	88
RetinaNet	78	85	74

showed exceptional accuracy in differentiating between healthy, Septoria-infected, and Stripe rust-infected wheat samples after repeated parameter optimization and fine-tuning.

The results of this study demonstrate the revolutionary function of AIoT and its influence on the SDGs in agricultural disease identification (Saberi Anari 2022). Using cutting-edge multi-object approaches, the newly created dataset was thoroughly examined using cutting-edge GATs, building on the success of the ensemble model. Notably, GATs' exceptional capacity to capture deep relationships and linkages within data proved useful in discovering trends across various wheat diseases. Each node precisely represented individual wheat disease samples through a smooth translation into a well-defined graph structure, and the edges skilfully demonstrated crucial links between them (Kong et al. 2022). The effective absorption and distribution of critical information across the network were made possible by the creative use of GATs, demonstrating the ability of AIoT in disease control and precision agriculture (Owoyemi et al. 2020).

4.1 Discussion of Results

In Fig. 3 below, we showed our training and validation accuracy of the model. The model was trained using the technique shown in Fig. 1, and the validation dataset was used to calculate the accuracy, precision, recall, and F1 score. The model's F1-score was 91%, its recall was 94%, its precision was 89%, and its accuracy was 92%. These findings show that the model was highly precise and recallable in its classification of illnesses.

Based on the training and validation loss, as shown in Fig. 4, the model performs proficient illness classification with a high degree of accuracy on the training data. However, it has more mistakes in the validation data, indicating that it may be overfitting to the training set. Overfitting can result in high training accuracy but low validation accuracy, emphasizing the importance of generalizing successfully to new data. We use Mathew's Correlation Coefficients (MCC) to measure this, a statistic that balances true positive and true negative rates, offering a thorough assessment of categorization performance (Kusharki et al. 2022; Mahmood and Köse 2021). Our model performs admirably, with an MCC of 91%, increasing trust in its outcomes and capacity to overcome overfitting problems.

The model adequately classified 92% of the data and correctly identified 89% of the positive data. The model was also able to identify 94% of good outcomes. These

Fig. 3 GATs training and validation accuracy

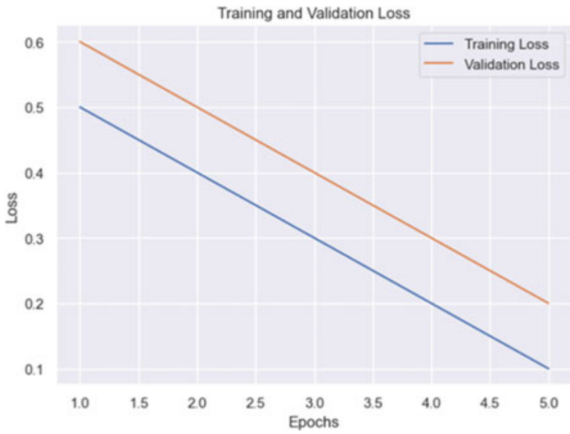

Fig. 4 GATs training and validation loss

findings suggest that the model effectively classified diseases with a high degree of precision and recall. The experimental findings are very positive and illustrate the efficacy of the suggested technique for wheat disease classification. Fast R-CNNs, Mask R-CNNs, and RetinaNet worked together to detect healthy, Septoria-infected, and Stripe rust-infected samples with great accuracy and precision. The addition of GATs improved the model's performance even further, allowing it to detect comparable diseases with exceptional precision (Anwar et al. 2021).

The efficient use of GATs and multi-object techniques has shown their enormous potential in addressing agricultural research difficulties, particularly the identification of diseases and classification. The findings of this study have far-reaching ramifications since they aid in the development of complex models that facilitate early disease identification, improve crop management, and decrease output losses. Such achievements are especially important for Sustainable Development Goal 2 (Zero Hunger), which aims to eliminate hunger, achieve food security, improve nutrition, and promote sustainable agriculture. This ground-breaking work greatly advances SDGs relating to agriculture and food security by utilizing AIoT-driven methodologies. It equally provides farmers with critical crop disease diagnostic tools, improving food security and contributing to various SDGs. Reduced agricultural losses promote global health, stimulate innovation, and reduce poverty by raising farmer yields and incomes.

Early identification and quick reaction to agricultural diseases are made possible by the incorporation of AIoT technology. Such proactive actions support SDG 2, which aims to end hunger and advance sustainable agriculture. Additionally, SDG 3's goal of promoting health and well-being is aligned with AIoT's role in improving disease detection and pattern analysis. Additionally, by maximizing resource utilization and lowering environmental effects, the study contributes to SDG 12, which emphasizes responsible consumption and production. Finally, the effective application of AIoT and GATs in wheat disease detection demonstrates the potential for climate-resilient agriculture, which aligns with the climate action goal of SDG 13.

The implications of this research extend to diabetic patients, as reducing crop losses due to disease can provide a consistent food supply for those with diabetes. Maintaining a consistent food source is critical for controlling blood sugar levels, as changes in food availability can lead to serious health problems. The potential impact of this study on diabetes management is based on its ability to develop disease-resistant crop varieties that are common in diabetic patients, introduce disease detection and classification methods, and deepen understanding of the relationship between crop diseases and diabetes. As the research progresses, it has the potential to greatly improve the lives of diabetic patients worldwide by boosting food security and alleviating health-related issues connected with the disease. By studying this path indefinitely, the study hopes to improve the well-being and quality of life of those affected by diabetes all around the world.

5 Conclusion

In conclusion, this study demonstrated the efficacy and potential of using GATs and multi-object techniques to address key issues in agricultural research, particularly crop disease detection, and classification. The study demonstrates the successful development of complex models that can aid in the early diagnosis of plant diseases, enhancing crop management practices and lowering output losses. These findings are especially important for attaining SDG 2 (Zero Hunger), which aims to eliminate hunger, ensure food security, improve nutrition, and promote sustainable agriculture. This research provides farmers with essential information by establishing reliable and effective methods for detecting and classifying crop diseases, allowing them to raise healthy crops and contribute to feeding the world's population.

Furthermore, the study's impacts go beyond SDG 2 and include other Sustainable Development Goals. The impact on SDG 3 (Good Health and Well-being) is important, as minimizing crop losses due to disease can enhance the overall health of people around the world, particularly those who rely significantly on agriculture for a living. Also, the study supports agricultural innovation, which is critical for reaching SDG 9 (Industry, Innovation, and Infrastructure), and it contributes to poverty reduction by boosting farmer yields and incomes, which is in line with SDG 1 (No Poverty). Moreover, by emphasizing climate-resilient agricultural methods and disease control, this research contributes to SDG 13 (Climate Action) by encouraging sustainability and resilience in the face of environmental difficulties.

The ensemble multi-object approaches used in this study, such as Fast R-CNNs, Mask R-CNNs, and RetinaNet, were shown to be extremely effective in capturing numerous aspects of wheat diseases. Combining the predictions from various models resulted in a more reliable and exact classification of wheat diseases in images. Each model was critical in evaluating the images and predicting the existence of wheat diseases, and their combination through ensemble learning boosted classification accuracy and robustness even further. An important innovation was the conversion of the dataset into a graph structure and the subsequent use of GATs for analysis and classification. GATs exhibited their capacity to understand intricate dependencies and connections within the data, making it easier to spot similarities among various diseases. Through rigorous training, GATs effectively absorbed and communicated critical information throughout the network, providing insightful knowledge about the behavior of the model and the underlying data.

The experimental findings of this study demonstrated the efficacy and precision of the suggested method for classifying wheat diseases. The combination of Fast R-CNNs, Mask R-CNNs, and RetinaNet successfully distinguished between healthy wheat samples, infected with Septoria, and affected with Stripe rust. The performance of the model was further improved by the inclusion of GATs, making it possible to detect comparable diseases with outstanding precision. But it's important to recognize that this study has some flaws. Although the suggested approach produced impressive results, more research may be done to improve the models' ability to cover other crops. The model's performance on fresh, new data could be improved even further by adjusting and refining the training process. To fully realize the potential of GATs and multi-object techniques, it will be essential to conduct further research and development in this field. A more sustainable and secure supply of food can be ensured by utilizing the power of cutting-edge technology like GATs to help precision agriculture and crop disease management. Additionally, as the globe struggles to meet the needs of a growing global population and climate change, this research can act as a compass for introducing creative and efficient agriculture practices.

In summary, the effective application of AIoT and multi-object techniques offer enormous promise in agricultural research, providing a route to addressing critical difficulties in disease detection and crop management. The findings have far-reaching consequences for food security, health, innovation, poverty alleviation, and climate resilience. This research contributes considerably to accomplishing numerous SDGs and solving global concerns by promoting sustainable agriculture practices, improving disease detection, and assisting farmers in their attempts. This strategy has enormous potential to improve food production, ensure healthy crops, and empower farmers in the face of ever-changing environmental conditions.

Finally, this research represents a huge advancement in the application of AIoT-driven methodologies to transform agricultural research and disease detection. We have opened a plethora of options to address the complexities of crop diseases, improve food security, promote sustainable agriculture, and contribute to the achievement of numerous SDGs by utilizing the power of GATs and ensemble multi-object techniques. We are paving the way for a more resilient, wealthy, and food-abundant future for all as we continue to study and perfect these approaches.

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Sustainable Healthcare 5.0: Integration of IoT and Blockchain Technology with Federated Learning Model for Securing Healthcare Data

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Abstract Healthcare is one of the goals of Sustainable Development Goals (SDGs) 2030. Technological advancements have been considered an out-fold structure to fulfill the requirements of SDGs requirements. Especially providing a suitable and accessible healthcare environment may create an impact on human sustaining. However, providing a suitable healthcare environment for achieving the SDGs is hampered due to non-structural technological advancements. Integrating federated learning with Internet of Things (IoT) and blockchain technology can provide a significant platform for developing Healthcare 5.0. Federated learning (FL) is a collaborative machine learning paradigm that enables multiple nodes (worker nodes) to train models across multiple devices cooperatively without exchanging the original data. It is promisingly a new methodology that helps to build privacy-preserving systems and secure distributed learning models. Distributed architecture has inherent problems such as communication cost, scaling up the system (vertical scaling), scaling out the system (horizontal scaling), and dealing with the heterogeneity of the nodes in the model, and many more. Specifically, integrating federated learning with blockchain improves federated learning security and performance and increases the scope of application. This integration can be called Blockchain federated learning (BFL). This paper presents a federated learning process by integrating IoT and

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blockchain through the proposed architecture. The simulations conducted on the model reveal its solidity in modernizing Machine Learning for suitable applications.

Keywords Sustainable Development Goals (SDG) · Federated learning · Blockchain · Collaborative ML · IoT · Healthcare

1 Introduction

Healthcare facilities are designed for the protection and improvement of public health; nevertheless, they also possess social and environmental implications that may result in adverse consequences on individuals' well-being and the surrounding environment. The establishment of a hospital that incorporates sustainable practices in both its physical infrastructure and operational administration is essential in order to effectively promote the well-being and overall health of individuals seeking medical care. The consideration of both a primary necessity and a quality concern is vital, as healthcare systems must possess the capability to provide exceptional standards even in dynamic settings. A sustainable structure refers to a construction that is readily maintainable and possesses functionality from the perspectives of the environment, society, and economy. Its purpose is to align with the varied interests and requirements of all stakeholders involved.

The influence of public healthcare on national economies is significant and has become a subject of intense debate in both national and local contexts. Recent statistical data indicates a notable escalation in the expenses associated with the existing healthcare system. For instance, in Italy, these costs have risen from 5.5% of the Gross Domestic Product (GDP) in 2000 to 7.5% in 2012 (1). When examining the Italian context, there are several concerns pertaining to the physical infrastructure, in addition to the expenses associated with administration and excessive expenditures. The majority of these structures are outdated and deteriorating, so compromising their ability to provide an effective service to the community. Issues are not limited just to pre-existing structures, but they can also pertain to newly constructed hospitals. Despite being recently constructed, modern buildings may possess an inherent sense of antiquity due to the considerable amount of time required for them to become fully functional (2). In the context of new hospitals, these challenges can be addressed during the initial planning stage by utilizing established methodologies to assess the sustainability of the hospital, even prior to the commencement of construction. In the second and more pertinent instance, a crucial initial step in addressing the issue is to thoroughly comprehend the existing structures and their operational organization. This understanding will enable the subsequent implementation of customized methods aimed at enhancing the current situation. Healthcare structures are designed with the intention of safeguarding and enhancing public health. However, it is important to acknowledge that these structures can have social and environmental implications that may result in adverse consequences on both individuals' well-being and the broader context.

Establishing a hospital that demonstrates sustainability in its physical infrastructure and operational administration is the sole means by which the enhancement of well-being and the promotion of good health can be achieved for individuals seeking its services. The consideration of both a primary necessity and a quality concern is vital, as healthcare institutions must possess the ability to maintain high standards even in dynamic settings. A sustainable structure refers to a building or infrastructure that is designed to be readily maintained and fulfills its intended purpose while considering the environmental, social, and economic aspects. The aim is to accommodate the various interests and requirements of all parties involved. The topic of encouraging sustainability in hospitals through the development of a novel model for future implementations has also been examined by a Committee (Schroeder et al. 2012). They have outlined ten principles that are intended to serve as guiding principles for the hospital of the future. These principles primarily pertain to the social domain and to a lesser extent, the environmental domain, with no consideration given to the economic realm.

Nowadays, an amalgamation of machine learning, blockchain, and IoT with healthcare framework introduces a new architecture—Healthcare 5.0. Healthcare 5.0 offers patient remote monitoring and associated telemedicine, wellness monitoring and control, and personalized and connected health care. Moreover, sustainable healthcare 5.0 systems not only enhance health scenarios but also leverage opportunities to restore the environment to benefit the health and well-being of current and upcoming generations. This may create a road map for achieving *Sustainable Development Goals* (SDGs). Individual perceptions and misalignment with the hospital's strategy for secure data sharing have all been identified as potential barriers to the successful implementation of Healthcare 5.0.

To cope up with, a suitable infrastructure with technological and budgetary support, well designed business models, appropriate legal health policy standards, partnerships, and investment plans are required. In such a scenario, integrating distributed machine learning, such as federated learning, with immutable blockchain technology addresses the significant development issues of Healthcare 5.0. Federated learning is a distributed machine learning approach that enables multiple parties to collaboratively train a shared machine learning model without sharing their data (McMahan et al. 2017). The FL trains the global model with the data received from various distributed devices and keeps the data private.

Each device or data center in the collaboration trains a local model using its data in a federated learning setting. These local models are then sent to a central server, aggregating into a global model representing all the devices' collective knowledge. This process of local training and global aggregation is repeated iteratively, allowing the global model to improve over time. Figure 1 depicts the schematic diagram of federated learning. With the advent of AI and large data processing (i.e., Big Data) (Dharavath 2021), machine learning has become the analysis or processing tool for vast data. To perform data processing in the traditional machine learning model, the data must be present at the processing end (Priya and Ramesh 2020; Jain et al. 2021; Sharma et al. 2023). However, the users generate the data, which must be transmitted to the server. Whenever the data is sent, there is a possibility of an eavesdropping attack, and the attacker will also get the data, leading to privacy leakage. Even if the data reaches the server securely, we can't trust the server constantly.

Sometimes, the server is compromised or becomes malicious, or an external entity gets access to these data. They may use it for sale or in-house data analytics. As a result, we provide resources for no reward. So, the Federated Learning (FL) architecture offers a solution to address such security issues. The federated learning process typically involves the following steps (Yu et al. 2022):

i. **Selection of the Model**: The first step in federated learning is to select a machine learning model that will be trained using the distributed data. The model is typically a neural network pre-trained on a large dataset.

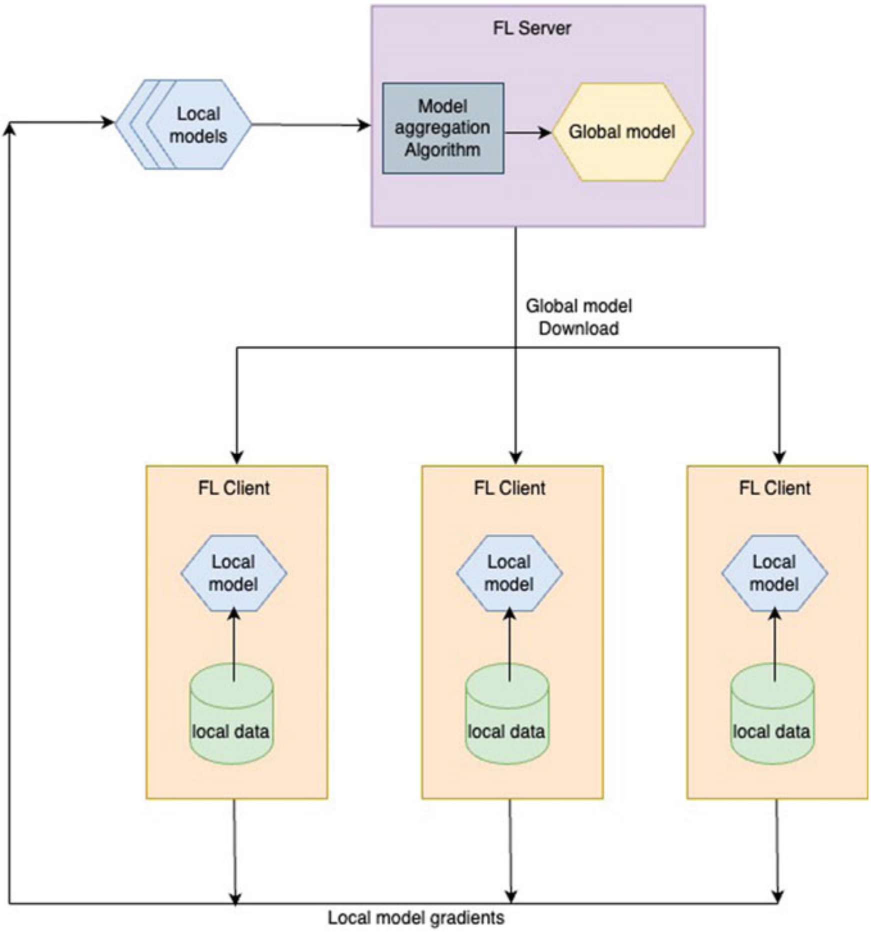


Fig. 1 Illustration of federated Learning

ii. **Data Collection**: The next step in federated learning is to collect the data that will be used to train the model. The data is distributed across multiple devices or servers and not centrally stored in one location.
iii. **Data Preparation**: The data collected from the devices is pre-processed and prepared for training. This involves cleaning the data, removing duplicates, and normalizing the data.
iv. **Model Initialization**: The selected machine learning model is initialized with random weights and sent to the devices for training.
v. **Local Model Training**: The devices train the model at their level using stochastic gradient descent (SGD) or other optimization algorithms. During training, the devices compute the gradients of the model parameters concerning the local data and send them back to the server.
vi. **Model Aggregation**: The server updates the model parameters based on the aggregated gradients collected from the devices. After this, the devices receive the updated model for future round operations.
vii. **Model Evaluation**: The model is evaluated on a validation dataset to measure its performance. The evaluation results are used to adjust the model hyper-parameters or to select a different model architecture. Repeat the steps of local model training—model evaluation for multiple training rounds to improve the model accuracy while preserving data privacy.
viii. **Model Deployment**: Once the training is complete, the final model is deployed on the devices for inference, such as making predictions on new data. Nevertheless, there are two main technical issues: all the involved members in FL must perform the required computations to reach the required standards of outcome. However, the FL server which is arranged to manage the activities of computation may not produce the results that are to be aggregated by the global model. This instance made the part of integrating blockchain and FL, which manages and overcomes the problems related to the centralized FL server.

One unresolved concern in the domain of IoT devices within the context of predictive healthcare pertains to the requisite volume of data necessary for achieving optimal efficacy. A substantial quantity of personal data is gathered, leading to concerns regarding security and privacy due to the sensitive nature of the data utilized for analysis. The processing capabilities of wearable devices impose restrictions that can result in vulnerabilities and potential breaches in the security of sensitive patient information. One further concern pertains to the integrity and reliability of the service. The prioritization of specific aspects within healthcare might lead to trade-offs in other areas. The field of remote healthcare heavily depends on the accuracy of wearable data and the precision of prediction models, making service integrity a critical aspect. Another concern that arises is the flexibility of the network that implements and provides these predictive healthcare services (Mishra et al. 2022a, 2022b, 2022c). The standardization of IoT devices is a prominent issue within IoT networks, mostly due to the introduction of heterogeneity. The presence of diverse wearable IoT devices necessitates the ongoing maintenance and updating of the medical server to ensure its compatibility with newly introduced devices. Consequently, apprehensions regarding adaptation pose constraints on the healthcare network's ability to maintain its relevance and sustainability throughout extended periods of service. So, the integration of blockchain with IoT architecture can provide a computationally infeasible architecture for Healthcare 5.0.

Specifically, blockchain is a decentralized and distributed digital ledger comprising a series of blocks containing a record of one or more transactions cryptographically linked together in a chain. The data in a blockchain is tamper evident. Once written, it cannot be modified. The key characteristics of blockchain are;

- **Decentralization**: A blockchain is a decentralized network, meaning no central authority controls the system. The related operations (i.e., transactions) are validated by the minors of the network rather than a single central entity.
- **Transparency**: The ledger is transparent, meaning anyone on the network can view all transactions that have taken place on the blockchain.
- **Security**: Transactions are cryptographically secured using standard algorithmic instances. This scenario creates an environment impossible to tamper the information stored in the blockchain. Each block in the chain contains a unique cryptographic hash that links it to the previous block, making it extremely difficult to modify transactions without detection.
- **Immutability**: Once data is recorded on a blockchain, it cannot be modified or deleted. This ensures that the information stored in the blockchain is tamper-proof and provides a permanent and auditable record of all transactions.
- **Consensus**: For a transaction to be added to the blockchain, a consensus mechanism ensures that all participants agree on the transaction's validity. This mechanism ensures that the network remains secure and reliable.
- **Smart contracts**: Smart contracts (Mishra et al. 2021a, 2021b), which are self-executing contracts with the terms of the agreement explicitly put into code, can also be used with a blockchain. Business procedures can be automated using smart contracts, eliminating the need for middlemen.

Blockchain technology can revolutionize the healthcare industry by offering a safe, open, and decentralized method for storing and sharing medical data when combined with federated learning in the medical sector (Lakhan et al. 2022; Mishra et al. 2023; Rao et al. 2023). The mentioned instances state some specific reasons why blockchain is considered necessary in the healthcare sector. The structure of the blockchain is illustrated in Fig. 2.

- **Data privacy and security**: Healthcare data must be safeguarded from unauthorized access and breaches since it is susceptible (Ramesh et al. 2023; Mishra et al. 2022a, 2022b, 2022c). Blockchain offers a safe and unhackable platform for storing and exchanging medical data, preserving patient privacy and lowering the likelihood of data breaches (Mishra et al. 2022a, 2022b, 2022c; Ramesh et al. 2020).

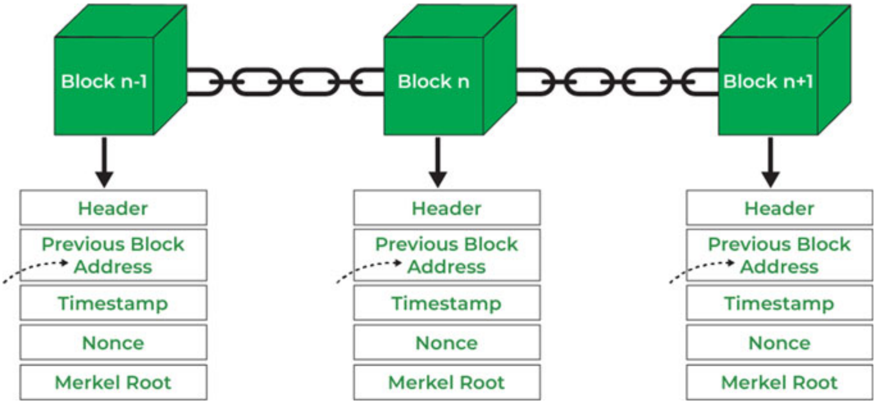


Fig. 2 Structure of blockchain

- **Interoperability**: Healthcare data is often siloed across various healthcare providers and systems, making sharing and accessing patient information difficult. Blockchain provides a decentralized system that can help to facilitate interoperability and enable the seamless sharing of medical data between different healthcare providers.
- **Patient empowerment**: Patients often do not control their medical data, making accessing and sharing their health information with different healthcare providers difficult. Blockchain provides a decentralized system that gives patients more control over their medical data and allows them to share their information securely and transparently.
- **Clinical trials**: Blockchain technology offers a safe and open mechanism for storing and sharing trial data, which can be utilized to increase clinical trials' efficiency and transparency.

Moreover, FL is an emerging technique that holds great potential in safeguarding privacy and thereby mitigating data breaches. It is well-suited for the decentralized nature of healthcare data. FL is a form of distributed machine learning that facilitates the collaborative development of decentralized ML models, while preserving data privacy by not requiring the sharing of private data. The process involves training distributed models on edge devices and exclusively exchanging updates of these models. The local training procedure eliminates the necessity of a global storage unit since it enables the direct processing of data on the same device. Thus, we incorporate FL architecture with Healthcare 5.0 to achieve proper privacy-preserving for patient's data. Thus, the significant contributions of IoT and Blockchain integration with Federated Learning are summarized in the following.

- Integrating the IoT, blockchain, and federated learning to ensure the privacy and security of medical data.
- Using Blockchain to store the medical data of patient records safely and securely.
- Reward the clients/users for participating in the model-building process.

1.1 Organization of the Paper

The rest of the paper is organized in the following manner. Section 2 correlates the related work of federated learning models with the illustration of the detailed architecture and operation of the proposed model, followed by the details of the execution setup in Sect. 3. The detailed performance analysis presents in Sect. 4. Finally, Sect. 5 concludes the model with future scope.

2 Related Literature and Proposed Model Architecture

This section will shortly revise some related works and provides and a suitable illustration on the model construction for IoT and Blockchain integrated functionalities.

2.1 Literature Review

The research work done by Wang and Hu (2021) begins by introducing the concept of federated learning. The authors then explain the potential benefits of federated learning, such as increased privacy and reduced communication costs. In this work, the authors explained how blockchain could enable secure and transparent data sharing and incentivize participation in federated learning. Kurtulmus and Daniel (2018) proposed an approach to enable users to train machine learning models on their own devices and contribute to a collective model without sharing their raw data with a central server. This work proposes a blockchain- based approach to on-device federated learning, where users run a blockchain node on their device to participate in the consensus process. Mishra et al. (2021a, 2021b), proposed a blockchain-based approach for evaluating and exchanging machine learning models. The authors argue that the traditional way of exchanging models, such as through marketplaces or third-party platforms, suffers from trust issues and lacks transparency.

Kim et al. (2018), proposed a blockchain-based approach to on-device federated learning and evaluates its performance in terms of latency. The authors evaluated the proposed approach through simulation-based experiments and compared it to a baseline approach that uses a central server for aggregation. Martinez et al. (2019), proposed a blockchain-based approach to incentivizing user participation in federated learning. The paper begins by introducing the concept of federated learning and its challenges, such as data privacy and the lack of incentives for user participation. Korkmaz et al. (2020), proposed a blockchain-based approach to decentralized, federated machine learning. The proposed approach, Chain FL, includes four main components: the blockchain network, the smart contracts, the federated learning platform, and the client devices. Short et al. (2021), proposed a new approach to federated learning by leveraging smart contracts on the Ethereum blockchain. The authors implemented and evaluated the proposed approach using a prototype implementation on the Ethereum blockchain. The utilisation of blockchain technology has the potential to facilitate the establishment of a comprehensive structure for the implementation of multirobot cooperative applications aimed at effectively managing the occurrence of COVID-19 outbreaks. These applications encompass various aspects, including the monitoring of outdoor and hospital-based End to End (E2E) delivery systems, as highlighted in reference (Alsamhi and Lee 2020). The system offers efficient data processing capabilities through the utilisation of machine learning techniques. These algorithms are applied to encrypted and electronically signed data, ensuring the protection of data privacy and the verification of access validity. The achievement of interoperability in this manner will facilitate enhanced cooperation among patients, physicians, and researchers, ultimately resulting in the development of more specialised and personalised treatment pathways.

Singh et al. (2022), implemented a new approach to federated learning that utilizes blockchain technology to enable secure and privacy-preserving collaboration. In this model, the blockchain is placed between the clients and the server, and the updates are uploaded directly to the blockchain, which is a slow process and degrades the system's performance. Behera et al. (2021), proposed a novel approach to federated learning using smart contracts on blockchains based on a reward-driven approach. The proposed approach involves using smart contracts to define the rules for federated learning and to incentivize the participants to contribute their data and computational resources.

2.2 *Model Construction*

Considering the significant issues of the above-discussed existing federated models, we choose to make a new blockchain-based federated learning system, which rewards the clients contributing to the global model's betterment. Figure 3 illustrates the proposed model. The model is operated by a set of pateints C = $\{1, 2, \ldots, N_C\}$. Initially, all the devices C_i collect the patient's data; store it in their local storage, and initiate the local training with defined local model algorithm. Finally, the generated local model is shared with federated server for model aggregation. Afterward, federated server initiate the global training on collected local model and generate the global model. The BlockFL operation of the device C_i at each epoch is described by the following steps;

Local model update: In federated learning, local model updates refer to the process of updating the machine learning model at each participating client C_i using their local data. Local model updates are performed independently and in parallel across multiple clients without sharing the raw data with the central server or other clients.

Aggregation: In federated learning, aggregation algorithms combine the updates from multiple clients into a single updated model. Several aggregation algorithms can

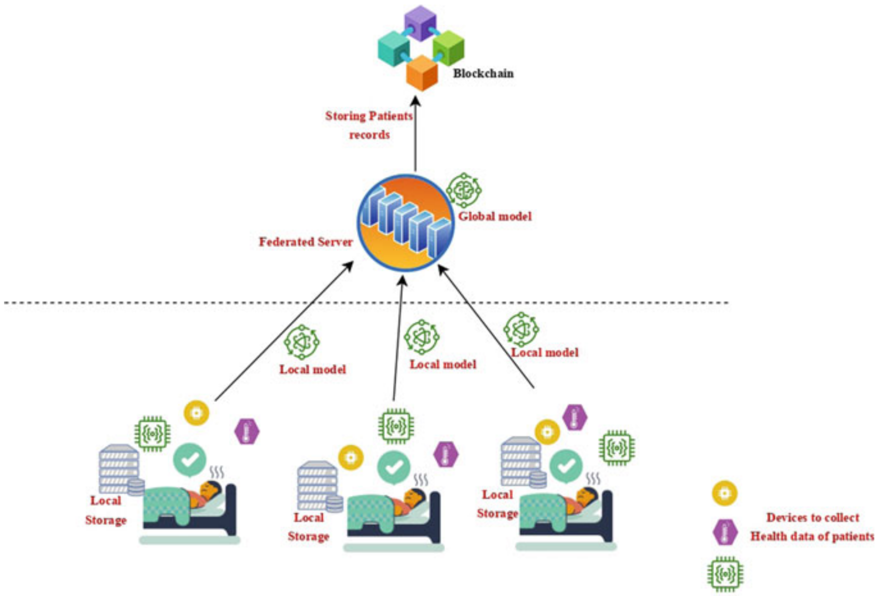


Fig. 3 Proposed system architecture

be used in federated learning, and the choice of algorithm depends on the specific use case and requirements (Ma et al. 2022). Here are some commonly used aggregation algorithms.

- **Federated Averaging**: This is the most commonly used aggregation algorithm in federated learning. It computes the weighted average of the model parameters across all clients. This algorithm is simple, efficient, and can be used for centralized and decentralized federated learning. The model here is built using the federated averaging method.
- **Federated Stochastic Gradient Descent (FSGD)**: This algorithm uses stochastic gradient descent (SGD) to optimize the model parameters at each client. Then it aggregates the updated parameters using a weighted average. This algorithm can be used when the model is trained using SGD.
- **Federated SGD with Local Updates**: This algorithm is similar to FSGD but allows each client to perform multiple local SGD updates before sending the updated parameters to the server. This can reduce the communication overhead and improve the convergence speed.
- **Federated Dropout**: This algorithm uses dropout to randomly select a subset of clients at each iteration and aggregates the updates from only those clients. This can improve the privacy and scalability of federated learning.
- **Secure Aggregation**: This algorithm uses cryptographic techniques, such as homomorphic encryption or secure multi-party computation, to securely aggregate the updates from multiple clients without revealing their raw data. This

can provide strong privacy guarantees but can be computationally expensive and requires specialized hardware.

Global model download: The global model download refers to downloading the updated machine learning model from the central server to the participating clients after aggregating the local model updates. Once the model has been developed at the server, it will be downloaded by all the clients for the next round of epochs. The global model download step is a key part of the federated learning process, as it allows the participating clients to benefit from the collective knowledge of the entire network while preserving the privacy of their local data.

The above steps are repeated until the preset number of rounds is reached or until the model's accuracy crosses a specific threshold value. Once the global model with good accuracy has been built, it is ready for tasks like classification or prediction problems. Afterward the verification of the member's identity, the corresponding block are generated in the following manner:

i. **Verification**: The goal of member verification in a blockchain network is to ensure that only trusted and authorized entities can participate in the network and to prevent malicious actors from compromising the security and integrity of the network. Once the model has been built and given the data samples, it processes and produces output. Now it is the responsibility of the blockchain member to push these results into the blockchain network after verifying the member's identity. The smart contract verifies the member's identity in this model.
ii. **Block generation**: Once the member verifies their identity, a new block will be generated, and results will be pushed onto the blockchain network using smart contracts.
iii. **Incentive mechanism**: Incentives refer to the rewards or benefits that motivate the participating clients to contribute their local data and computing resources to the shared machine learning model. Incentives are a key element of the federated learning process, as they can help to ensure that the participating clients are willing to invest their time, effort, and resources into the collective learning process.

As the clients are participating in the process of building the global model using their data and resources, hence it is appropriate to give incentives/rewards to them so that more clients are encouraged to participate in the model-building process (Ma et al. 2022; Sarkar et al. 2022). One common form of incentive in federated learning is the provision of monetary rewards, such as payment in cryptocurrency or cash, to the participating clients who contribute their local data and computing resources to the shared machine-learning model.

3 Experimental Analysis

This section illustrates the preliminaries required for performing the execution. The proposed methodology of FL with blockchain is configured on a machine with the following specifications. Figure 4 depicts the workflow of the proposed model and the required steps for executing the model preferences. Initially, Flower framework employs to collect data from various clients (patients) through internet web services. Afterward, the local training model generates the local updates shared with server. Then, the local updates are aggregated by server to generate the global updates, and update the global model. Afterward, all the devices download the global model and run at their local end with defined smart contract.

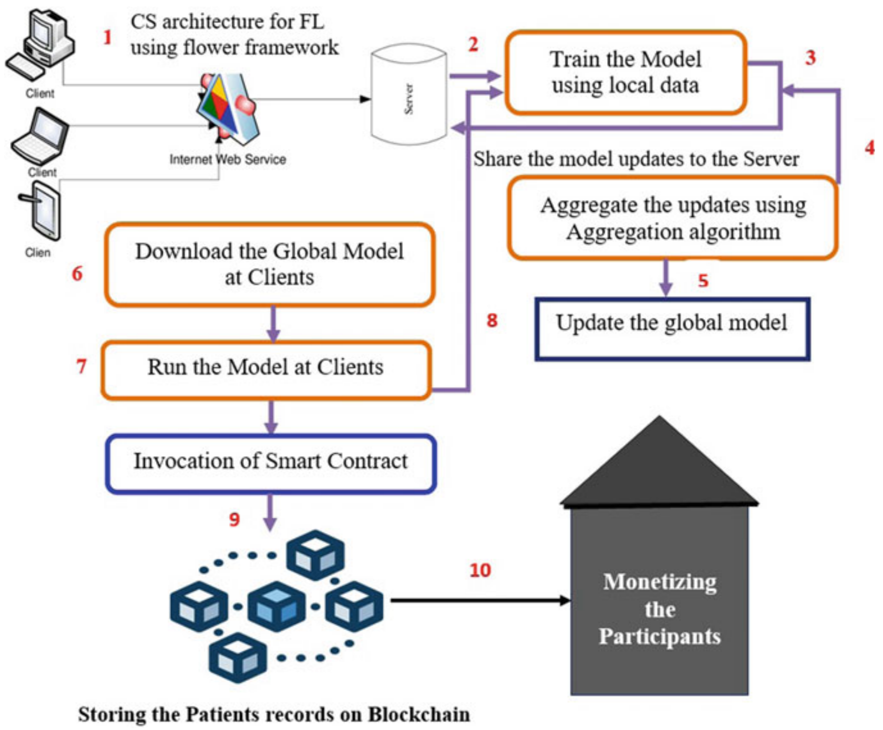


Fig. 4 Workflow of the detailed construction of the proposed model

3.1 Flower Framework

The Flower framework is an open-source Python library for building federated learning systems (Korkmaz et al. 2020; Beutel et al. 2020). It provides a high-level API for defining and training federated learning models and a set of tools for managing the communication and coordination between the devices and the central server. One of the key features of Flower is its support for heterogeneous devices, meaning devices with different hardware, software, and data characteristics can participate in the same federated learning system. Flower also provides a mechanism for aggregating the model updates from the devices while ensuring data privacy and security.

Flower is designed to be flexible and modular, making it easy to customize and extend for specific use cases. It also includes a set of pre-built examples and tutorials to help users get started quickly. Overall, Flower aims to simplify the building of federated learning systems and make them accessible to a broader range of developers and organizations.

3.2 GRPC Protocol

Google Remote Procedure Call (gRPC) (Fikri et al. 2022) is an open-source remote procedure call (RPC) framework developed by Google. It enables communication between different applications or services in a distributed system. At its core, gRPC is based on the protocol buffers data serialization format, a language-diagnostic format for structuring data. gRPC uses protocol buffers to define the data and methods that can be called between different applications or services. This makes it easy for developers to define and share interfaces between different parts of a distributed system. gRPC supports various programming languages, including C++, Java, Python, Go, Ruby, and many more. It provides a simple and efficient way to handle complex distributed systems. It allows developers to define service interfaces using protocol buffers and then generate the necessary code to implement those interfaces in their chosen language. One of the key advantages of gRPC is its support for high-performance, bi-directional streaming communication. This enables real-time updates and efficient data transfer between different parts of a distributed system. GRPC is a flexible framework for building distributed systems and enabling communication between different applications or services.

3.3 Proof of Authority (PoA)

Proof of Authority (PoA) (Qu et al. 2022) is a consensus algorithm used in some blockchain networks to validate transactions and secure the network. Unlike Proof of

Work (PoW) or Proof of Stake (PoS), which rely on computing power or stake ownership to secure the network, PoA uses identity and reputation to validate transactions and create new blocks. In a PoA network, a set of trusted nodes or validators creates new blocks and validates transactions. These validators are known as authorities and are selected based on their reputation, expertise, or other criteria. The authorities are responsible for verifying and adding the transactions to the blockchain. They can be incentivized to act honestly and maintain the network's integrity, as their reputation and status as a validator are at stake. One of the main benefits of PoA is that it requires less computational power and energy consumption than PoW, which is used by networks like Bitcoin and Ethereum. Since PoA relies on trusted validators instead of mining or staking, it can achieve faster transaction processing times and higher scalability.

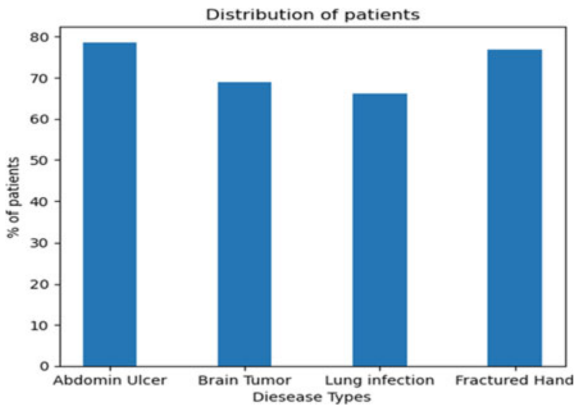
4 Result Transformation and Analysis

As per the proposed architecture and workflow, the model is implemented on the Ganache terminal with Remix environment. We employ Remix, Metamask, and the local version of Ethereum—Ganache—latest Geth client (1.9.0) to test the practicability and performance of various smart contracts designed for all the operations of the model. The Remix is Ethereum's authorized online integrated development environment (IDE). The smart contract can be developed, assembled, tested, deployed, and integrated using Solidity on a web page. Ganache offers various virtual user accounts—patients. Figure 5 shows the consolidated data of all patients with various disease types. After that, Fig. 6(a, b, and c) show the performance of the system with several rounds 10, 20, and 50, respectively, and we can observe that the accuracy of the model is directly proportional to the number of epochs. These figures show the performance of the proposed system and describe the consolidated data of all the patients predicted by our model. Further, Fig. 7 shows how the patient's records are stored in the blockchain. Finally, Fig. 8 shows the performance analysis of the blockchain network, which stored the records in the blockchain blocks.

5 Discussion

From the result transformation section, the experiments conducted were out-lined with suitable specifications. Figure 5 exemplifies the mechanism of consolidated data of all patients, where the distributed learning model performs the re-quired operational rounds and observes suitable symptoms of the disease. With the help of the parallel integration, part ran on the other client. The result part is integrated and stores the required result(s) in the global model. In order to perform the same, several rounds were looped in different capacities, i.e., 10, 20, and 50, respectively. To protect the similar information of various patients, the information of the global model has

Fig. 5 Workflow diagram of CrossFIM



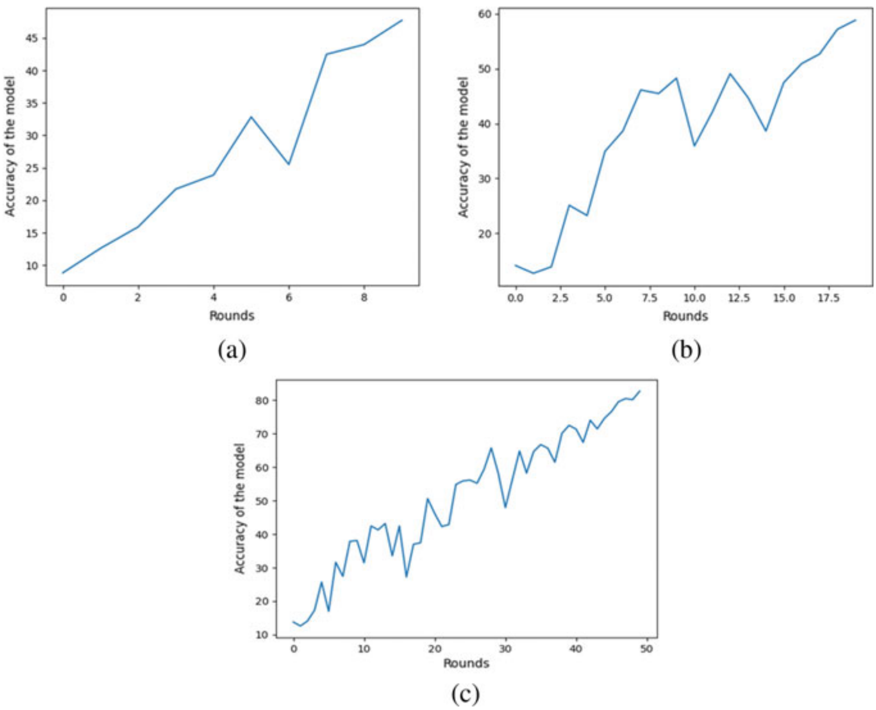


Fig. 6 Accuracy of the model (**a**) with 10 epochs/rounds (**b**) with 20 epochs/rounds (**c**) with 50 epochs/rounds

```
From First Node:
Total Patient records count =  1000
Printing all records:
Patient- 1  details: ['Negative', 'Negative', 'Positive', 'Positive']
Patient- 2  details: ['Negative', 'Negative', 'Positive', 'Positive']
Patient- 3  details: ['Positive', 'Negative', 'Negative', 'Negative']
Patient- 4  details: ['Positive', 'Positive', 'Negative', 'Positive']
Patient- 5  details: ['Negative', 'Positive', 'Negative', 'Negative']
Patient- 6  details: ['Negative', 'Negative', 'Negative', 'Negative']
Patient- 7  details: ['Positive', 'Negative', 'Positive', 'Negative']
Patient- 8  details: ['Positive', 'Positive', 'Positive', 'Positive']
Patient- 9  details: ['Negative', 'Negative', 'Positive', 'Positive']
Patient- 10  details: ['Negative', 'Negative', 'Negative', 'Negative']
Patient- 11  details: ['Negative', 'Negative', 'Positive', 'Negative']
Patient- 12  details: ['Positive', 'Negative', 'Positive', 'Negative']
Patient- 13  details: ['Negative', 'Positive', 'Positive', 'Negative']
Patient- 14  details: ['Positive', 'Positive', 'Positive', 'Negative']
Patient- 15  details: ['Negative', 'Negative', 'Positive', 'Negative']
Patient- 16  details: ['Positive', 'Negative', 'Negative', 'Positive']
Patient- 17  details: ['Positive', 'Positive', 'Negative', 'Positive']
Patient- 18  details: ['Positive', 'Negative', 'Positive', 'Positive']
Patient- 19  details: ['Positive', 'Positive', 'Positive', 'Negative']
Patient- 20  details: ['Negative', 'Negative', 'Positive', 'Negative']
Patient- 21  details: ['Positive', 'Negative', 'Negative', 'Positive']
Patient- 22  details: ['Negative', 'Positive', 'Positive', 'Negative']
Patient- 23  details: ['Negative', 'Negative', 'Negative', 'Positive']
Patient- 24  details: ['Negative', 'Negative', 'Positive', 'Positive']
Patient- 25  details: ['Negative', 'Negative', 'Positive', 'Negative']
Patient- 26  details: ['Positive', 'Negative', 'Positive', 'Negative']
Patient- 27  details: ['Positive', 'Positive', 'Positive', 'Negative']
Patient- 28  details: ['Positive', 'Positive', 'Negative', 'Negative']
Patient- 29  details: ['Negative', 'Negative', 'Negative', 'Positive']
Patient- 30  details: ['Positive', 'Negative', 'Negative', 'Negative']
```

Fig. 7 Patient's records

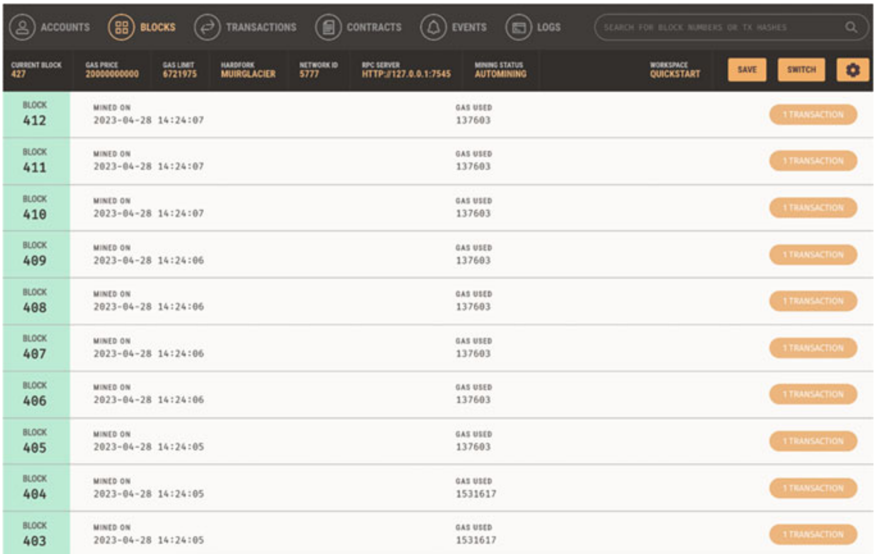


Fig. 8 Ganache terminal

been sent to the blocks of blockchain for maintaining integrity. This strategy also helps in reviewing the health equality lens during consultation. This mechanism protects the records of the patients in a secure way to utilize for further analysis. On the other hand, this also ensures strong equity in health monitoring systems by reducing inequalities and achieving health-related sustainable development goals.

In existing Healthcare 4.0 architecture, the majority of medical records that are housed on cloud servers are susceptible to internal attacks, which pose a greater threat compared to external attacks. The medical field encompasses confidential patient data, and safeguarding privacy is an essential component of the healthcare system. The level of privacy concern for individual patients varies based on their respective data. The primary concern revolves around the provision of robust privacy measures while ensuring the integrity and protection of da-ta. FL, also known as Federated Learning, is an innovative approach that enables the secure and privacy-conscious distribution of data processing among several nodes within a network. The method facilitates distributed model training without the need for any exchange of raw data. Nevertheless, despite the advantages it offers, federated learning (FL) might result in the failure of a sole server responsible for aggregating the learning process, as well as significant delays in communication. In addition, it is possible for a malicious node to upload a model that is not dependable, so disrupting the learning process of the federated learning system. Hence, the utilization of blockchain as a ledger technology presents an at-tractive solution for addressing concerns related to security and scalability. This is mostly due to its capacity to facilitate decentralised models without relying on a central server.

Blockchain technology enables the secure aggregation of data models from several sources. Consequently, the blockchain technology possesses the characteristics of immutability, traceability, and transparency, which can be associated with federated learning (FL) in order to effectively tackle privacy protection concerns. Mishra et al. (2022a, 2022b, 2022c) conducted a comprehensive analysis and evaluation of the properties of blockchain-enabled federated learning (FL). They identified emerging challenges and proposed potential avenues for further research in sever-al domains.

The utilization of blockchain technology to enhance and empower various systems and processes. Florida (FL) has the potential to be a significant advancement in the field of healthcare. The utilization of existing medical data in ma-chine learning (ML) is limited due to various factors, including restricted access to data and its storage in separate data silos. Therefore, the potential of medical da-ta to improve outcomes for various stakeholders, including patients, doctors, laboratories, and other institutions, is constrained. Machine Learning (ML) is unlikely to achieve its maximum capabilities unless it has access to precise and reliable data. Furthermore, ML must eventually transition from a research context to being implemented in clinical practice. This transition could be facilitated through the utilization of blockchain technology. FL effectively addresses the obstacles related to the dissemination and protection of sensitive medical information by facilitating collaborative training among multiple entities without the need to share or centralize datasets. Furthermore, this advancement possesses the capacity to foster novel avenues of research and economic growth, while concurrently enhancing the quality of medical treatment on a global scale.

The practical implementation of the proposed model facilitated its improvement and showcased its user-friendly and convenient nature. The results that were acquired have been efficiently digested and utilised to emphasize and prioritize specific actions that can be taken to enhance sustainability. The novel procedure surpasses traditional evaluation schemes, which primarily focus on environmental factors, by comprehensively examining all dimensions of sustainability in a highly interdisciplinary manner. Thus, this scenario provides a mechanism for achieving SDGs requirements.

The implementation of system testing in a substantial number of operational Indian hospitals could prove beneficial in establishing a comprehensive database regarding the present state of the National Healthcare System of India. This database would encompass several aspects such as the technologies employed, management practices, resource utilization, and user satisfaction. In conclusion, it is imperative to conduct a comprehensive examination and analysis of the Indian context when considering the widespread implementation of this tool. This examination should encompass not only an assessment of the current state of the art and best practices, but also an evaluation of the existing conditions, including the genuine needs, available and necessary resources, and most importantly, the actual performance.

6 Conclusion

This work proposes architecture for a federated learning method integrated with IoT and blockchain for securing healthcare data. We discussed how the mentioned architecture is implemented with IoT and FL. The current trend in technical advancement is the combination of blockchain and Federated Learning. Through federated learning and blockchain technology, the problems like a single point of failure, high-jacking problems and patient privacy can be solved. It should be noted that the integration of FL and blockchain is still in its early stages, and new knowledge domains need to be researched to address challenges. This mechanism can be used as an important step for understating the equity lens for analyzing and maintaining the data for further analysis. This research presents a novel assessment approach aimed at determining the sustainability of a healthcare industry, whether it is already established or in the process of being designed, within the European environment. The Sustainable Healthcare system addresses the limitations of existing evaluation methods by implementing a multidisciplinary approach and offering a user-friendly interface. The purpose of this procedure is to provide assistance in identifying the primary weaknesses of the Healthcare 4.0 and determining the order of priority for implementing fixes the security issues with economic and social implications. This system will also help the consultation to focus on the importance of health measurement issues of SDGs and accountability mechanisms.

As the future part is concerned, the IoT and Blockchain integration with Federated Learning will be simulated with a Redactable blockchain variant for the health industry on a large scale to achieve the standards of SDGs.

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IoT-Enabled Machine Learning for Enhanced Diagnosis of Diabetes and Heart Disease in Resource-Limited Settings

John Amanesi Abubakar, Aghedo Emmanuel Odianose, and Omolola Faith Ademola

Abstract Diabetes and heart disease are complex and widespread health issues that significantly impact global well-being. Timely and accurate diagnosis is vital for effective management and treatment. However, in regions with limited access to medical professionals, achieving swift assessments becomes challenging. To address this crucial healthcare need, this study proposes an innovative approach that leverages the synergy of Internet of Things (IoT) technology and machine learning techniques. By integrating IoT capabilities into a web-based application, medical laboratory results can be seamlessly connected and analyzed in real-time, enabling healthcare providers, pharmacies, and patients to access critical information remotely. This study makes use of Support Vector Machines (SVM) and logical regression algorithms. The dataset was acquired from Kaggle, and preprocessing was done to ensure robustness. The models achieve a result, with the Support Vector Machine (SVM) model achieving 83.5% accuracy and the logical regression model reaching 81.9% accuracy. Moreover, the models demonstrate favorable precision, f1-score, and recall metrics, validating their reliability in diagnosing diabetes and heart disease. This IoT-driven web application exemplifies the potential to transform healthcare accessibility and quality, contributing to the advancement of the Sustainable Development Goal 3 (Good Health and Well-being). The integration of IoT and machine learning technologies showcases how innovative solutions can effectively address global health challenges, fostering a brighter future for healthcare worldwide.

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Keywords IoT · SDG-3 · SVM · Logical regression · Diabetes · Heart disease · Web application

1 Introduction

These days most people are busy trying to put food on the table for their family or for other reasons and this usually affects their health, which they usually do not pay attention to. Due to this numerous lifestyle diseases arise as they age, with diabetes and heart disease being two of them (Tripathi and Kumar 2020; Malik et al. 2021). Diabetes claims about 1.5 million lives annually (Balakumar et al. 2016). This type of disease occurs when the pancreas in the body cannot create enough insulin (type-2 diabetes) or the immune system destroys the beta cells residing in the pancreas (type-1 diabetes), doctors do not know why this (type-1 diabetes) occurs, but they believe that genes have a role to play in this (Tripathi and Kumar 2020). The insulin produced by the pancreas plays an important role in maintaining the sugar level in the body, thereby preventing a risky case of the blood sugar in our body being too low or too high. There are other types of diabetes such as gestational diabetes (this is usually recorded in women who have not had diabetes before being pregnant but now do during the period of pregnancy. This type of diabetes usually leaves after the birth of the child but might surface later in the child's life as type-2 diabetes) (Dutta et al. 2019). Diabetes affects everyone but type-1 diabetes usually affects teens and children, while type-2 diabetes affects adults usually above 40 (Cheng et al. 2021). This disease is terrible and usually causes complications that are life-threatening such as nerve damage, heart, and blood vessel disease, etc. (Rosengren and Dikaiou 2023).

Heart disease is another life-threatening disease that takes about 17.9 million lives annually according to WHO (Huo et al. 2018). It is a range of conditions that affect the heart. Some of the heart diseases that have been recorded so far are atherosclerosis, heart infection, congenital heart defects, arrhythmias, cardiomyopathy, and heart valve disease (Huo et al. 2018). When experts and advanced technology are not available diagnosing and controlling this disease is impossible. Before machine learning was used in diagnosing this disease doctors made use of the patient's medical record, physical examination of concerning symptoms, and examination of report (Ahmad et al. 2022; Ghosh et al. 2021; Ravi and Madhavan 2022; Saboor et al. 2022; Tuomilehto 2013). But since the branching out of machine learning into medicine using classifiers and artificial fuzzy logic have been used to diagnose this disease in patients.

Machine learning, a branch of artificial intelligence, is concerned with developing computer algorithms. Machine learning in healthcare has opened a new world of possibilities for the identification of diseases, diagnosis, and prediction, medical imaging, etc. (Kibria et al. 2022). Machine learning is a scientific subject that looks at how computers can learn without explicit programming (Latif et al. 2019). Supervised and unsupervised learning are the most common algorithms under machine learning. Supervised learning uses input–output pairs where the input is matched to the output, thereby showing that external help is involved (Harrison and Sidey-Gibbons 2021). Unsupervised learning is left to infer on deducing patterns or conclusions autonomously from the provided input (Deo 2015). This project focuses on determining whether a patient has either diabetes or heart disease using input fields backed by machine learning models. This project makes use of logical regression for heart disease prediction and a support vector machine for diabetes prediction.

Maniruzzaman et al. (2020) decides to carry out a comparison test with some well-known machine learning algorithms, four to be exact adaboost, naïve Bayes, decision tree, and random forest. To achieve their aim, they adopted protocol partitions (k2, k5, and k10). In this project, what differentiates it from others is that logical regression was employed to risk factors for diabetes making use of odd ratios and p-value. The system with the best accuracy was the random forest model in collaboration with the logical regression feature selector which got an accuracy of 94.25% and an area under the curve of 0.95 using a protocol partition of k10.

Tigga and Garg (2020) researched how to detect diabetes type-2 in patients early. The generated their dataset using offline and online questionnaires using family background, health, and lifestyle as the basis for it and compared it with the dataset gotten from the PIMA Indian dataset. They were compared using several machine learning algorithms such as logistic regression, support vector machine, random forest, decision tree, naïve Bayes, and K-Nearest Neighbor. Using the dataset generated by themselves the model with the highest accuracy was Random Forest with an accuracy of 94.1% while using the PIMA Indians dataset the model with the highest accuracy was both logistic regression and support vector machine with an accuracy of 74.4%. The authors also make use of tenfold cross-validation for effectiveness.

Panda et al. (2022) researched how to create a model that can predict diabetes with good precision. In this paper, feature selection was highly emphasized as it could determine your algorithm's accuracy level, and then four algorithms were used to see which had the best accuracy at predicting diabetes of all models. The highest accuracy was achieved using the gradient boosting algorithm with an accuracy of 81%.

Mohan and Jain (2020) researched how effective support vector machine can be used in the diagnosis of diabetes. It involved the use of support vector machine kernels to determine which will give the best accuracy. The best support vector machine kernel was RBF with an accuracy of 82% and this model was used for prediction.

Singh and Virk (2023) researched to find a model that can predict heart disease in patients effectively. The dataset used was obtained from UCI and several algorithms were tested. They also tried to find the similarity between the different attributes used in the dataset. Support vector machine gave a precision of 0.995 and a recall of 0.995, random forest gave a precision of 0.997 and a recall of 0.997, decision tree gave a precision of 0.851 and a recall of 0.848, and naïve Bayes gave a precision of 0.904 and a recall of 0.904.

Hamdaoui et al. (2020) proposed a system to be used clinically to help in the diagnosis of heart disease. Using machine learning algorithms such as random forest, support vector machine, naïve Bayes, decision tree, and K-nearest neighbor. The model with the best accuracy when used with both train-test spilt and cross-validation is naïve Bayes with an accuracy of 84.28% and 82.17%.

Rajendran and Karthi (2022) proposed a new way to predict heart disease effectively. It involved entropy feature-based engineering and pre-processing to get better features that lead to better performance by the model. In this research different machine learning algorithms were used for analyses along with some specific pre-processing such as removing outliers, entropy feature-based engineering, and imputing missing value. The model with the best accuracy was the ensemble model (logistic regression + naïve Bayes) with an accuracy of 92.7%.

Kavitha et al. (2021) proposed a new way to predict heart disease using classification, and regression for data mining. The proposed system makes use of two machine learning algorithms namely: decision tree and random forest also known as a novel technique. The accuracy gotten from the novel technique is 88.7%. Chang et al. (2022) concentrated on identifying type-2 diabetes. They made use of unsupervised learning algorithms such as K-means cluster and principal component analysis and relevance ranking to accomplish feature selection on the dataset. The accuracy gotten from the algorithm used 78.67% from using naïve bayes, 79.57% from using random tree, and 74.78% from using J48 decision tree.

Khanam and Foo (2021) decided to compare the ability of various machine algorithms to predict diabetes in patients. Data pre-processing in their model involved identifying missing values, locating, and removing outliers, choosing features, and normalizing. For the models used an accuracy of 73.14% was achieved with decision tree, 77.14% was achieved with random forest, 78.28% was achieved using naïve bayes, 79.42% was achieved with K Nearest Neighbor, 77.71% was achieved with support vector machine, and 79.42% was achieved using adaboost among some of the algorithms used.

In the next section, Sect. 2 discussion on the system design which comprises of the major part, which is the software, the algorithm for the developing the system are all explained. Section 3 presents the system result and discussion. The focus is on the performance metrics used to evaluate if the patient has diabetes or heart dis-ease models, such as accuracy, precision, recall, f1-score, and confusion matrix. Section 4 further discusses the topic and Sect. 5 concludes.

2 System Analysis and Design

This section outlines a comprehensive methodology employed in this research. It covers the step-by-step procedure and methods utilized for predicting diabetes and heart diseases through support vector machine and logistic regression. Additionally, it discusses the process of data acquisition and the development of a dedicated website to deploy the predictive model.

Figure 1 illustrates a comprehensive system for predicting heart disease using data from Kaggle, encompassing data acquisition, preprocessing, model creation

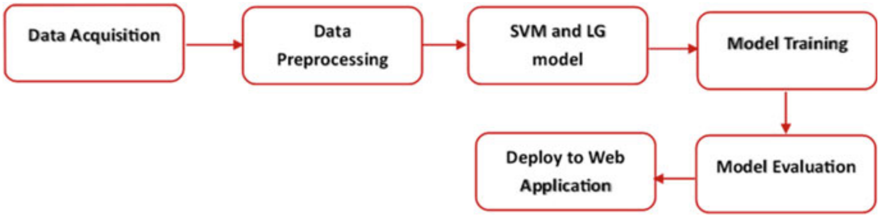


Fig. 1 Block diagram of the system methodology

with Support Vector Machine (SVM) and Logistic Regression, model training, evaluation, and deployment on the web. The diagram offers an overview of the system's sequential flow, emphasizing the significance of each step in achieving an accurate and accessible predictive model.

In Fig. 1, a comprehensive block diagram outlining the entire system's workflow is presented. The first crucial step in this process is data acquisition, where relevant datasets pertaining to diabetes and heart disease are obtained from the Kaggle platform. These datasets serve as the foundation for building a predictive model. Upon successful data acquisition, the next stage involves data preprocessing. This step is vital to ensure the data's quality, consistency, and readiness for analysis. Data cleaning techniques are applied to handle missing values, outliers, and inconsistencies. After data preprocessing, the heart of the system lies in the creation of the predictive model. Two different algorithms, namely Support Vector Machine (SVM) and Logistic Regression, are utilized for Diabetes and Heart Disease respectively. Subsequently, the model undergoes a training phase using the preprocessed data. During this stage, the model learns from the provided data, fine-tuning its internal parameters to capture patterns and relationships between input features and the corresponding target labels (presence or absence of heart disease). Once the training is completed, the model enters the evaluation phase. The performance of the model is assessed using various metrics like accuracy, precision, recall, and F1-score, to gauge how well it can generalize to unseen data and make accurate predictions. In the later section, the model is well discussed, and the evaluation result is also discussed. Finally, the last step in the system's workflow involves deploying it to the web. The deployment process makes the model accessible to end-users through a web-based interface. This allows individuals to interact with the model and obtain predictions for new input data conveniently.

2.1 Model Design

In this research, two distinct algorithms are employed, as mentioned earlier. Each algorithm serves the purpose of predicting a specific outcome. Based on a thorough literature review, it has been determined that the Support Vector Machine (SVM) algorithm is most suitable for diabetes prediction, while Logistic Regression (LR) proves to be the optimal choice for heart disease prediction. These algorithms have demonstrated exceptional accuracy when applied to the available data. To evaluate the performance of the predictive models, the study utilizes various modules to conduct training, testing, and validation processes. Through these steps, the accuracy of each model is carefully measured and assessed. Additionally, precision metrics are employed to gain insights into the models' ability to make accurate and reliable predictions. By employing the Support Vector Machine (SVM) and Logistic Regression algorithms for diabetes and heart disease prediction, respectively, and utilizing appropriate evaluation techniques.

2.1.1 Specifications of the Support Vector Machine (SVM) Model

The diabetes prediction algorithm Support Vector Machine (SVM) utilizes mathematical calculations to assess the likelihood of a patient having diabetes. The initial step in this process involves identifying the hyperplane that effectively separates the probability of diabetes occurrence from the probability of its absence, while considering the input features associated with each data point. The goal is to maximize the margins between the features and target predictions.

The hyperplane of the Support Vector Machine (SVM) is determined by the Eq. (1) (Borah and Gupta 2022):

$$w \times x + b = 0 \tag{1}$$

where 'w' represents the input features, 'x' denotes the input vector, and 'b' represents the bias term. This equation helps establish the decision boundary that discriminates between positive and negative instances, aiding in classifying data points effectively. The algorithm then tries to find the largest distance between the features and targets, also referred to as margins using Eq. (2) (Borah and Gupta 2022).

$$\frac{2}{||w||} \tag{2}$$

Here, ||w|| represents the Euclidean norm of 'w', representing the magnitude of the weight vector. Maximizing this margin ensures the Support Vector Machine (SVM) can make accurate predictions while maintaining robustness to variations in the data.

2.1.2 Specifications of the Logistic Regression (LR) Model

The algorithm used for heart disease prediction (LR) makes use of mathematical computations to ascertain the chances a patient will have heart disease or not. The variables needed are divided in-to two: the independent variables which include the input gotten from the patient, such as chest pain, cholesterol, etc., and the dependent variable which is the outcome of the model in binary form (0 and 1) which represents the absence and presence of heart disease.

The dependent variable of the model is determined by using this formula also known as a logistic function in Eq. (3) (Zabor et al. 2022):

$$p(x) = \frac{1}{1 + e^{-z}} \tag{3}$$

where p is the outcome or predicted probability that a patient has heart disease or not, e is the base of the natural logarithm, and z is the combination of the input features and their coefficients in Eq. (4) (Zabor et al. 2022):

$$z = b_0 + b_1.x_1 + \cdots + b_n.x_n \tag{4}$$

where $b_1 - b_{\mathrm{n}}$ is the coefficient of the input feature, b_0 is the intercept variable, and x is the values of the respective input features.

2.2 Methodology

Figure 2 shows the flow chart of the model design for analysis. From the initial stage to the final stage. It compasses the two machine learning models.

The dataset used in this study was sourced from Kaggle. For diabetes, the dataset comprises of 768 data points and is organized into 8 columns, namely pregnancies, glucose level, blood pressure, skin thickness, insulin level, body mass index (BMI), diabetes pedigree function, and age. The heart disease dataset contains 303 data points and is structured into 13 columns. These columns include age, sex, chest pain type, resting blood pressure (trestbps), cholesterol level (chol), fasting blood sugar (fbs), resting electrocardiographic results (restecg), maximum heart rate achieved (thalach), exercise-induced angina (exang), ST depression induced by exercise relative to rest (old peak), slope of the peak exercise ST segment (slope), number of major vessels colored by fluoroscopy (ca), and thalassemia status (thal). Sample of the diabetes dataset and heart dataset can be visualized in Figs. 3 and 4 respectively.

Upon acquiring the dataset, it is imported into the algorithm using the pandas module. To ensure data integrity and gain initial insights, the "info()" function is applied to the saved CSV file. This function not only provides an overview of the dataset but also aids in detecting any missing values that might be present. Additionally, to gain a deeper understanding of the numeric variables, the "describe()" function from pandas is utilized, generating a comprehensive statistical summary that includes essential metrics such as count, mean, standard deviation, minimum, 25th quartile, 50th quartile (median), 75th quartile, and maximum values. To prepare the dataset for further analysis, standardization is imperative. Addressing incomplete data is a crucial step in this process. By employing the "isnull()" function, the algorithm identifies the columns containing missing values, allowing for a comprehensive

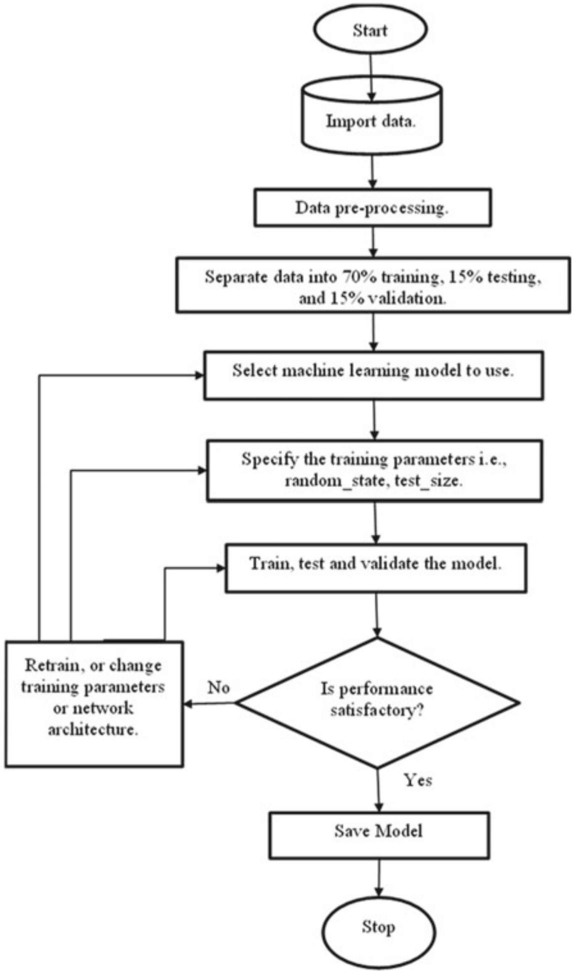


Fig. 2 Flowchart of the machine learning model

assessment of the extent of incomplete data. By utilizing the "sum()" function, the total number of columns with missing values is computed. Once these preliminary evaluations are completed, the algorithm offers two viable strategies for handling incomplete data. First, the option to drop the rows with missing values is presented. This approach ensures a complete dataset, eliminating any potential biases caused by incomplete observations. Alternatively, the algorithm also provides the option to replace the missing values with the mean or median of their respective columns. This imputation technique helps to retain valuable data and minimize the impact of missing values on the overall dataset. Through these steps, the algorithm ensures that the dataset is appropriately treated for any incomplete data, setting the foundation for accurate and reliable analysis and modeling. By addressing missing values, the

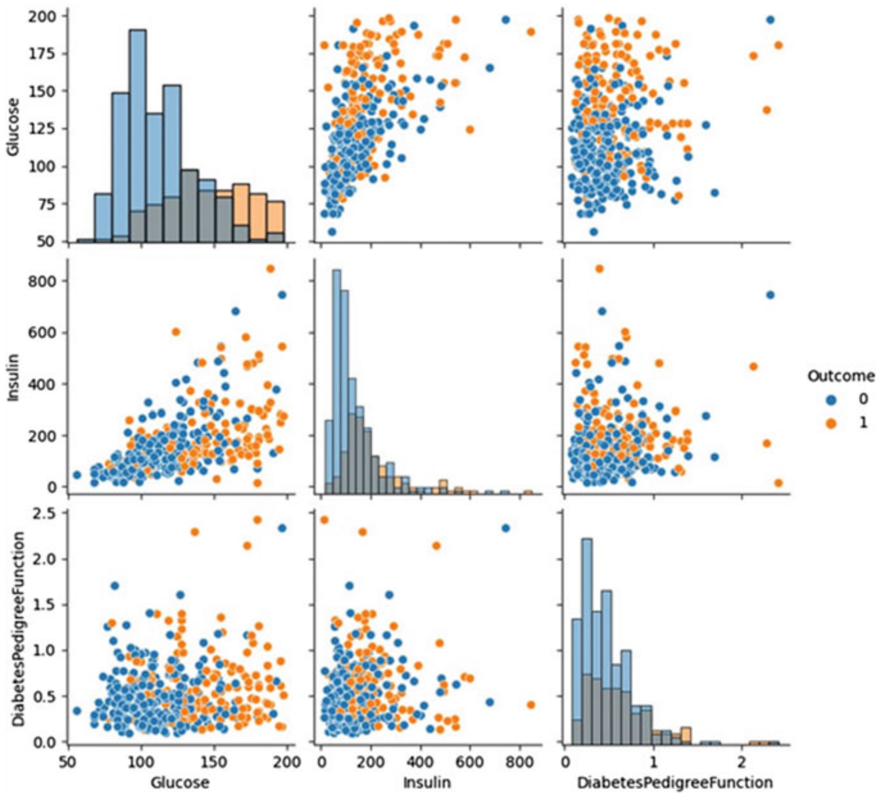


Fig. 3 A scatterplot matrix of the diabetes dataset

algorithm ensures the dataset's completeness, enhancing its suitability for subsequent research and furthering progress in achieving the study's objectives.

The dataset was splited into 70%, 15% and 15% for training, testing and validation respectively. The data frames are separated into two main categories: features, comprising all the relevant parameters obtained from the patient, and labels, consisting of the corresponding outcomes derived from the patient's provided information. This division is achieved through the utilization of the "train_test_split" function from the skLearn (a Python module), which offers the flexibility to specify the desired proportion of data for testing purposes using the "test_size" parameter. Additionally, the "random_state" parameter ensures the randomization necessary to split the dataset effectively. Consequently, the "train_test_split" function generates six datasets, aptly named X_train, Y_train, X_test, Y_test, X_val, and Y_val, representing the subsets dedicated to training, testing, and validation. An essential aspect of this process is understanding the shape of the dataset, which aids in accurately partitioning the data into the respective subsets. This knowledge of the dataset's structure is indispensable for maintaining data integrity and ensuring that the model

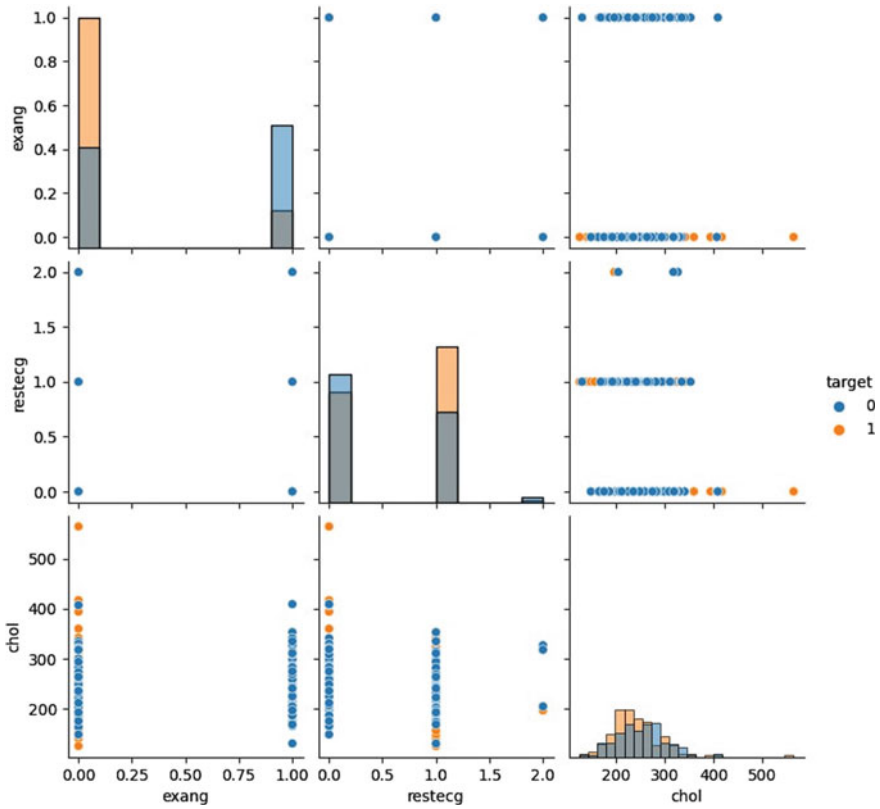


Fig. 4 A scatterplot matrix of the heart disease dataset

is trained, tested, and validated with representative data, ultimately enhancing the model's performance and reliability.

2.3 Flowchart Algorithm

The algorithm for the process depicted in Fig. 6 is as follows:

Step 1: Start.
Step 2: Import Dataset.
Step 3: Perform Data Preprocessing.
Step 4: Split the dataset into 70% training, 15% testing, and 15% validation.
Step 5: Select the Machine Learning Model.
Step 6: Specify the training parameter.
Step 7: Train, test and validate Model.
Step 8: Is Performance Satisfactory.

- If Yes, go to Step 9.
- If No, go back to Step 5, Step 6 and Step 7.
Step 9: Save Model.
Step 10: Stop.

2.4 Performance Evaluation Matrices

Once the model has completed training, it undergoes evaluation on a separate test set to assess its performance in generalizing to new and unseen data. This evaluation provides an estimation of the model's ability to perform on previously unseen samples. To evaluate the model's performance on the test set, various metrics such as accuracy, recall, precision, and F1-score are employed. In each evaluation metric, certain key terms are commonly used in their respective equations (Mishra et al. 2017):

a. True Positives (TP): This refers to the number of instances that are accurately predicted as positive, indicating that both the actual and predicted class values are correct.
b. True Negatives (TN): This represents the number of accurate negative predictions, indicating that both the predicted and actual class values are correct and negative.
c. False Positives (FP): These refer to the instances where the predicted class is positive, but the actual class is negative or incorrect.
d. False Negatives (FN): This refers to the instances where the predicted class is negative, but the actual class is positive or correct.

Accuracy is a widely used evaluation metric, and it is calculated as the ratio of correct predictions to all predictions. The mathematical expression for accuracy is given in Eq. (5):

$$Accuracy = \frac{number\ of\ correct\ precictions}{number\ of\ all\ predictions} = \frac{TP + TN}{TP + FP + FN + TN} \tag{5}$$

Precision measures the percentage of accurately predicted positive samples among all the predicted positive observations, as given in given in Eq. (6):

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall, also referred to as sensitivity or true positive rate, represents the proportion of correctly predicted positive observations to the total actual positive class observations. The mathematical expression for recall is given in Eq. (7)

$$Recall = \frac{TN}{TP + FN} \tag{7}$$

The F1 score is commonly used to gauge a model's performance and is computed using both recall and precision. It considers both false positives and false negatives when calculating the score. The F1 score is particularly useful when the cost of false positives and false negatives is roughly the same. The mathematical expression for the F1 score is given in Eq. (8):

$$F1\,score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{8}$$

2.5 Web Deployment

The deployed model utilizes a web application to facilitate user interaction. The web application is developed with Streamlit framework for the front-end and Flask framework for the back-end. These frameworks work together to enable the user to input relevant data, which is then processed by the trained machine learning model to make accurate predictions regarding the presence or absence of the ailment.

Figure 5 portrays an illustrative diagram that outlines the interactions between different actors and the system to obtain outputs. This diagram serves as a representation of the system's user flow. The process begins with an actor (the user) accessing the web application through a website. The user selects the specific disease for which they desire a prediction. They then proceed to input the required parameters, providing relevant information for the prediction process. Once the necessary input is submitted, the system executes the machine learning model, which operates behind the scenes. This trained model analyzes the provided data and generates a prediction based on the learned patterns and associations from the training phase. As a result, the user receives a correct prediction regarding the presence or absence of the ailment they selected. The web application's seamless integration of the front-end and back-end frameworks allows for a user-friendly experience, where the prediction process is carried out effectively, providing valuable insights to aid in medical decision-making.

3 Result Analysis

In this section, an in-depth analysis of the outcomes obtained from the machine learning model for predicting diabetes and heart disease is presented. To evaluate the model's effectiveness, a range of performance metrics, including accuracy, precision, recall, F1-score, and the confusion matrix, are employed. The subsequent discussion of the results and findings offers invaluable insights into the model's performance, shedding light on its ability to correctly classify instances and avoid misclassifications. Through a comprehensive overview of the evaluation metrics, the

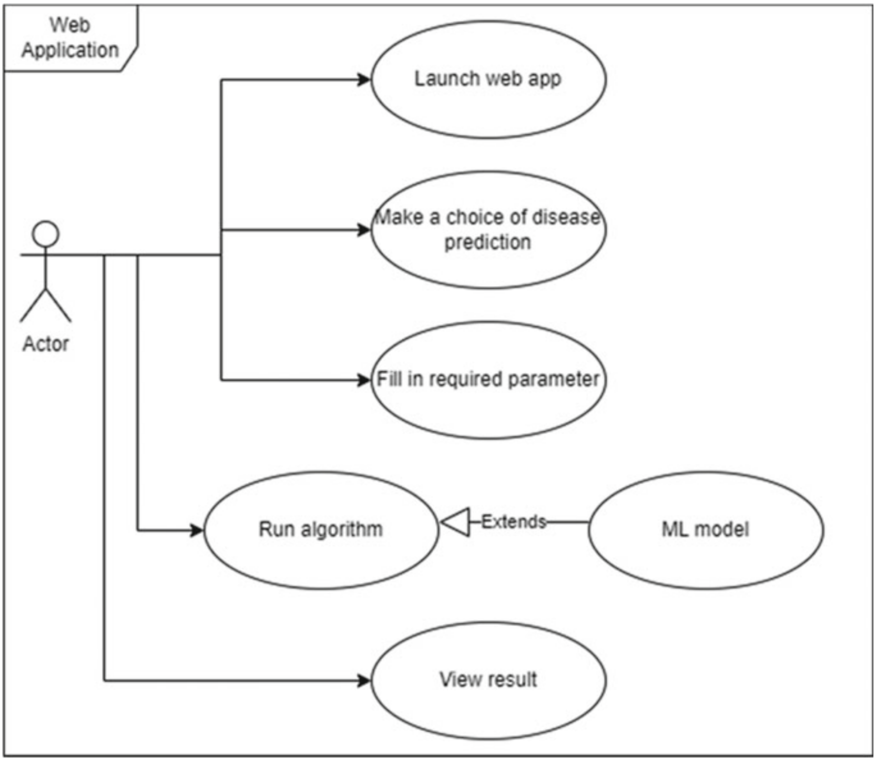
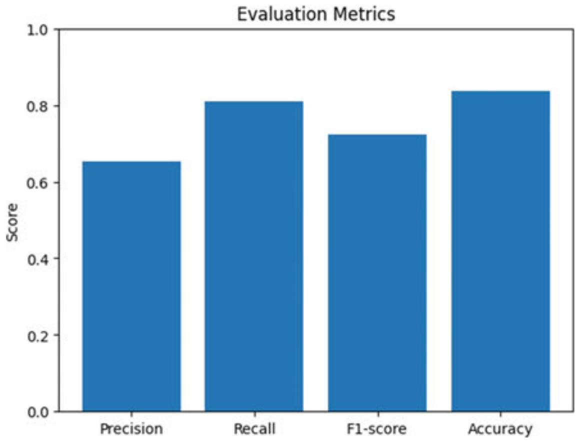


Fig. 5 Use case diagram

Fig. 6 A bar chart representation of the Support Vector Machine (SVM) performance



strengths and limitations of the proposed prediction system are thoroughly assessed, providing a detailed understanding of its efficacy in accurately predicting the presence or absence of diabetes and heart disease, respectively. By considering multiple evaluation metrics, a holistic perspective of the model's performance is attained, contributing to a robust validation of its reliability. The findings derived from this rigorous analysis carry significant implications for the field of medical prediction and decision-making. The discussion of the results serves as a crucial step in validating the model's suitability for real-world applications, supporting healthcare professionals in making accurate and timely assessments. The comprehensive examination of the model's performance offers valuable insights into its potential role in enhancing medical diagnostics, contributing to improved patient care and health outcomes. By addressing both the successes and limitations of the model, this analysis provides a foundation for further refinement and optimization, advancing the field of medical predictive analytics. Overall, the comprehensive analysis of the results showcases the model's capabilities and potential, guiding future research and applications in the domain of healthcare, and reinforcing the importance of data-driven decision-making in medical practice.

3.1 Support Vector Machine (SVM) and Logical Regression (LR) Performance Evaluation

In the previous section, the model's evaluation metrics were discussed, including accuracy, precision, recall, and F1-score. These metrics are used to assess the performance of the model in making predictions on new data. Tables 1 and 2 display the diabetes and heart disease prediction models' performance on new data.

Figures 6 and 7 provide a visual representation of the performance of each model. Based on the information presented in the Tables 1 and 2, it is evident that the models performed well on new data.

For the diabetes model as shown in Table 1, it achieved a higher recall score than precision. Recall, also known as sensitivity, measures the model's ability to correctly identify positive cases out of all the actual positive cases. A higher recall score indicates that the diabetes model is effective in capturing a larger proportion of positive cases, which is crucial in medical diagnosis. However, since it has a lower

Table 1 Performance evaluation of the support vector machine (SVM) model

Accuracy	Precision	Recall	F1-Score
83.5%	63.5%	80.1%	72.3%

Table 2 Performance evaluation of the logical regression (LR) model

Accuracy	Precision	Recall	F1-Score
81.9%	90.9%	78.9%	84.5%

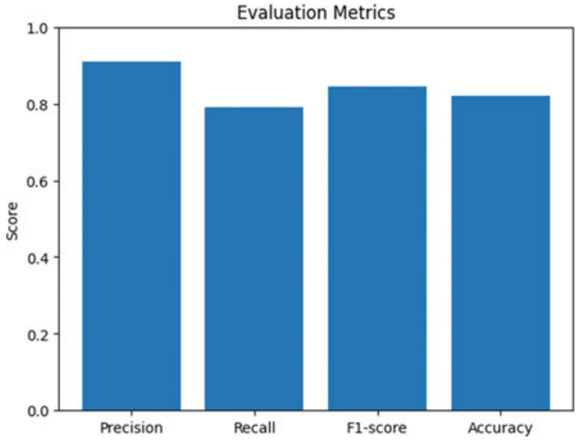


Fig. 7 A bar chart representation of the logical regression (LR) performance

precision score, it may also produce more false positives, meaning it could identify some cases as positive that are, in fact, negative.

The heart disease model result as seen in Table 2 obtained a higher precision score than recall. Precision is a measure of the model's accuracy in correctly predicting positive cases out of all the cases it labeled as positive. A higher precision score indicates that the heart disease model makes accurate positive predictions. However, because it has a lower recall, it may miss some actual positive cases, meaning it could fail to identify some patients with heart disease.

Figures 8 and 9 depict the confusion matrices for each model. The confusion matrix is a tabular representation that provides a detailed breakdown of the model's predictions, showing true positives, true negatives, false positives, and false negatives. It allows us to gain insights into the types of errors made by the model. The main diagonal of the confusion matrix represents correctly classified data, while the off-diagonal elements represent instances of incorrect classification.

For the diabetes model, the confusion matrix shows that it correctly classified 49 true negatives (instances correctly predicted as negatives) and 17 true positives (instances correctly predicted as positives). However, it also misclassified 4 actual positive cases as negatives, which are false negatives, and 9 actual negative cases as positives, which are false positives.

As for the heart disease model, its confusion matrix reveals that it correctly classified 20 true negatives and 30 true positives. These are instances correctly identified as negatives and positives, respectively. However, the model also made 8 false negatives, misclassifying actual positive cases as negatives, and 3 false positives, misclassifying actual negative cases as positives.

Analyzing these confusion matrices helps us understand the strengths and weaknesses of each model in terms of correctly identifying positive and negative cases for their respective target classes (diabetes or heart disease). By studying the misclassifications, we can gain insights into where the models may need improvement and how their performance compares to each other.

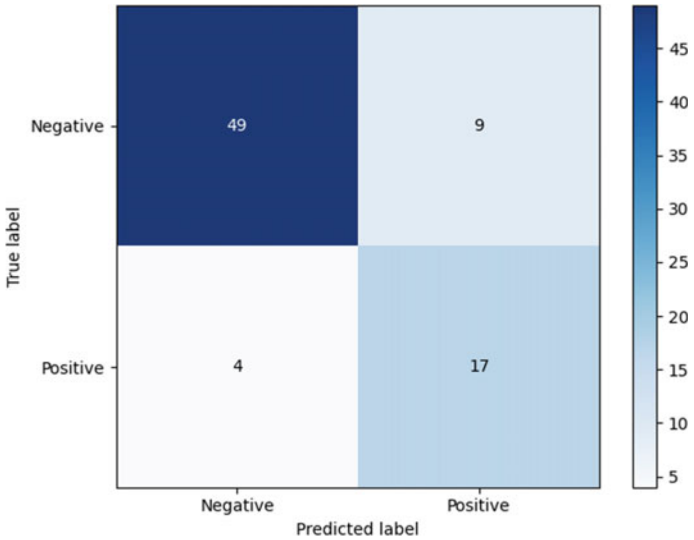


Fig. 8 The confusion metric of the support vector machine (SVM) model

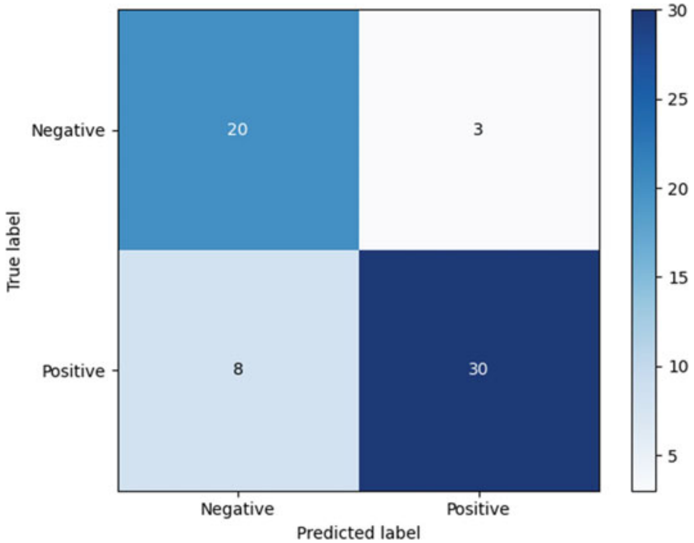


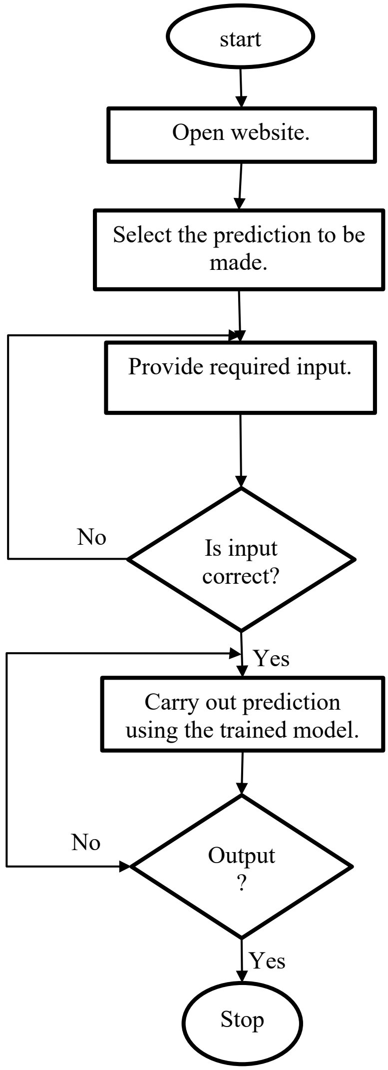
Fig. 9 The confusion metrics of the logical regression model

3.2 Model Deployment

Once the algorithm was trained, tested, validated, and evaluated, it was made accessible to users by deploying it to the web using Streamlit along with a.sav file. This allowed users to interact with the model and obtain predictions for their specific cases.

Figure 10 presents a flowchart provides a clear and visual representation of how the webpage operates, guiding users through the process of selecting a prediction type, inputting the required data, verifying the data, and ultimately obtaining the prediction based on the provided information. This flowchart outlines the step-by-step process of how the webpage operates, starting from when the webpage is opened until the prediction is made.

Fig. 10 Web application flowchart



The flowchart begins with the user opening the webpage. Next, the user is prompted to select the type of prediction they want to make, either diabetes or heart disease. Once the prediction type is selected, the user is then asked to input the required data, which may include various medical or personal information relevant to the prediction. After the data is provided, there is a verification step to ensure the input data is correct and complete. If the data is verified as correct, the system proceeds to the next step, which is to carry out the prediction using the provided data. On the other hand, if the input data is found to be incorrect or incomplete, the user is prompted to input the correct data before proceeding with the prediction.

3.3 Flowchart Algorithm

The algorithm for the process depicted in Fig. 10 is as follows:

Step 1: Start.
Step 2: Open the website.
Step 3: Select the prediction to be made.
Step 4: Provide the required data.
Step 5: Is Input Correct.
- If Yes, go to Step 6.
- If No, go back to Step 4.
Step 6: Carry out prediction using the trained model.
Step 7: Is Output Correct.
- If Yes, go to Step 8.
- If No, go back to Step 6.
Step 8: end.

Figure 11 presents a general information page that provides an overview of the diseases being predicted. This page likely contains essential details about the conditions being assessed, such as diabetes and heart disease, explaining the significance of the predictions and the purpose of the application.

Figure 12 illustrates the diabetes prediction page, where users can input specific information required for obtaining a correct prediction. This page likely prompts users to enter relevant data, such as age, blood glucose levels, medical history, or other vital factors that the model needs to make an accurate diabetes prediction.

Figure 13 represents the heart disease prediction page, where users can input necessary information to correctly predict the presence of the disease. This page includes fields to input factors like age, blood pressure, cholesterol levels, exercise habits, and so on. By providing a user-friendly interface with dedicated pages for each disease prediction, users can easily interact with the algorithm and obtain personalized predictions based on their specific data. This deployment via Streamlit makes it convenient for users to access the predictive model online and receive valuable insights about their health conditions.

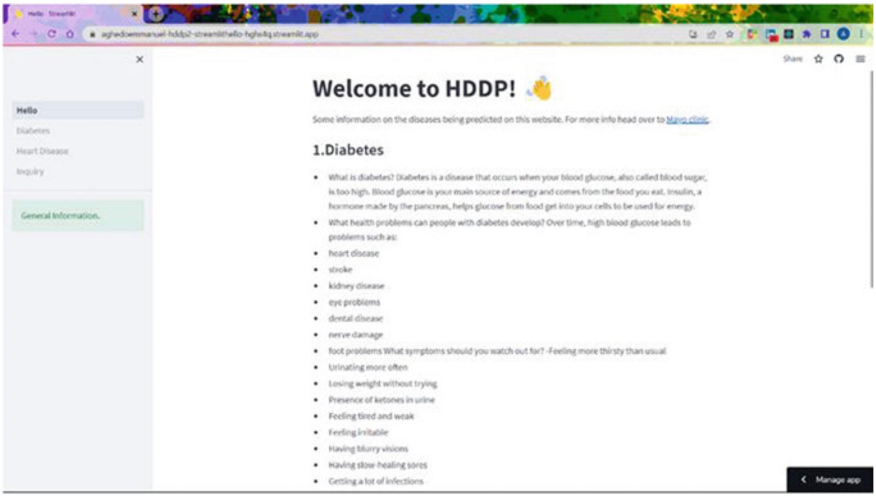


Fig. 11 General information page

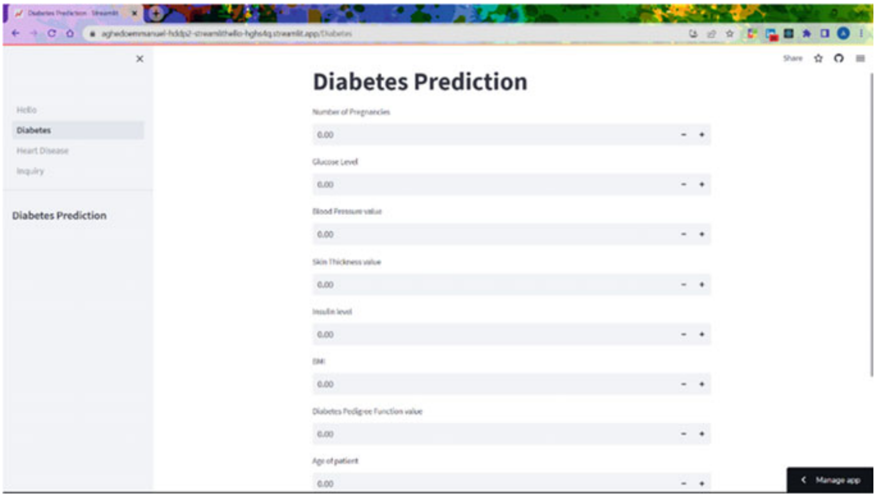


Fig. 12 Diabetes prediction page

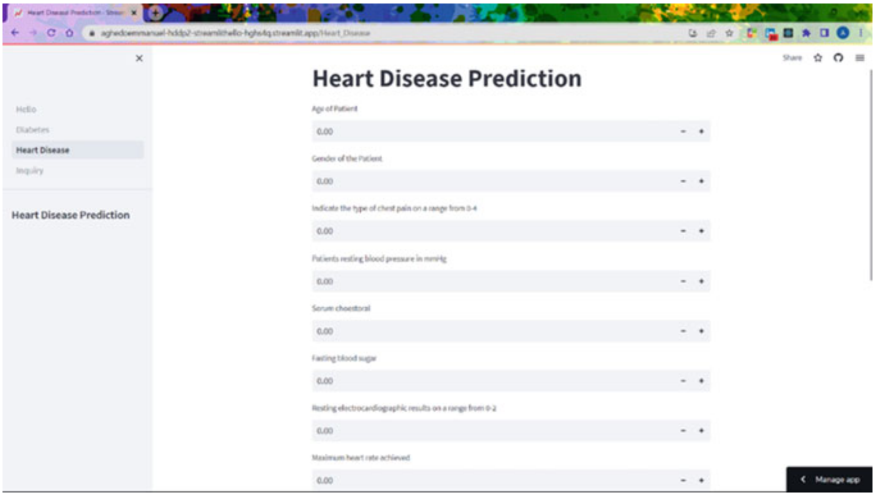


Fig. 13 Diabetes prediction page

4 Discussion

This section highlights the paper's alignment with Sustainable Development Goal 3 (Good Health and Well-being) based on the result obtained. Sustainable Development Goal 3 (SDG 3) is one of the 17 global goals established by the United Nations as part of the 2030 Agenda for Sustainable Development. Each goal addresses diverse social, economic, and environmental challenges with the aim of creating a more sustainable world by 2030. Specifically, SDG 3 emphasizes the importance of ensuring healthy lives and promoting well-being for people of all ages.

1. **Improving Diagnostics**: As previously stated the study focuses on developing accurate prediction models for diabetes and heart disease using machine learning algorithm. Timely and precise diagnosis is crucial for effective disease management, especially for conditions like diabetes and heart disease that have significant impacts on global health. In a recent study by Olisah et al. (2022), machine learning algorithms were employed to predict diabetes and heart disease outcomes with high accuracy, showcasing the potential of these techniques in improving diagnostic precision. Building on the success of previous research done by Olisah et al. (2022) our research leveraging machine learning and IoT technologies. As seen in Tables 1 and 2, it can be visualized that machine learning algorithm performed well in the prediction of the two diseases.
2. **Enhancing Healthcare Accessibility**: The integration of IoT technology into a web-based application allows for seamless connectivity and real-time analysis of medical laboratory results. This empowers healthcare providers, pharmacies, and patients with remote access to critical health information, irrespective of their

geographical location. Irshad et al. (2023) highlighted the significance of IoT-enabled healthcare applications in bridging accessibility gaps in remote areas, enabling real-time health data analysis and diagnosis. Aligned with the findings of Irshad et al. (2023) our study leverages IoT technology to create a web-based platform that offers seamless connectivity for healthcare providers, enabling remote access to critical health information and contributing to improved healthcare accessibility.

3. **Supporting Early Detection and Treatment**: The emphasis on recall (sensitivity) in the diabetes model highlights the importance of correctly identifying positive cases among all actual positive cases. Early detection of diseases like diabetes and heart disease is crucial for timely intervention and appropriate treatment. Nithya et al. (2022) have highlighted the critical role of early intervention in improving patient outcomes for non-communicable diseases. Developing the models with high recall rates, the paper helps in the early identification of patients with these conditions, thus supporting SDG 3 objective of reducing premature mortality from non-communicable diseases.
4. **Advancing Healthcare Technology**: This study showcases the potential of integrating machine learning techniques with IoT capabilities to transform healthcare services. Such technological advancements have the potential to revolutionize healthcare systems and improve health outcomes globally. Hopia et al. (2015) has emphasized the transformative potential of these technologies in revolutionizing healthcare delivery and improving health outcomes on a global scale. SDG 3 aims to strengthen healthcare capacity and infrastructure, and this paper's focus on innovative technologies aligns with that objective.
5. **Promoting Global Health Collaboration**: The paper utilizes a dataset sourced from Kaggle, a platform that encourages collaboration and knowledge sharing among data scientists and researchers worldwide. By utilizing publicly available datasets, the study demonstrates the importance of global collaboration in addressing health challenges. Sharing data and research findings can lead to the development of more robust and accurate models (Naudet et al. 2018), ultimately contributing to better health and well-being for all.

In conclusion, this paper's alignment with SDG 3—Good Health and Well-being is evident across its objectives, methodologies, and results. By referencing existing studies and recent literature, we contextualize our contribution within the broader landscape of global health research and innovation. Through improving diagnostics, enhancing healthcare accessibility, supporting early detection and treatment, advancing healthcare technology, and promoting global health collaboration, our work contributes meaningfully to the realization of SDG 3 vision, ultimately working towards a healthier and more sustainable future for individuals worldwide.

5 Conclusion

The primary focus of this research was to design an innovative Internet of Things (IoT) based web application that harnesses the power of machine learning models to accurately predict whether a patient has diabetes or heart disease, thereby making a significant contribution to the realization of SDG 3—"Good Health and Well-being." Through the integration of IoT technology, the developed application enables the collection of real-time health data from patients, encompassing vital parameters such as blood glucose levels, blood pressure, and other relevant health indicators. This continuous and remote monitoring empowers proactive health management, facilitating early disease detection and prevention. By promoting timely interventions and personalized healthcare, the system directly aligns with SDG 3 overarching objective of ensuring healthy lives and promoting well-being for all.

The system's efficacy in accurately identifying diabetes and heart disease is derived from the intelligent analysis of patients' input data. Based on correctly inputted data, the application achieves precise and reliable predictions, enabling healthcare professionals to make informed decisions and tailor treatments to individual patients' needs.

Looking ahead, the system presents several promising avenues for further improvement and expansion. By extending the IoT sensor network and data collection capabilities, a more comprehensive understanding of patient health can be attained. This opens the door to personalized and targeted healthcare interventions, enhancing patient outcomes and advancing SDG 3 goals.

To enhance the system's accuracy and relevance, future endeavors could focus on developing more detailed datasets, including distinct datasets for diabetes type-1 and type-2. Incorporating data from diverse patient populations would also enrich the overall dataset, leading to a more robust and inclusive predictive model. This inclusivity is vital for ensuring the system's effectiveness across diverse demographics, contributing to the pursuit of equitable healthcare access, a key aspect of SDG 3. The successful development and deployment of this IoT-based prediction system mark a significant step towards achieving SDG 3 objectives. By enhancing healthcare accessibility and promoting preventive measures through technology-driven solutions, the application supports the provision of quality healthcare for all. Emphasizing continuous improvements in machine learning models and IoT data integration lays the groundwork for further advancements in healthcare technology, with the ultimate goal of better serving patients' needs and fostering healthier communities. In conclusion, this research showcases the immense potential of IoT and machine learning in revolutionizing healthcare delivery, ultimately advancing SDG 3 vision of ensuring good health and well-being for all. By harnessing the capabilities of technology and data-driven solutions, the IoT-based web application serves as a promising step towards more efficient and effective healthcare management, fostering a brighter and healthier future for individuals and communities worldwide.

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Achieving Sustainable Development Goals in Cyber Security Using AIoT for Healthcare Application

Meenu Vijarania, Swati Gupta, Akshat Agrawal, and Sanjay Misra

Abstract The way of automation and modernization became relevant and common as the demand for digital technology with IoT and AI has increased, which helped to decrease manual labour and boost overall productivity. Cybersecurity was developed to guard against threats in the online environment to lessen these dangers. To provide a safe and risk-free environment in the online world, cybersecurity operates as an online guardian to safeguard against online frauds and dangers. Organizations are becoming more dependent on one another, which drives the growth of interorganizational networks where one of the most crucial challenges is cybersecurity and sustainable development. Sustainable cyber safety programmes are crucial for everyone's lives since personal data can be exploited for online crimes and frauds as well as to ruin someone's personal life if it is compromised or misused. The purpose of the study is to draw attention to healthcare systems' vulnerabilities because they handle sensitive financial information and personally identifiable information about patients, both of which are susceptible to cyberattacks. Many healthcare organisations are using cutting-edge technologies to provide breach-proof safeguards to safeguard sensitive data. Moreover, specific training is done for consistent backup and recovery procedures. To protect health-related information, access control approaches are used. To maintain sufficient security, strong passwords and changing procedures are used. Further, the incorporation of artificial intelligence into everyday objects (AIoT) has become a key enabler for achieving the Sustainable Development Goals (SDGs), especially in the area of cybersecurity. The SDGs address issues such as cybersecurity worries, and AIoT provides creative solutions to reduce these risks.

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Methodologies for encryption and decryption are also used to convey sensitive and vital data without any difficulty. In the modern day, we must adopt new trends in intelligent social health systems powered by the Internet of Things (IoT). Cybersecurity is essential to safeguarding the security of healthcare institutions and defending them against online fraudsters.

Keywords Cybersecurity · Cloud · AIoT · Antivirus · Sustainable Development Firewall Systems · And Breach

1 Introduction

Today's organisations, especially those in the healthcare industry, must contend with a number of urgent concerns, including cybersecurity. Among the sensitive and private information that healthcare organisations collect from individuals are medical histories, diagnoses, test results, and billing information. Given the expanding use of technology in healthcare, the security of this data is even more crucial. A significant cybersecurity concern for the healthcare industry is the possibility of data breaches, which can lead to patient safety compromises, medical fraud, and identity theft. The objective of this research project is to evaluate the importance of cybersecurity in healthcare and the challenges that healthcare organisations face when attempting to implement practical cybersecurity measures. because, generally amounts of financial and personal data it holds, the healthcare sector is one of the most frequently attacked.

In order to protect the security and privacy of sensitive medical data, maintain the reliability of healthcare systems, and advance health and wellbeing, it is imperative that cybersecurity for healthcare apps achieve sustainable development goals (SDGs) (Sanjay et al. 2020). Data breaches, ransomware attacks, and other cyberthreats that could have serious repercussions for patients and healthcare providers must be protected against with cybersecurity measures. Protecting patient data, electronic health records (EHRs), and private health information are the main goals of healthcare cybersecurity which are required for achieving SDG 3: Good Health and Well-being and SDG 9: Industry, Innovation, and Infrastructure. Further, the spread of Internet of Things (IoT) devices in the healthcare industry has widened the assault window for online dangers. Infusion pumps, pacemakers, and insulin pumps are examples of medical equipment that must be secured to avoid unauthorised access and possible patient injury. For healthcare IoT ecosystems to be resilient, sustainable cybersecurity practises must be embraced. (Sun et al. 2018) To build a strong cybersecurity culture within healthcare organisations, healthcare professionals and staff must be encouraged to become more aware of and trained in cybersecurity. Constant training is one of the sustainable development goals in cybersecurity to guarantee that staff can identify possible risks and act appropriately (Rohan et al. 2023).

According to an IBM survey, the average cost of a data breach in the healthcare industry is $7.13 million, making it the most expensive industry to be affected.

Healthcare data is frequently more valuable than credit card data since it contains a lot of personal information that can be used for fraud and identity theft. Therefore, it is necessary to protect the confidentiality, integrity, and accessibility of patient information, which necessitates cybersecurity. The industry is exposed to a number of cybersecurity concerns, such as insider threats, malware, ransomware, and phishing schemes. One of the most common types of cyberattacks in the healthcare sector is phishing. These attacks involve an assailant sending an email or message that appears to be from a reputable source but is a false attempt to steal sensitive information. Malware and ransomware attacks cause computer systems to become infected with harmful software that can steal or encrypt data. Insider attacks, whereby employees or contractors with access to sensitive data may willfully leak it or improperly exploit patient information, represent another significant cybersecurity concern. Implementing reliable cybersecurity measures in the healthcare sector can be challenging for a number of reasons. It is difficult for healthcare organisations to invest in cybersecurity systems and competent workers due in large part to a lack of funding. The complexity of healthcare systems, which might involve numerous manufacturers, software applications, and medical devices that are vulnerable to cyberattacks, is another challenge.

The backlash from staff and patients who find cybersecurity measures like encryption and two-factor authentication obtrusive or difficult is however a typical occurrence for healthcare institutions. By applying cybersecurity best practises, healthcare firms can reduce their risk of data breaches and protect themselves from assaults. Some of these best practises include the usage of multi-factor authentication, regular software and system updates, employee cybersecurity training, and regular risk assessments.

AIoT improves threat detection, anomaly identification, and incident response in real time by fusing AI's analytical skills with the interconnection of IoT devices. This is essential for protecting sensitive data, financial systems, and key infrastructure from online threats. AIoT also facilitates intelligent data filtering and encryption, which aids in attempts to maintain data privacy and compliance. In addition, it supports SDGs 9 (Industry, Innovation, and Infrastructure) and 16 (Peace, Justice, and Strong Institutions) by fostering robust systems that can withstand cyberattacks.

The paper is organized as follows. After this brief introduction the literature review is provided in Sect. 2. Section 3 presents the Cyber security Challenges in the HealthCare and also covers Blockchain, Cloud computing and Artificial Intelligence for cyber security. Section 4 discussed Cyber risks and Threats in the healthcare sector. Security Measures in Healthcare are covered in Sect. 5. Relevance of Sustainable Development Goals in Healthcare Cybersecurity were covered in Sect. 6. Section 7 provides the conclusion and suture direction.

2 Related Literature

In (Ahmed et al. 2022) authors attempts to fully characterize, measure, and model the current state of cybersecurity in healthcare facilities. Healthcare businesses will be able to comprehend the impending operational risks and determine which controls to enhance or incorporate into their system in order to reduce such risks thanks to the proposed model.

In order to combat the recent rise in cyberattacks (such as phishing campaigns and ransomware attacks), which have been used by attackers to exploit vulnerabilities in technology and people introduced through changes to working practices in response to the COVID-19 pandemic, the goal of this article is to identify key cybersecurity challenges, solutions adopted by the health sector, and areas that needed improvement (He Y. et al. 2021).

The two main factors that make healthcare vulnerable to cyber threats are the rapid evolution of technology and changing federal policies. Healthcare IT infrastructure is a popular target for medical information theft as the sector struggles with new technologies and security standards. Hence, it is essential to devote time and resources to maintaining and protecting the security of patient information and healthcare technology against unwanted access (Kruse et al. 2016).

In (Kruse et al. 2017) presented a comparative analysis of the many applications of cyber-security and the variations in risk levels for various sectors. The study will concentrate on the usage of cyber-security for the healthcare industry and the various methods employed to safeguard the IoT-based healthcare sector. The report examines several security vulnerabilities to the healthcare sector. In this essay, we'll concentrate on how Advanced Encryption Standard (AES) is applied in electronic health records (EHR) to protect the healthcare sector from cyberattacks.

In (Argaw et al. 2019) the study is carried out to locate, catalog, and characterize the various areas of research in the scientific literature on cyberattacks on hospitals. To map the literature, six study topics were created: information security methodology, connected medical devices and equipment, hospital information systems, raising awareness and lessons gained, context and trends in cybersecurity, and specific types of assaults. In the future, the field can improve and grow these study areas. However, the analysis found that there is generally a rising demand for studies and suggestions on the area.

Digital technology is becoming more and more important to health systems all over the world. With recent assaults emphasizing the hazards to patients and targeted organizations, such dependency necessitates that healthcare institutions consider effective cybersecurity and digital resilience as a core component of patient safety. We created and distributed a survey to investigate the current cybersecurity landscape and preparation level across international healthcare companies in order to better understand how well-prepared enterprises are to handle this challenge. The main issues raised were loss of faith in the organization, dangers of service interruption, and data security, especially the manipulation or loss of electronic health records (O'Brien et al. 2020).

In (Abbas et al. 2022) authors significantly contributed to the empirical analysis and literature already available on digitalization and public health care. According to the study's findings, cybersecurity measures greatly enhanced healthcare digitization and reduced institutional dysfunction in Asia. This study sheds light on how cybersecurity measures improve institutional quality and service quality in the Asian health sector, which will aid in the development of sustainable standards and long-term policy decisions in the years to come.

Healthcare organizations should prioritize cybersecurity and explore the potential of technology to enhance cybersecurity measures. Future research should focus on the effectiveness of these solutions and their implementation in real-world healthcare systems.

2.1 Discussion

It's crucial to emphasise noteworthy findings from both the suggested study areas and the existing research in order to provide a thorough discussion on accomplishing Sustainable Development Goals (SDGs) in cybersecurity for healthcare applications in contrast to existing literature. This will make it easier to recognise any gaps, difficulties, and future breakthroughs in the area. The following discussion describes these elements:

A. **Sharing Data While Protecting Privacy:** Existing Literature Prior studies have emphasised the significance of striking a balance between patient privacy protection and data sharing for research and analysis. To enable privacy-preserving data exchange, methods like homomorphic encryption and safe multi-party computation have been investigated.

   Future Direction: To accommodate sizable healthcare datasets, future research could concentrate on improving the scalability and efficiency of these systems. In order to provide patients more choice over how their data is shared, research may also focus on user-centric consent management systems.

B. **Threat Detection and Prevention Driven by AI:** In the current Literature the ability of AI-driven cybersecurity solutions to detect unidentified threats has attracted interest. Deep learning techniques, behaviour analysis, and anomaly detection are frequently used in these strategies.

   The development of AI models that can adapt to the shifting threat environment may be the focus of future research. Adversarial machine learning approaches are being studied in order to increase the resistance of AI-driven defences to complex attacks.

C. **Existing Literature on Medical IoT Security:** Studies have highlighted the weaknesses of medical IoT devices and suggested fixes including device authentication, encryption, and intrusion detection systems.

The creation of lightweight cryptographic protocols appropriate for devices with limited resources as well as the integration of hardware-based security mechanisms into medical IoT devices are potential future directions for research.

D. **Existing Research on Blockchain for Health Data Integrity Blockchain:** The technology has been studied for its potential to improve data integrity and auditability, particularly in the interchange of health information.

3 Cyber Security Challenges in the HealthCare Sector Considering SDG

3.1 Integration of Blockchain and SDG in Healthcare Sector for Cybersecurity

Blockchain technology functions as a distributed ledger system in which data used for transactions or communication is kept in a network of digital blocks that is accessible to the public. Although blockchain technology has many potential uses in the healthcare industry, there are also several obstacles to take into account, such as scalability, interoperability, and regulatory compliance. In order to maximise the potential impact of using blockchain technology in healthcare on reaching sustainable development goals, stakeholders must carefully analyse their implications and work together. Blockchain can be used in healthcare to support SDGs in the following ways:

3.2 Improvements in Data Management and Privacy (SDGs 3 and 16: Peace, Justice, and Strong Institutions):

A decentralised, immutable ledger offered by blockchain can improve the confidentiality and privacy of medical records. More control over their data is given to patients, who can securely share it with healthcare professionals. Additionally, it can make it easier for organisations in the healthcare industry to securely share information, improving care coordination and improving diagnostic accuracy (Kuo et al. 2017).

4 Management of the Medical Supply Chain (SDGs 3 and 9: Industry, Innovation, and Infrastructure):

Pharmaceuticals, vaccinations, and medical supplies may all be tracked and traced using blockchain across the supply chain. The timely supply of necessary medications and equipment can be ensured by this transparency, which can aid in the prevention of counterfeit goods (Radanović and Likić 2018).

3.Micropayments and Incentive Mechanisms (SDG 10: Reduced Inequalities and SDG 3: Good Health and Well-Being):

Micropayments are made possible by blockchain and can be used to reward positive actions and increase adherence to treatment regimens. This can help people take better care of their health, which can be especially helpful in underserved places (Zheng et al. 2017).

5 Studying and Conducting Clinical Trials (SDGs 3 and 9: Industry, Innovation, and Infrastructure):

Data exchange for research and clinical trials can be made transparent and secure thanks to blockchain technology. Researchers can increase the integrity and trustworthiness of research findings by making the trial data available as an immutable record (Khezr et al. 2019).

5.1 Sustainable Healthcare Ecosystem Using Cloud Computing for Cybersecurity

In order to solve cybersecurity issues and help realize numerous Sustainable Development Goals (SDGs), cloud computing in healthcare is essential. The relationship between healthcare cloud computing, cybersecurity, and different SDGs is explained below:

SDG #3: Promoting Health and Well-Being Healthcare practitioners can safely store and distribute patient data via cloud computing, protecting the safety and confidentiality of sensitive medical data.

SDG #9: Industry, Innovation, and Infrastructure—Cloud-based cybersecurity solutions and infrastructure guard healthcare systems from online dangers and support the development of a robust and secure healthcare IT environment.

SDG #16: Peace, Justice, and Strong Institutions—Cloud-based cybersecurity measures improve the dependability and integrity of healthcare systems, fostering confidence between patients and healthcare professionals.

SDG #17: Partnerships towards the Goals—Collaboration among healthcare organizations, cloud service providers, and cybersecurity specialists encourages group efforts to address cybersecurity issues and create a safer healthcare ecosystem.

Sensitive health data is protected by the combination of cloud-based technologies and reliable cybersecurity procedures, which also makes it easier to provide high-quality healthcare services globally. Cloud computing can help achieve SDGs for improved healthcare, innovation, security, and working together for sustainable development.

Patients, stakeholders, and healthcare providers all stand to gain from the transformation that cloud computing has brought to the healthcare industry. However, there are disadvantages as well because cloud computing technology is susceptible to cyberattacks that could put the confidentiality, integrity, and accessibility of sensitive medical data in danger. This paper investigates the security concerns created by cloud computing in the healthcare sector and makes recommendations for mitigating risks and enhancing security. Cloud computing technology has risen in popularity in recent years due to its versatility, scalability, and affordability. The healthcare sector has also adopted cloud computing technologies to store and manage vast quantities of sensitive data, including electronic health records (EHRs), medical images, and patient information. Medical professionals can now treat patients more effectively while spending less money as shown in Fig. 1, 2.

5.2 Integration of Sustainability Development Using Artificial Intelligence and Machine Technology in Healthcare for Cybersecurity

Using machine learning and artificial intelligence (AI) in conjunction with sustainability development concepts offers a promising way to improve healthcare cybersecurity while fostering environmental responsibility. The security and effectiveness of healthcare cybersecurity practises are improved by using AI for threat detection, data protection, and incident response (Rastogi M. et al. 2022). Real-time cyber threat detection and mitigation are made possible by AI-driven algorithms and behaviour analysis, protecting patient data and vital medical systems. Additionally, blockchain-based attribute-based encryption and other AI-powered data security techniques like encryption safeguard patient privacy while enabling secure data sharing for medical research. Faster identification, containment, and recovery from cybersecurity breaches are made possible by incident response techniques that incorporate AI and machine technologies. Additionally, AI's resource optimisation capabilities can lower data centre energy use and increase hardware effectiveness, helping to create a more sustainable healthcare ecosystem.

To lessen these hazards, healthcare practitioners can take a number of steps. To ensure that only authorised personnel have access to sensitive information, they can, for example, implement tight access controls like multi-factor authentication and

Fig. 1 Relation of cyber security with sustainable development

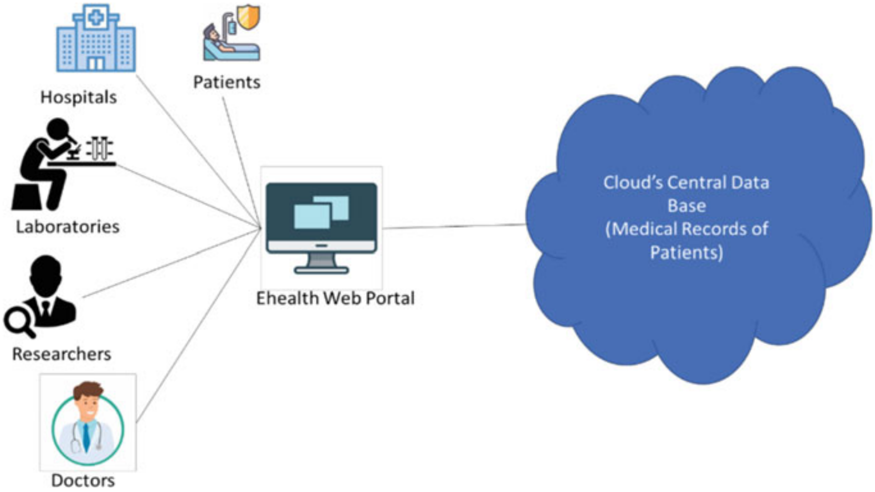

Fig. 2 Healthcare data stored in cloud (Sivan and Zukarnain 2021)

encryption. They can also include AI and ML model validation and testing techniques to detect and prevent adversarial assaults and model poisoning attacks.

Another strategy for understanding how AI and ML models produce their recommendations and projections is to use explain ability and interpretability methodologies. Healthcare practitioners can make use of this information to correct any biases or errors in the models. Additionally, AI and ML monitoring and alerting systems can help medical professionals identify any unusual behaviour or deviations from usual patterns.

Healthcare businesses need to make sure that companies selling AI and ML technology follow the law and have adequate security measures in place to protect sensitive data. This requires thorough due diligence on vendors before entering into contracts and ongoing monitoring of their compliance with privacy and security standards.

Healthcare has a lot of promise for using AI and ML technologies to increase operational effectiveness, reduce costs, and enhance patient outcomes. However, it also poses significant cybersecurity risks that must be lessened by implementing the appropriate security measures. By implementing strict access controls, model validation and testing procedures, explainability and interpretability techniques, monitoring and alerting systems, and making sure regulatory requirements are being followed, healthcare providers can enhance cybersecurity and protect sensitive patient data.

6 Cyber Risks and Threats in the Healthcare Sector

Due to the digitization of medical information and the usage of internet-connected medical devices, the healthcare sector is currently dealing with a growing number of cybersecurity challenges. There are more hazards and concerns as the healthcare sector rapidly adopts electronic health records and other digital technology. Healthcare cybersecurity threats have emerged as one of the most urgent issues, especially as more health data is digitised and shared among healthcare providers online. Technology is continuing to change the healthcare sector. Due to the sensitive nature of patient data and the possible financial gain from hacking into healthcare networks, the healthcare industry is a top target for cybercriminals. Healthcare organisations are being targeted by cybercriminals for their valuable patient data, which can be exploited for identity theft, fraud, and other crimes.

Here are some of the key cybersecurity issues facing the healthcare industry:

Ransomware attacks: Attacks with ransomware that can impair operations and compromise private patient data target healthcare organisations in particular. Malware known as ransomware encrypts data and demands money in return for the decryption key. These assaults pose a serious risk to healthcare organisations because they may stop vital patient care services from being provided. By blocking access to medical records and delaying patient care, these attacks have the potential to seriously disrupt the delivery of healthcare services. Attacks with ransomware not only cost businesses money, but they also endanger patient safety. Cybercriminals also encrypt data belonging to an organisation during these assaults and demand payment to decrypt it. Malicious software is utilised in these attacks to encrypt data, thereby locking it up until a ransom is paid.

Insider threats: Insider attacks are a serious problem for healthcare organisations because they frequently handle sensitive data and information. Healthcare organisations must also be on the lookout for insider threats, in which case authorised users or staff members may negligently or wilfully endanger patient data. Employees may unintentionally or maliciously cause data breaches by disclosing sensitive information improperly, falling for phishing scams, sharing passwords mistakenly, utilising unprotected devices, or stealing protected health information (PHI). The healthcare sector is increasingly concerned about insider threats as staff members either knowingly or unknowingly expose important patient data. Data breaches and financial damages for the company may result from this.

Vulnerabilities in medical devices, Third-party, IoT Devices: As medical devices become more plugged into hospital networks and the internet, they become more susceptible to cyberattacks (Vijarania, M. 2022). Medical gadgets grow more vulnerable as more of them are connected to the internet. This makes them a possible target for hackers who can use these kinds of flaws to break into the network of a healthcare organisation and steal patient data, which could cause the patients considerable harm because their private and medical information might be made public. To manage patient information, many healthcare organisations collaborate with third-party vendors, such as suppliers of electronic health records. These vendors themselves may be vulnerable to cyberattacks, which could expose the patient data of the healthcare organisation to hackers. However, there have also been more vulnerabilities as IoT devices have become more prevalent in the healthcare sector. Medical implants, wearable technology, and other IoT devices may not have sufficient cybersecurity safeguards, making them more vulnerable to hacking and data breaches.

Third-party vendor risk: Healthcare organisations must also take into account the cybersecurity threats posed by their third-party suppliers, including software developers, cloud storage providers, and producers of medical equipment. Healthcare organisations utilise outside vendors for a variety of services, including the processing and storing of data. However, because these vendors might have access to private information, they pose a security risk. These vendors may or may not have the essential cybersecurity measures in place if proper safeguards are not in place, increasing the risk of data breaches and other cyber-attacks.

Phishing attacks: Phishing attacks are one of the most common cyber risks now affecting the healthcare industry. Attackers frequently impersonate trustworthy organisations, such as hospitals or healthcare providers, in order to gain sensitive data. These assaults are carried out via emails or SMS texts. Some of the most frequent phishing scams in the healthcare industry are the ones listed below: Targeted phishing This sort of fraud targets specific employees or organisational divisions. The hacker carefully chooses their targets and modifies their phishing message to make it appear more genuine. Whaling is a second type of phishing attack that targets senior officials within a company. The goal is to steal private information or gain access to important accounts. Next is the Business Email Compromise (BEC) This sort of phishing attack uses compromised email accounts to send phoney emails to other employees, customers, or suppliers. To trick the target into sending the attacker money or personal information is the goal. Phishing attacks offer a significant risk to the healthcare industry because they may lead to the theft of cash, intellectual property, or private patient data. A successful phishing attempt may also violate compliance guidelines, which could have legal repercussions like as fines. To lessen the risk of phishing efforts, healthcare firms should concentrate on building robust security measures, such as email filtering and people training programmes. Organisations should make sure they have a comprehensive cybersecurity policy in place in order to address new dangers.

Data breaches: Healthcare organisations can suffer significant financial and reputational harm from data breaches, like any other sector, the healthcare sector is a top target for cybercriminals looking to steal personal data. When private patient information, such as medical records, insurance information, and social security numbers, are made public, it can lead to identity theft, fraud, and medical identity theft. A healthcare data leak may result in people receiving inadequate medical care, among other serious consequences. This could undermine patients' trust in medical providers and the effectiveness of required treatment and care.

As shown in Fig. 3, Healthcare organisations need to prioritise spending on effective cybersecurity solutions and measures to combat these expanding problems. These should include employee training, regular vulnerability assessments,

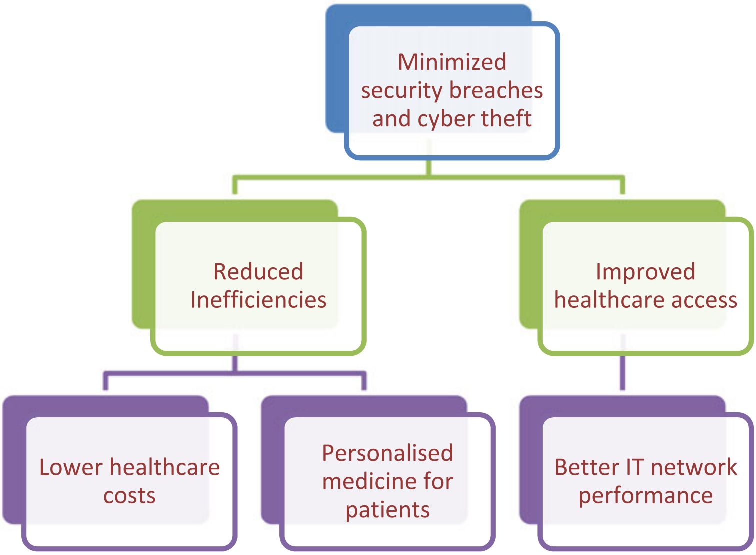

Fig. 3 Reasons for modernizing legacy healthcare systems

and multi-factor authentication for access to sensitive data, as well as training staff to recognise potential threats and respond quickly and effectively to mitigate risks. Organisations should make an effort to confirm that third-party vendors have appropriate cybersecurity policies in place in order to protect patient data. Overall, the rising number of cybersecurity concerns in the healthcare sector emphasises the necessity of heightened alertness and preventative actions to safeguard sensitive patient data. Healthcare institutions must spend money on cybersecurity tools.

6.1 Phishing Schemes, Use of Internet of Things (IoT) Devices, Insider Threats, Cloud-Based Environments

The complexity and connectivity of digital health ecosystems increase along with the cybersecurity threats that are associated with their creation, deployment, and use. The most frequent cybersecurity risks include insider threats, the use of internet-of-things (IoT) devices, phishing schemes, and cloud-based environments. Organisations should be aware of these risks and take action to mitigate them as they pose serious security risks to the organisations by potentially compromising sensitive data or the systems used. Healthcare organisations need to take a thorough and proactive strategy to cybersecurity that takes into account the special features of their digital health ecosystem in order to reduce these risks. This strategy should include creating policies and processes, putting security controls in place, and continual monitoring of system activity.

6.1.1 Phishing Schemes

One of the most frequent cyber risks involves phishing scams, which deceive victims into divulging valuable data like passwords, credit card numbers, or personal information. Typically, these attacks take place on websites for instant messaging, social media, or email. To steal users' login credentials or personally identifiable information, cybercriminals frequently construct bogus websites or entice people to click on harmful links. People should exercise caution when clicking on links or opening emails that seem suspicious, and they should always double-check the source before disclosing any personal information that could be used for identity theft, financial loss, or other cybercrimes. Spear phishing is among the most typical phishing assaults in the healthcare sector. This kind of assault targets particular members of staff or divisions within an organisation. The hacker picks their victims wisely and alters their phishing message to make it seem more authentic. The whaling is the second: High-ranking employees inside an organisation are the intended victims of this kind of phishing attempt. The intention is to steal confidential data or get access to vital accounts. The Business Email Compromise (BEC) is the next: This kind of phishing assault sends phoney emails to other employees, clients, or suppliers using hacked email accounts. The intention is to deceive the target into sending the attacker money or private information. Phishing attacks pose a serious risk to the healthcare sector because they can result in the theft of confidential patient information, money, or intellectual property. A successful phishing attempt may also violate compliance rules, which could result in fines and other legal implications. Healthcare organisations should concentrate on developing strong security measures, such as email filtering and personnel training programmes, to reduce the danger of phishing attempts. In order to meet new risks, organisations should make sure that they have a thorough cybersecurity policy in place that is frequently reviewed and updated.

6.1.2 Use of Internet-Of-Things (IoT) Devices

The use of IoT devices has expanded quickly in recent years, however there are serious security dangers associated with using these devices. IoT devices frequently lack adequate security, making them attractive targets for hackers who might exploit them to break into other networks or devices. IoT devices, like smart appliances, thermostats, and security systems, are increasingly popular, but this poses a potential threat to cyber security because these devices frequently collect and transmit sensitive data, like financial or personal health information, which can be valuable to cybercriminals. Additionally, because these devices frequently store sensitive information, they can be targeted by hackers to gain access to home networks and individual users' data IoT gadgets also present new entry points for attackers to use as they are made to be connected to the internet. People should take precautions to lower their risk of cyberattacks, including changing their default passwords, updating their software, and turning off any unneeded features that could enhance their device's attack surface. Because IoT devices frequently lack robust security features, using them poses serious risks, including those associated with connected cars, wearable technology, and smart homes(*WSN Based Efficient Multi-Metric Routing for IoT Networks | 16 | Green*, n.d.). These devices may be used as entry points by hackers to break into company networks and steal confidential data.

The healthcare sector has seen a sharp rise in cybersecurity concerns as more patients, physicians, and medical gadgets connect via the IoT. IoT devices that transport sensitive personal and medical data, like medical equipment, wearables, and mobile health applications, are more susceptible to cyberattacks. These gadgets can also be employed to increase cybersecurity, though. For instance, they can be utilised to improve security frameworks and protocols or to observe and track the actions and behaviours of cybercriminals. Healthcare practitioners can identify possible dangers before they happen by using IoT devices for predictive analysis. By providing real-time tracking of patient health data, enabling quicker decision-making, and better patient outcomes, the integration of IoT devices can also enhance healthcare delivery. The maintenance of cybersecurity standards for these devices, protection of data privacy, and creation of new laws and processes to regulate their use are some of the obstacles that come along with these advantages. Many healthcare organisations are investing in threat detection and response systems, strengthening access controls, and creating thorough data protection plans that include encryption and secure data storage in order to address these cybersecurity concerns. In conclusion, healthcare professionals can take proactive measures to make sure they are using these devices safely and effectively, despite the fact that there are potential hazards connected to their use. IoT devices can be a valuable tool for strengthening patient safety and enhancing healthcare results when they are used with strict cybersecurity protocols and careful attention to data privacy.

6.1.3 Insider Threats

Insider risks happen when individuals with authorised access to a company's systems use that access for fraudulent, criminal, or other bad purposes. This might involve unintentional data exposure, system sabotage, or theft of private information. To spot any questionable behaviour, organisations should implement access controls and keep an eye on user behaviours. Such people may divulge trade secrets, private client information, or intellectual property, which could seriously harm the business. Companies should perform background checks, put access controls in place, and keep an eye on employee behaviour to reduce insider risks. Insider threats can be challenging to identify and stop, and they can seriously harm a company's finances and reputation. A security risk posed to an organisation by its own workers or other trusted insiders, such as contractors, vendors, or partners, is referred to as an insider threat. Insider attacks in the healthcare sector can seriously harm patient data, financial records, and other sensitive information. The introduction of electronic health records (EHRs) and the growing digitization of medical records have increased the industry's susceptibility to insider threats and cyberattacks. EHRs hold a plethora of private and medical data that can be taken, sold, or utilised fraudulently or for other nefarious purposes. Regrettably, there are many insider risks in the healthcare industry, with employees and other insiders being responsible for numerous hacks and data breaches. The following types of insider threats are frequently encountered in the healthcare sector. First, malevolent insiders: These are employees or other esteemed insiders who intentionally steal or leak private information for financial gain or other purposes. Second, unintended insiders: These are employees whose carelessness, ignorance, or stupidity lead to security lapses or data breaches. Lastly, compromised insiders are employees whose access rights or credentials have been stolen, compromised, or illegally used by outside adversaries. In order to limit insider threats, healthcare organizations need to implement strong security policies, access controls, and monitoring systems. Additionally, they must offer consistent training and awareness campaigns to inform staff members of the dangers and repercussions of insider threats. Finally, insider threats in the healthcare sector are an increasing worry, and healthcare organisations need to be proactive in addressing them. Failure to do so may have detrimental effects on patients' personal information and their health as well as major financial, reputational, and legal repercussions.

6.1.4 Cloud-Based Environments

Organisations are increasingly storing and processing data in cloud-based settings. Although the cloud has many advantages, there are also significant security risks, particularly in regards to data loss or theft. Cloud-based systems can be attractive targets for cybercriminals searching for sensitive data since they hold enormous volumes of data that can be accessed from anywhere. To access the data, attackers can use holes in the cloud-based architecture or steal login information. Strong access controls, encryption, and monitoring tools can help organisations reduce these risks and ensure the security of cloud-based environments. Organisations should also implement multi-factor authentication, encryption, and continuous system monitoring. Every year, there are more cyberattacks targeting the healthcare sector, raising questions about the security and privacy of patient data (Vijarania et al. 2021a, b). Cybercriminals launch such attacks to get access to patient data or to interfere with the healthcare system, seriously harming the reputation of the sector and resulting in losses of money. The adoption of cloud-based systems has risen to the top of the industry's priority list because they provide a centralized location for managing, processing, and storing patient data, which can enhance access to treatment, save operating costs, and raise the standard of services. Healthcare providers must, however, take strong security precautions to protect patient data in cloud-based systems in order to take advantage of the benefits that they present. The security paradigm in cloud-based systems takes a shared responsibility approach, with customers responsible for protecting their applications and data and cloud service providers responsible for maintaining the infrastructure. Therefore, in order to protect patient data from malicious attacks, healthcare providers must choose reliable cloud service providers and implement robust authentication and encryption mechanisms.

Healthcare providers must also have a solid security architecture with security mechanisms like intrusion detection, event monitoring, and data loss prevention in order to detect and stop security breaches. Regular security audits and assessments can be used to examine the efficacy of security measures and identify vulnerabilities. In conclusion, using cloud-based technologies can significantly improve the efficiency of the healthcare industry, but it's also essential to take security precautions. By placing a high priority on cybersecurity and implementing robust security measures, healthcare providers may lessen the risks associated with cloud computing and provide patients with better treatment. The healthcare sector is becoming more and more reliant on technology, which increases its exposure to cybersecurity risks. Healthcare firms face a variety of cyberthreats. Phishing techniques, the use of internet-of-things devices, insider threats, and cloud-based settings are some of the frequent dangers. All of these are possible causes of a breach. Healthcare firms must make substantial investments in cybersecurity defenses to counter these attacks. Healthcare businesses must establish robust security measures to safeguard patient data and prevent interruptions to care. This also include investing in data encryption, putting in place stringent access restrictions, and educating staff to recognize phishing emails. The healthcare industry is increasingly dependent on technology, which exposes it to cybersecurity concerns. Numerous cyberthreats are a concern for healthcare organizations. Some of the common risks include phishing techniques, the use of IoT devices, insider threats, and cloud-based environments. These are all potential reasons for a breach. To combat these risks, healthcare organizations must invest significantly in cybersecurity defenses. To protect patient data and avoid service delays, healthcare organizations must implement robust security measures. By implementing security measures that target specific cybersecurity threats, organizations can reduce the likelihood of a cyberattack and reduce its impact if it does occur.

7 Security Measures in Healthcare to Protect Medical Information

The healthcare sector is particularly vulnerable to cybersecurity vulnerabilities because it handles sensitive patient data. Numerous security measures must be implemented by healthcare providers, including:

- Access restrictions Unauthorised people are prohibited from accessing sensitive data thanks to access controls. These precautions should include user account management, multi-factor authentication, and password policies.
- Encryption transforms data into a code that can only be broken with a unique key, protecting it from unauthorised access. Data must be encrypted both in transit and at rest.
- Sensitive information is split into secure regions with network segmentation so that only permitted people may access them.

- Firewalls monitor and filter incoming and outgoing network traffic, blocking potentially dangerous data.
- Patch management is necessary to keep all software and hardware current and secure against known vulnerabilities.
- Employee education: It's essential that staff receive education about cybersecurity threats, best practises, and how to recognise and report security problems.
- Planning for incident response ensures that healthcare companies have a clear plan in place for responding to cybersecurity problems, including a process for notifying parties and communicating with them.
- Preparing for disasters and backups: Making sure that data can be retrieved in the event of a cyberattack or other catastrophe is made easier by planning for backups and disasters.
- Compliance with rules: Healthcare providers must follow all applicable laws, including HIPAA, GDPR, and other data protection standards.
- By implementing these security measures, healthcare providers can enhance cybersecurity and preserve sensitive patient data. Remembering that cybersecurity is an ongoing process requiring regular monitoring and development is essential. Healthcare organisations must continuously be vigilant and adapt their security procedures as threats evolve.

7.1 Use of Anti-Virus in Cybersecurity in Healthcare Systems

Computers are guarded against malware such as Trojan horses, spyware, viruses, worms, and other threats with anti-virus software. When these kinds of programmes have already infected the computer, certain antivirus software also works to remove them from the system. Anti-virus programmes are frequently referred to as "anti-malware" or "anti-malware software". On a wide range of computers, including desktops, laptops, servers, workstations, tablets, and smartphones, antivirus software is used. As of 2019, Avast, Kaspersky, McAfee, and Norton were the most widely used antivirus programmes (Javaid et al. 2023). Some of these software providers are well-known and have a long history. Others are currently among the most popular options for antivirus software because they have lately gained popularity among consumers. It's crucial to keep in mind that all of the software mentioned above is excellent and has their place in protecting computers from various viruses that may affect the computers and the data stored in them.

It is obvious that healthcare businesses need to do more to strengthen their cybersecurity, with the cost of a data breach now projected to be over $4 million. The sheer volume of data that healthcare companies must safeguard, however, has become one of their largest concerns in recent years. Sensitive information like medical histories, treatment plans, and financial information are frequently contained in patient records. Because of this, it is a desirable target for thieves who can use it to steal identities or sell the data on the black market. Another problem is the continued use of these obsolete technologies by many healthcare organisations, which leaves them more open to assault. In 2015, it was projected that about half of all hospitals were still running Windows XP, which Microsoft no longer even provides security updates for. Since these systems are no longer receiving security updates, hackers will find them to be an easy target.

What then can be done to enhance cybersecurity in the healthcare industry? Making sure all systems are up to date and patched with the most recent security patches is one of the most crucial measures. Although it may seem like a straightforward task, it is frequently disregarded in the hectic world of healthcare. Investing in strong antivirus and firewall solutions is another crucial step. These will aid in defending the network against malware and preventing hackers from accessing the systems. In case of a breach, it's crucial to have a strong incident response plan in place (Nifakos et al. 2021). This should cover all actions that might be beneficial in the event of a cyberattack, such as alerting patients, calling the police, stopping additional harm, and others.

7.2 Securing Monetary Data

For many organisations, cybersecurity in healthcare systems is a significant problem. As shown in Fig. 4, showing the methodologies of antivirus in cyber security for protection in health care. Healthcare information is among the most sensitive data available, making cyber threats to it extremely important. Making sure that all financial data is securely secured is only one of many strategies to increase cybersecurity in the healthcare industry. This will lessen the risk of cybercriminals gaining access to patient data and financial information. The healthcare sector is increasingly moving towards digitization, which makes it vital to take into account the security of the hospital healthcare systems. Cyberattacks on healthcare organisations can have a big impact, perhaps affecting patient safety as well as the theft of sensitive data and personal information about the patients. According to a recent survey, data breaches have occurred in roughly 60% of healthcare organisations in recent years. As a result of the huge increase from the prior years, healthcare organisations need to do more to strengthen their cybersecurity. For many organisations, cybersecurity in healthcare systems is a high priority. The most sensitive information that businesses have about a person is their healthcare information. Patients and the organisation could suffer greatly as a result of a breach in healthcare data. The organisations need to have robust cybersecurity procedures in place to protect this data. This also entails making sure that all of the equipment used to access the healthcare data are secure, that only authorised personnel have access to the data, that the data is encrypted, and that it is not accessible to anyone who is not authorised.

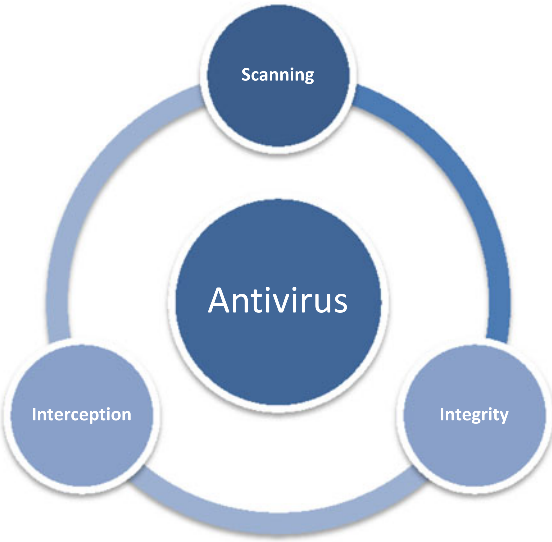

Fig. 4 Methodology of antivirus in cyber security system for protection in healthcare sector

7.3 Cybersecurity Solutions for Healthcare

The importance of security issues for healthcare providers has increased as a result of the industry's growing reliance on technology. Given the importance and sensitivity of healthcare data, the industry is one of the most regularly targeted by cyberattacks. Important infrastructure, patient data, and electronic health records must all be safeguarded using cybersecurity in order to avoid unauthorised access, theft, and damage. This study will look at the technology used in healthcare cybersecurity (Barad, 2019).

Technologies used in Cybersecurity for Healthcare are mentioned below:

Firewalls: All incoming and outgoing traffic between a network and the internet is managed and monitored by a firewall, a piece of technology. In the healthcare sector, firewalls are routinely employed to protect sensitive data from external threats and stop unauthorised access to the network. Firewalls, which can be hardware- or software-based, give an extra line of defence against potential cyberattacks.

Encryption: Data is converted into a code through encryption so that unauthorised individuals cannot read it. Encryption is used in the healthcare sector to safeguard sensitive data, including patient health records, financial information, and intellectual property. Encryption ensures that unauthorised people cannot access the data, even if it is lost or intercepted.

Intrusion Detection and Prevention Systems (IDPS): A piece of technology called an intrusion detection and prevention system (IDPS) keeps an eye out for improper behaviour or system or network policy violations. Thanks to IDPS's real-time detection and prevention of cyberattacks, healthcare providers can react quickly to potential risks. To recognise and thwart cyberattacks, IDPS uses a variety of techniques, including as signature-based identification, behaviour-based detection, and anomaly-based detection.

Two-Factor Authentication (2FA): A security solution known as two-factor authentication (2FA) requires two different forms of identity before granting access to a system or network. In the healthcare sector, 2FA is widely used to prevent unauthorised access to sensitive data. Two-factor authentication can be provided through smart cards, one-time passwords, or biometric data like fingerprints or face recognition.

Virtual Private Network (VPN): A VPN is a piece of technology that creates a safe, encrypted connection between a remote user and a network to allow for safe online communication. VPNs are often used in the healthcare sector to permit remote network access without compromising security. VPNs will be highly useful for healthcare providers who need to access patient data from afar. The healthcare industry is regularly the target of cyberattacks, and successful attacks can have dire consequences. For the purpose of providing healthcare practitioners with cybersecurity, the technologies discussed in this article are essential. Firewalls, encryption, IDPS, two-factor authentication, and VPNs are a few of the crucial technologies used in healthcare cybersecurity. The adoption of these technologies is necessary to protect sensitive data, crucial healthcare infrastructure, and patient privacy.

8 The Relevance of Sustainable Development Goals in Healthcare Cybersecurity

This section emphasises the significance of adopting security-by-design concepts during the development of healthcare apps in order to ensure sustainable cybersecurity in healthcare (Mondejar et al. 2021). The SDG goals covered are as follows:

Good Health and Well-Being: SDG 3 (*Digital Technologies to Achieve the UN SDGs* n.d.): To ensure patient safety and maintain the integrity of medical data, cybersecurity in healthcare applications is essential. This will ultimately improve the quality of healthcare.

SDG 9: Industry, Innovation, and Infrastructure: It states that the development of dependable healthcare infrastructure and the promotion of innovation are both dependent upon secure and resilient healthcare systems.

Partnerships towards the Goals, SDG 17: To effectively manage cyber threats and establish sustainable cybersecurity in healthcare, collaboration among stakeholders is essential. This includes governments, healthcare providers, and technology companies.

The cybersecurity network and system are crucial to the advancement of the e-government system and innovation in service delivery mechanisms. In developing countries, ICT has completely changed governance and greatly improved the provision of modern services (Abbas et al. 2022). Others claim that an effective cybersecurity system encourages digitization, expands access to the national network, and enhances public confidence in Asian economies (*Securing Cyberspace: International and Asian Perspectives | Manohar Parrikar Institute for Defence Studies and Analyses* n.d.). Andoh-Baidoo et al. (Andoh-Baidoo 2013) contend that despite scarce resources, a well-designed cybersecurity framework could enhance the calibre of cyber systems and service delivery in the sub-Saharan African region.

Despite justifiable criticism, we chose to use principles as the foundation of our ethical analysis because its four moral tenets can be related to the key goals of the use of ICT in healthcare as shown in Fig. 3, which are effectiveness and quality of services, privacy of information and confidentiality of communication, usability of services, and safety. They are described as follows:

Efficiency and Quality of Services: One of the key goals of ICT systems in the healthcare industry is the management of information to improve the effectiveness of the health care system and lower its expenses. For instance, new services that offer therapy or procedures with better health-related outcomes are examples of improvements in healthcare on a qualitative level.

Confidentiality of Data: Using ICT to handle patient data presents a moral dilemma in terms of quality on the one hand, and privacy and secrecy on the other—yet both are crucial goals in healthcare.

Usability of Services: Usability is "the level of effectiveness, efficiency, and satisfaction with which users of a system can realise their intended task." Users with varying degrees of ICT proficiency can be patients, medical personnel, or administrators in the context of health, depending on individual preferences and socio demographic factors.

Safety is the elimination of dangers that pose a harm to one's health. Interdependence exists among usability, efficiency, quality, and safety (Fig. 5).

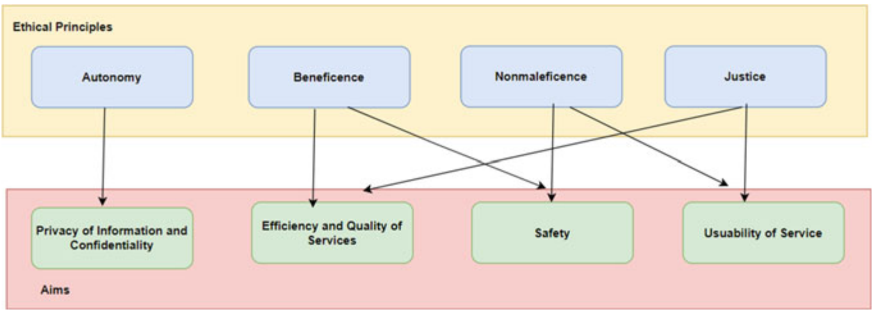

Fig. 5 Mapping between ethical principles and aims

9 Conclusion

Cybersecurity is essential to safeguard patient data and maintain patients' trust in healthcare organizations. Healthcare organizations struggle to put in place effective cybersecurity defences, but they may lower the risk of incursions with the right tools, planning, and training. Healthcare organizations must invest in cybersecurity solutions and stay current on the most recent cybersecurity threats and best practices in order to protect patient data. Cybersecurity in healthcare is a critical problem that needs to be addressed. Healthcare organizations must take the required security precautions to protect their data and systems given the rising usage of technology in the industry. Healthcare organizations may make sure that the privacy of both their patients and employees is maintained by putting strong security measures in place. The severe problem of healthcare cybersecurity needs to be addressed. It is crucial that healthcare organizations take the required security precautions to protect their data and systems given the growing usage of technology in healthcare. Healthcare organizations may make sure that both their patients' and staff' privacy is protected by putting in place robust security measures.

To ensure the highest level of patient data protection, healthcare organizations must also maintain compliance with all applicable laws and regulations. This calls for constantly evaluating their systems and processes to ensure they are up to date with the most recent industry standards. Healthcare organizations should have a multi-layered security plan that includes both physical and digital security standards. This approach should incorporate both preventative and remedial measures, such as encryption, authentication, monitoring, and incident response. Healthcare organizations can ensure that patient data is safe from malicious attackers by implementing a thorough cybersecurity policy. In the future research direction, the emphasis can be laid on developing cutting-edge methods for distributing healthcare data to various stakeholders while protecting patient privacy and abiding by data protection laws this can be achieved by using cryptographic techniques. Hence, The SDGs' larger goal of creating a more secure and sustainable digital future coincides perfectly with the role that AIoT plays in bolstering cybersecurity frameworks as it continues to develop.

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Machine Learning as a Methodological Resource in the Classroom

Jesús López-Belmonte, Pablo Dúo-Terrón, José-Antonio Marín-Marín, and Antonio-José Moreno-Guerrero

Abstract We currently find ourselves in a society dependent on the electronic devices that surround us. Many of these machines work through programming, robotics and Artificial Intelligence (AI) in daily tasks and every day we consciously or unconsciously use it, such as the use of smartphones, computers, cars, kitchen robots, the use of credit cards. Sometimes these devices in our personal lives, cities or industries are connected to the Internet and are called the Internet of Things (IoT). For a device to respond to human actions, it needs a training called "Machine Learning". Machine Learning is a branch of artificial intelligence that focuses on developing algorithms and models that allow machines to learn and make decisions based on data and previous experience, rather than being explicitly programmed. This process can be transferred to the classroom as a methodological and transversal resource in different educational stages from early childhood education, promoting computational thinking of students. In this chapter we present the operation of LearningML with some practical educational examples. The objective of the study is to analyze the impact of the LearningML machine learning resource in a learning situation in sixth grade students of Primary Education. Specifically, the results of the learning situation related to the Sustainable Development Goal (SDG) 11, sustainable cities and communities, and the impact among students will be analyzed. It can be concluded that AI has become an important part of our daily lives and schools should teach students about the knowledge and ethical use of these technologies. ML enables students to acquire basic problem solving and computational thinking skills.

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There are open online educational programmes and resources that allow interdisciplinary projects to be carried out and students to develop their digital competence from Pre-school, Primary, Secondary and Post-secondary. AI offers very interesting educational possibilities, as it allows students to learn about how machine learning algorithms work and how they can be applied in real life. In addition, multidisciplinary and interdisciplinary content can be worked on and the relevance of learning with the available technological tools and devices is highlighted in order to train critical students who are prepared to meet the needs of the labour market.

Keywords Education · Artificial intelligence · Machine learning · Quality education

1 Introduction

The history of Artificial Intelligence (AI) dates back to the 1950s. In 1983, Professor Kai-Fu Lee (2021), one of the world's leading AI experts and former president of Google China, developed the first voice assistant programme, eventually creating Apple's first voice assistant. Subsequently, AI technology has been advancing (Chen et al. 2020), leading to the development of more sophisticated AI systems with the ability to understand and respond to complex requests from a human (Rey 2023), such as Machine Learning, Deep Learning, chatbots, generative AI…

AI has experienced exponential growth in the last year compared to the last decade (Luan et al. 2020), which has resulted in the incorporation of AI in many everyday tasks without us realising it. The latest Internet of Things (IoT) industry analysis predicts that the number of connected devices will double globally between 2022 and 2027 (Fernández 2023). IoT refers to the digital interconnection of everyday objects with the Internet, for example, it is common to use virtual assistants such as Siri, Google, Cortana or Alexa on our mobile phones, make purchases, make queries, administrative procedures or appointments through chatbots, and even use voice recognition. Since the advent of the Internet, our lives have changed significantly in this respect, but classrooms still use wooden blackboards, chalk and a lack of technological resources and training in the use of AI (Xia et al. 2022).

AI is presented as an emerging tool that contributes to the personalisation of learning (Knox 2020) and trains youth for a changing labour market marked by new social requirements (Ayuso and Gutiérrez 2022). Considering that AI is becoming an increasingly important part of our lives (Gao et al. 2021), schools should be the first place to educate and teach students about the knowledge and ethical use of these technologies. The European Commission for Education (2022) includes in its digital plan 2021–2027 the idea that AI is undeniably changing our education and training systems, and this change will continue to grow in the coming years (Kaur et al. 2021). Moreover, knowing and understanding the basic functions of AI, as well as developing competences that integrate computational thinking will be organic elements of digital literacy for all citizens in an increasingly intelligent society (INTEF 2022).

One of the fundamental pillars for understanding AI is Machine Learning (ML) or automatic learning (Gresse von Wangenheim et al. 2021; Luan and Tsai 2021), used for all kinds of digital applications aimed at classifying data, predicting and recognising by means of electronic devices (Rodríguez et al. 2020), being fundamental for the development of computational thinking in schools from an early age as a transversal, multidisciplinary and interdisciplinary methodological resource (Staribratov and Manolova 2022). Computational thinking, through Machine Learning, allows students to acquire basic problem-solving skills (Okonkwo and Ade-Ibijola 2021) that are based on computer science concepts and techniques such as decomposition, pattern recognition, abstraction and algorithms (Sanusi et al. 2022; Wing 2008, 2011). Implementing AI in schools presents opportunities and challenges, including ethical issues for students, and is the best way to prepare critical and aware citizens, motivate young people and develop computational thinking skills (Rodriguez 2023).

Fundació Jaume Bofill (2022) points out that ML allows a focus on designing multidisciplinary projects that enable students to develop meaningful learning and social improvements through an active role in the use of such algorithms and technologies. Educational resources based on ML projects aim for teachers and students to become creators of AI solutions (Munir et al. 2022), so that they can understand in a practical and fun way how these systems work and learn about both the opportunities and challenges of their use in everyday life (INTEF 2019).

Currently, we can find open educational programmes and resources online on the Internet (Winkler-Schwartz et al. 2019), from Pre-school, Primary, Secondary and Baccalaureate to carry out interdisciplinary projects, while students develop their digital competence. These resources are, for example, LearningML, Machine Learning for Kids or Teachable Machine. These programmes have the ability to learn without being programmed to do so (Pérez-Marín et al. 2020), use algorithms to learn from different data patterns with texts, sounds, images, body poses or sets of numbers (Dohn 2020), with which prediction and classification models are built from data sets (Iskrenovic-Momcilovic 2019). In addition, real projects can be developed linked to the educational programming platform Scratch 3.0 (Fagerlund et al. 2021) or mobile applications with App Inventor, both developed by the Massachusetts Institute of Technology (MIT) in Cambridge.

The opportunities offered by AI and ML in education are more than remarkable. The personalisation of learning, the prediction of educational results, access to education and educational innovation are just some of the benefits that these technologies can offer. On the other hand, they undoubtedly raise challenges such as equity, data privacy and the need for adequate training for teachers and students. These approaches are aligned with the Sustainable Development Goals proposed by the United Nations (UN 2015). Specifically, and in reference to Sustainable Development Goal SDG 4, that of ensuring inclusive, equitable and quality education that promotes lifelong learning opportunities for all. This technology can promote the training of teachers and learners in the latest technological literacy and skills, providing access to lifelong learning opportunities that facilitate their active participation in society and their employability, ensuring that all people have access to quality education without discrimination. This will provide a quality and equitable education that will be the key to social, economic and environmental progress.

Throughout the chapter, various aspects related to the state of the art are addressed. A methodological precision of the experience is carried out so that the reader can understand the training experience carried out. Next, the research carried out is presented so that other researchers interested in the subject can replicate the study. The findings are presented and discussed below. Finally, the main conclusions are presented and the limitations, future lines and prospects derived from this research are established.

1.1 LearningML and Scratch in Education Projects with AI

For the experimental phase of this study, the programmes LearningML.org and Scratch were selected, both of which are free software, meaning that the author gives permission to reuse them (González 2011; Zhang and Nouri 2019).

The first LearningML (https://web.learningml.org), developed and created by Professor Juan David Rodríguez, is an educational platform for students and teachers to learn content and fundamentals about AI and develop Computational Thinking skills. This programme allows students to investigate, explore and interact with transversal contents of any educational area and stage from 8–9 years of age.

In this experience, the authors focused on learning and awareness of recycling. To do this, the students had to first look for information in a group about the types of waste that can be classified and the destination of the container according to its colour.

After gathering information, a recycling chatbot and an AI detector of real images with the webcam of the devices were developed.

1.1.1 Creating Chatbots

In the phase of creating chatbots, defined as AI software-based technologies (Mateos-Sánchez et al. 2022; Wollny et al. 2021), without human intervention, that respond to questions asked by a human (Moreno-Guerrero et al. 2023). Students on the devices must access the LearningML website and enter in the "Train" section a classification of bins by colour (Yellow = plastics; Blue; paper and cardboard; Green = Glass; Grey = food waste). In each of them, they have to enter the data by means of texts pertaining to each container. Keywords or phrases can be entered at the student's discretion (Hwang and Chang 2021). It is important that there is a balance in the data entry, i.e. that there is a similar number of data in each category as can be seen in Fig. 1, with 9, 9, 9, 9 and 12.

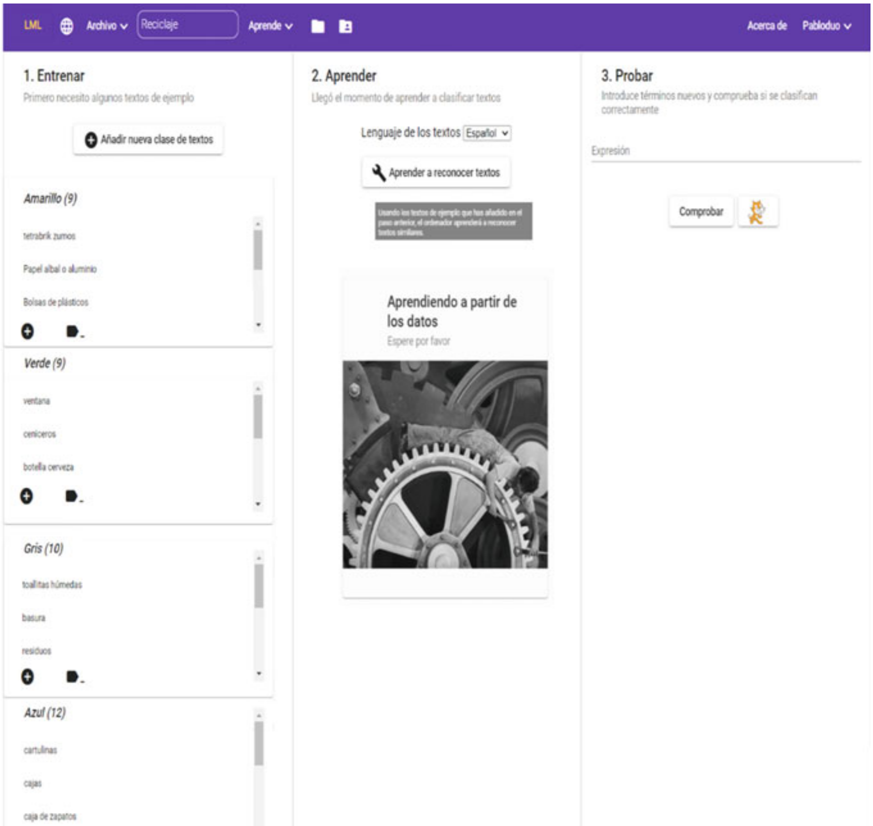

Fig. 1 Category classification in LearningML by text

Once the data has been sorted, click on the "Learn to recognise text" button. This section lasts just a few seconds and we can see the image of some repair technicians in the central part of Fig. 1. LearningML, being an unsupervised AI program, i.e., the modelling process of the program is carried out only with the data entered by the student, without any other external data (Arteaga 2015), proceeds to training.

Once the system has been trained, we can test in Sect. 3 of image 1, if our program is well trained and works. To do so, we introduce a new text, without it necessarily being the same as the classified ones, such as Where do I throw a shoebox? In Fig. 2, we can see that the AI makes a prediction about where it thinks the shoebox should be placed.

The next step to create the chatbot is to click on the cat shown in Fig. 2 and the program transfers the LearningML data to the Scratch program, that is, in computer science terminology, a fork (López et al. 2015), which allows cloning the LearningML data in Scratch. This cat is the symbol of the Scratch 3.0 programme designed by the Lifelong Kindergarten Group of the Massachusetts Institute of Technology Media

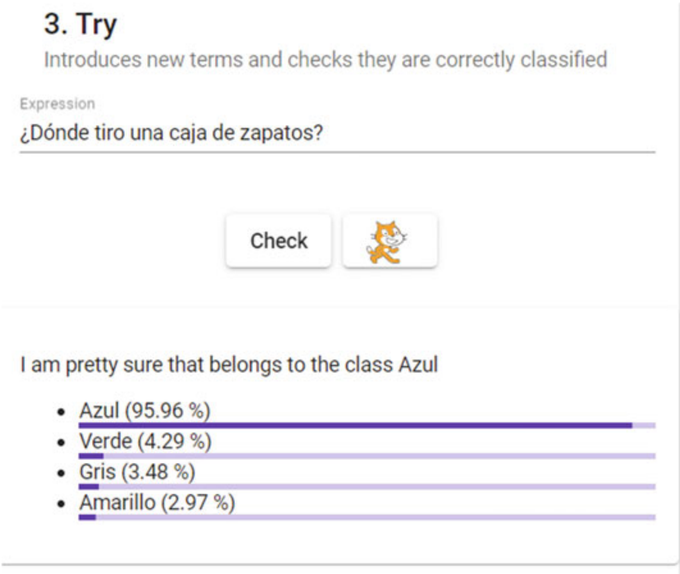

Fig. 2 Testing the new text

Lab (MIT) (Talan 2020) led by Mitchel Resnick, researcher, teacher and designer of creative and educational technology tools (Resnick et al. 2017) and which is based on a visual block programming language for children (Cerón 2023).

On the left side of Scratch we find the programming blocks. In the lower left part, the author of the programme has introduced two new blocks, in green, to the Scratch interface, which allows the LearningML data to be integrated into Scratch.

In Fig. 3, corresponding to the Scratch 3.0 interface and the programming blocks, we can see the algorithm that the students carry out. For this, the following algorithm is used:

- Pressing the *green flag* (orange block) starts the chatbot to work.
- Say via the *text-to-speech block*, extracted from extensions, "Hello, write a waste and I'll tell you which bin to throw it in" (Green block). This block gives the programme a voice and more realism.
- A *block where the background always appears* with the four containers that can be seen in the background of the containers on the right side of the Fig. 3 (orange block). In addition, this block contains four conditionals that are explained below.
- *Question sensor block* (blue colour), which asks a question "Hello, write a waste and I will tell you which bin you should throw it in". This block allows the user who interacts in this game, what he/she types on the keyboard, the program saves it in a *variable called "answer"* (blue colour with the shape of an oval) that we will use in the following step.

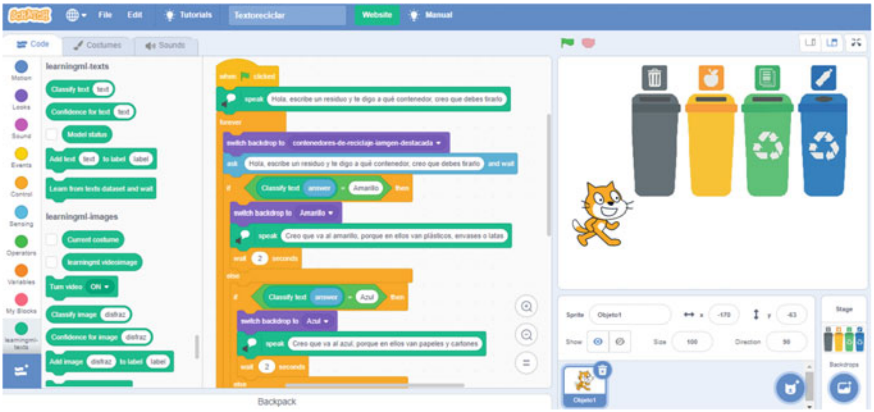

Fig. 3 Algorithm for the creation of the chatbot with Scratch

- *Conditional block* (orange colour), we use it four times in a similar way, changing the colour label of the container. Within this conditional, the students use the *mathematics block "equal"* in the shape of an elongated green hexagon. To incorporate the *Machine Learning block Texts with "Classify text"* and enter the "*answer variable"* which should be equal to the colour of the container.
- If the prediction of the chatbot's answer considers that the answer is oriented to the yellow container, the *background block* is added with the name corresponding to the assigned background so that it is shown, in addition, another *text-to-speech block* is incorporated with the answer that the student programmer wants to offer the user, in this case: "I think it goes to the yellow one, because plastics, containers or cans are thrown in it".

In this way, the programme will always ask the same question aloud and depending on the user's question regarding a waste, the machine will answer aloud its prediction by pronouncing the colour of the container, along with an explanation. In this way, the students create a chatbot about recycling.

1.1.2 Real Object Detector with AI and LearningML

As with text, image training with LearningML is performed using unsupervised machine learning algorithms. These algorithms use a dataset of images extracted from the device or made "in situ" of real objects, through labelled training to learn to identify patterns and features in the images.

The training process begins with the collection and labelling of an image dataset, in this study real photos of debris (Fig. 4). This implies that each image in the dataset must be labelled with information corresponding to what the image represents (Fig. 5). For example, if we are training a model to classify images of waste into bins, each image in the dataset must have a label indicating which bin a waste goes into.

Once the labelled dataset is available, an unsupervised machine learning algorithm is used to train a model, because the creator has set up the nodes to predict the training classifications and their similarities. During training, the model adjusts its parameters to minimise the difference between its predictions and the labels of the training images.

Once the model has been trained, its performance is evaluated and tested using an independent test dataset, i.e., pictures are taken of real objects that can be recycled

Fig. 4 Photo-based waste training

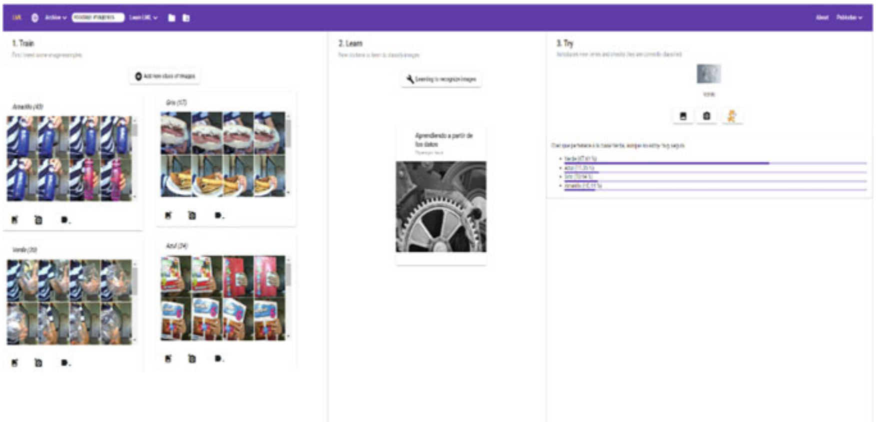

Fig. 5 LearningML image training

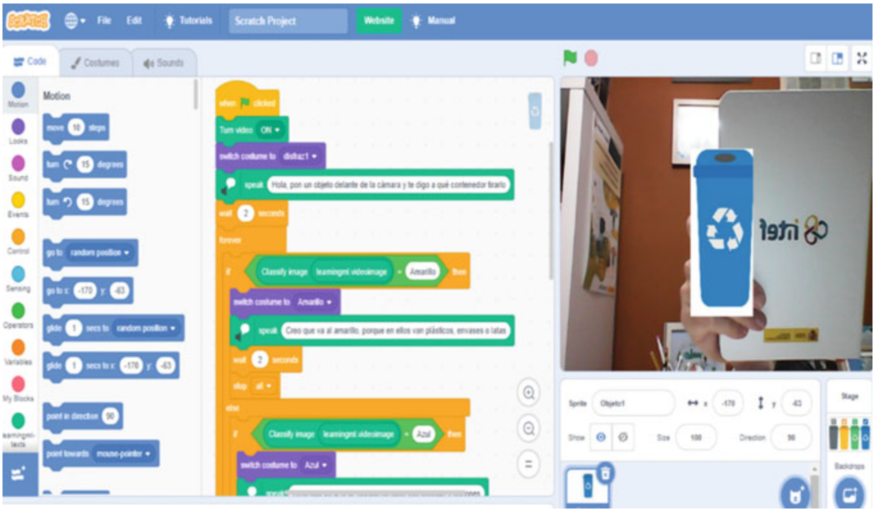

Fig. 6 Scratch program recognising real images

but have not been classified in the training phase. If the model performs well on the test dataset, it is considered ready to be used for classification of new images.

It is important to note that the process of training images with Machine Learning can be computationally intensive and may require large amounts of training data to produce accurate results. In addition, the quality of the training dataset is critical to the success of the final model.

To carry out the recognition and interaction of the computer with the user, again click on the cat icon to dump the images into the Scratch program. This time, looking at Fig. 6.

On this occasion, the students have to programme the computer to say aloud which container it should be thrown into when it detects an object in front of it. Looking at Fig. 6, we can see the algorithm that the students carry out. For this, the following algorithm is used:

- Pressing the *green flag* (orange block) starts the chatbot to work.
- Then the *block turn on the webcam* (green colour) so that it can detect objects that are put in front of the webcam.
- *Programming block change the disguise* (purple colour), corresponding to a background without containers so that the clean image of the video can be seen.
- Say via the *text-to-speech block*, extracted from extensions, “Hello, put an object in front of the camera and I’ll tell you which container to throw it into” (green block). This block gives the programme a voice and more realism.
- Next, a “*Wait 2 s” block* (orange), this allows the user who puts the object in front of the camera to have 2 s to place it in front of the camera after pressing the green flag.
- A *block that always* contains four conditionals that are explained below.

- *Conditional block* (orange colour), we use it four times in a similar way by changing the colour label of the container. Within this conditional, students use the *mathematics block "equal"* in the shape of an elongated green hexagon. To incorporate the *Machine Learning block images with "Classify image*" and within this, recognise the image of the video showing the Scratch reality, called "*recognise video image"*. The latter must match the LearningML classified text and the name of the Scratch costumes. The students will sort them by colour, these will be yellow, blue, green and grey.
- If the prediction of the image recognition answer considers that the answer is oriented to the yellow bin, the yellow bin disguise is added and another *text-to-speech block* is incorporated with the answer that the student programmer wants to offer the user, in this case: "I think it goes to the yellow bin, because plastics, containers or cans are thrown in it".

2 Justification and Objectives

There is no doubt that educational innovation must be present today in the different learning spaces to adapt the training process to the needs and demands of students who have been born hand in hand with technology. For this reason, today's society requires a different and appropriate instructional action to the requirements of an increasingly technological society (Moreno-Guerrero et al. 2021).

Methodologies, like society, have evolved considerably. The role of the student goes from being passive to being an active agent and promoter of his own learning. For this reason, the application of active methodologies combined with technology is essential to comply with the precepts of a technological era. In addition, with this it is possible to introduce the student into a wide range of learning possibilities thanks to the advantages and benefits that the use of new media and digital resources brings (López-Belmonte et al. 2021).

In this article, the authors focus on a case study involving 11 and 12 year old Primary School students using an active methodology without textbooks, through flexible spaces based on the Classroom of the Future project (Dúo-Terrón et al. 2022). LearningML is used as a learning resource to carry out a transversal learning situation with the implementation of digital technologies and algorithms, fundamental contents to understand how AI works.

The aim of the study is based on analysing the impact of the machine learning resource LearningML in a learning situation in sixth grade Primary School students. In addition, the secondary objective is to study the results of the learning situation related to Sustainable Development Goal (SDG) 11, sustainable cities and communities, and the impact between male and female students.

3 Study Method

The study method is quantitative based on experimental design based on a learning situation through ML and learning SDG 11, sustainable cities and communities to raise awareness among primary school students about the importance of the 2030 agenda of the European Commission (Almendros et al. 2023). A pre-test and a post-test are conducted during the research to analyse the results and impact of ML during the experimentation phase.

3.1 Participants

The sample of participants corresponds to a group of 17 students in the sixth level of Primary Education, aged between 11 and 12 years, 9 of the female gender and 8 of the male gender. All students come from an unfavourable socio-demographic environment, where all students speak Spanish as a second language, using Dariya, which is a dialect of Arabic, as a vehicular language (Fernández 2020). Two students are excluded because they did not complete the pre-test and post-test.

The students included indicate that they have basic knowledge and skills with the educational programming block program, Scratch. However, they have no experience in developing programs with AI or ML through LearningML.

3.2 Procedure

This study was approved by the Ethics Committee under code 2292/CEIH/2021. In addition, the anonymity of the students was guaranteed, complying with the precepts of the Declaration of Helsinki and good research practices. The educational centre has parental authorisations and the study was conducted with the authorisation of the head of the centre in accordance with art. 120.4 of the Organic Law 2/2006 and the autonomy of Spanish educational centres.

This study was carried out in October 2022 and was conducted by a Primary Education teacher and teacher trainer in advanced digital competences and ambassador of the Classroom of the Future by the Ministry of Education and Vocational Training in Spain. The first step of the research was a pre-test, carried out by 17 students, with an online educational platform in a synchronous way, where students had to respond to different waste and classify them into coloured bins according to their material (Fig. 7). In addition, students were asked if they had previously programmed with AI, using LearningML and Scratch.

The pre-test phase, which is attached in Appendix A, consists of 16 questions related to the classification of waste types and the container in which it is deposited. In this sense, students are shown a question accompanied by an image that supports

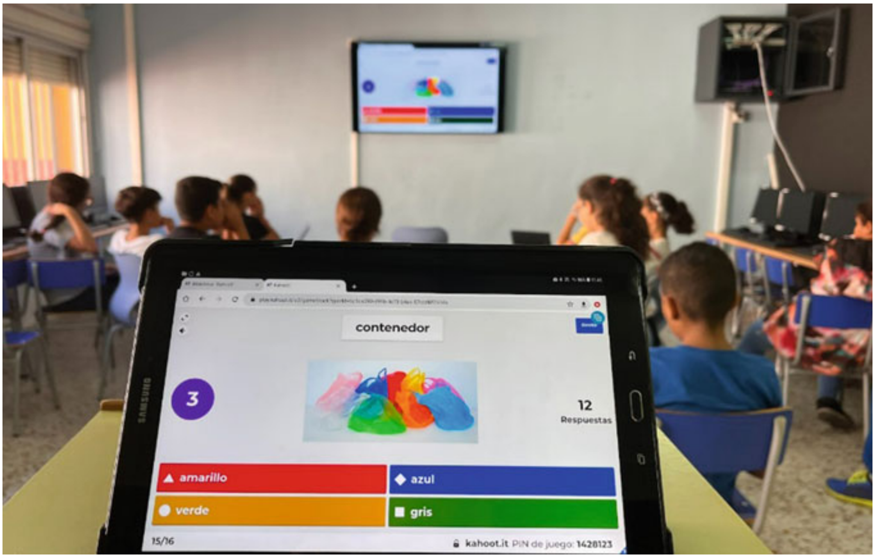

Fig. 7 Pre-test phase

the question. In order to cater for the diversity of those students who do not read correctly (Fig. 7), students have 30 s to choose the correct answer with the colour of the container where the waste is deposited.

Then, five experimental sessions were carried out based on active methodologies and using AI with ML where students must interact, investigate, explore, develop, create and present a learning situation to families, adopting the methodology and spaces of the Classroom of the Future (Figs. 8 and 9). These sessions were divided into two sessions to develop a chatbot with texts, two sessions to programme a real object detector with the computer through AI, and a final session to present the project to the families.

Finally, the post-test questionnaire is administered again to compare the results.

4 Results

Table 1 shows the results of the pre-test and post-test questions in relation to the students' learning about recycling during the experience. Very large differences can be observed in questions 5 and 8. These questions were related to knowing where to deposit a glass bottle or a glass water glass or a glass wine glass respectively, both answers had to be selected with the green container. In contrast, the differences are minimal in question 1, which asks where to dispose of a tetra break juice carton, which is in the yellow container. Question 14, too, has a minimal difference in improvement

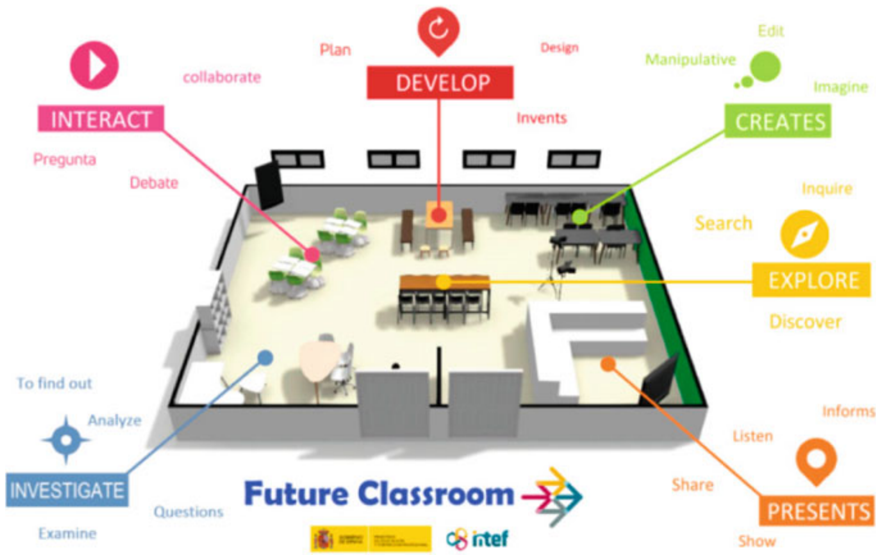

Fig. 8 Classroom of the future. INTEF

Fig. 9 Students during the experience

and relates to where to dispose of an infusion sachet, the answer to which is the grey bin.

The results in relation to the mean of the previous table are shown in Table 2 and 3. It can be seen that, prior to the experience, no student had any knowledge of programming AI with LearningML, however, all of them claim to know Scratch, a visual block-based programming learning programme.

Table 1 Pre-test and post-test of the students during the experience

Question	Pre-test (%)	Post-test (%)	Difference
1	64.00	68.00	+ 4.00
2	35.00	93.00	+ 58.00
3	28.00	81.00	+ 53.00
4	71.00	100.00	+ 29.00
5	21.00	100.00	+ 79.00
6	35.00	75.00	+ 40.00
7	14.00	87.00	+ 73.00
8	21.00	87.00	+ 68.00
9	57.00	100.00	+ 43.00
10	71.00	93.00	+ 22.00
11	42.00	81.00	+ 39.00
12	14.00	62.00	+ 48.00
13	14.00	75.00	+ 61.00
14	71.00	81.00	+ 10.00
15	57.00	100.00	+ 43.00
16	35.00	68.00	+ 33.00

Table 2 Pre-test and post-test questionnaire mean results

Knowledge and use of Scratch (%)		Knowledge and use of LearningML (%)		Pre-test (☐)	Post-test (☐)	Difference (☐)
Yes	**No**	**Yes**	**No**			
100.00	0.00	0.00	100.00	40.62	84.44	+ 43.82

Table 3 Mean results according to gender in pre-test and post-test

Pre-test (☐)		Post-test (☐)	
Male	**Female**	**Male**	**Female**
44.50	38.00	84.42	84.22

5 Discussion

The history of Artificial Intelligence (AI) dates back to the 1950s, but in recent decades, it has experienced exponential growth compared to the last decade. AI has become an increasingly important part of our daily lives, and schools should be the first place to educate and teach students about the knowledge and ethical use of these technologies. AI is presented as an emerging tool that contributes to the personalisation of learning and trains youth for a changing labour market marked by new social requirements (Rey 2023).

One of the fundamental pillars for understanding AI is Machine Learning (ML), used by all kinds of digital applications aimed at classifying data, predicting and recognising by means of electronic devices. Computational thinking, through ML, allows students to acquire basic problem-solving skills based on computer science concepts and techniques such as decomposition, pattern recognition, abstraction and algorithms. Implementing AI in schools presents opportunities and challenges, including ethical issues for students, and is the best way to prepare critical and aware citizens, motivate young people and develop computational thinking skills (Ayuso and Gutierrez 2022).

There are open online educational programmes and resources on the Internet that allow interdisciplinary projects to be carried out and students to develop their digital competence from Pre-school, Primary, Secondary and Baccalaureate stages. These programmes have the capacity to learn without being programmed to do so, and real projects can be developed linked to the educational programming platform Scratch 3.0 or mobile applications can be created with App Inventor, both developed by the Massachusetts Institute of Technology (MIT) in Cambridge. AI and ML are tools (Staribratov and Manolova 2022).

AI enriches learning environments in the context of Higher Education and awakens students' interest and taste for using technologies in their future teaching practice. We therefore consider that, thanks to this training experience, we have contributed to empowering students, mostly women, to design inclusive educational content in the form of textual projects and AI images (Ayuso and Gutiérrez 2022).

Due to its transversality, multidisciplinary and interdisciplinary content can be worked on (Staribratov and Manolova 2022) from other educational areas and stages. The authors consider that any content that can be classified could be appropriate to work with LearningML, such as vertebrate and invertebrate animals, different stages of history, types of musical instruments, primary, secondary or tertiary work sectors, etc.

AI as a resource offers very interesting educational possibilities, as it allows students to learn about how ML algorithms work and how they can be applied in real life. Through LearningML, students can access learning tools and resources that allow them to develop skills in creating ML models and training models for specific tasks, such as image classification. This allows them to learn in a cross-disciplinary way.

In addition, the programme can also be used by educators to teach students about topics such as ethics in AI and responsible decision making in the development of AI applications.

6 Conclusions

It can be concluded that the use of AI with LearningML as an educational resource in primary school from 11–12 years of age improves results, without the need to use textbooks, by making use of active methodologies based on interacting, investigating, developing, creating and exposing. LearningML is a valuable tool for those interested in AI and ML, as it offers an accessible way to learn and experiment with these topics. Its educational potential is very broad, and can be used by students and educators from the age of 10 and up alike to improve their understanding and skills in this constantly evolving field.

Furthermore, it can be determined that active methodologies were employed in which students investigated and created, encouraging learning through manipulation and teamwork. Instead of emphasising the importance of acquiring knowledge in AI and digital competences, the relevance of learning with the available technological tools and devices is highlighted. Technology should not be seen as an end in itself, but as a means to develop critical and less manipulable learners in our digital society, prepared to meet the needs of the labour market and to develop digital skills. Furthermore, the development of Computational Thinking and STEM competences was promoted in line with the educational curriculum. Finally, it is observed that the gender gap is considerably reduced in this context.

7 Limitations

It is important to keep in mind that the research was conducted using a limited sample of students with basic programming skills. Therefore, it is suggested that programming skills should be encouraged at an early age through adapted programmes such as Scratch or Scratch Jr, from the age of 5, so that students can successfully carry out STEM or STEAM projects. It should be noted that this is a small sample and results could vary in a larger group.

In addition, it should be noted that both the pre-test and post-test questions were supported by pictures due to the reading comprehension level of students using Spanish as a second language.

8 Future Research Lines

It is proposed as a future line of research to study the use of LearningML in education and the level of satisfaction it provides as an educational resource for teachers at different stages. To this end, a comparison will be made with a control group that does not use this tool. The impact of LearningML in other areas and educational stages will also be investigated.

Another aspect to be studied will be the analysis of the level of cooperative learning and key competences when using this methodology in a transversal way. The aim is to extend studies on the use of AI in education and explore other educational programme options such as ML for Kids or Teachable Machine, which use sound or posture recognition.

In short, the aim is to deepen the application of emerging technologies in the field of education to improve the quality of teaching and train students in digital skills that are relevant today.

9 Theoretical and Practical Implications of This Research

The theoretical implications of this research are evidenced by the very use of AI in education, which is booming. Specifically, machine learning (LearningML) is an emerging technology that is having a significant impact on education. This technology is based on the use of ML algorithms to improve the effectiveness of learning. The theoretical implications of using AI with LearningML in education are numerous and profound.

Firstly, it is important to note that LearningML allows learners greater personalisation of their learning process. ML algorithms can identify the strengths and weaknesses of each student, allowing the pace and difficulty of content to be tailored to suit their individual needs. In this way, learning can be improved and dropout rates can be reduced.

Another theoretical implication of using AI with LearningML in education is the ability to provide more effective and detailed feedback. ML algorithms can analyse student performance in real time and provide immediate feedback on their mistakes and successes. This feedback helps students improve their performance effectively and efficiently.

In addition, LearningML can also improve learning assessment. Algorithms can analyse large amounts of data and provide a more accurate and detailed assessment of student performance. This allows educators to make more informed and accurate decisions about each student's learning process.

The use of LearningML also has theoretical implications for how the learning process is understood. Traditionally, learning has been understood to be based on the acquisition of knowledge and skills. However, LearningML also enables students to acquire problem-solving and critical thinking skills. By analysing large amounts of data and providing immediate feedback, ML algorithms help students develop skills in analysing information and making informed decisions.

LearningML can also have implications for the way it is taught. Traditionally, the educational approach has been teacher-centred. However, with the use of LearningML, a learner-centred approach can be adopted.

In terms of practical implications, AI with LearningML (Machine Learning) has been revolutionising the way education is approached. From automating administrative tasks to personalising learning, the use of AI in education has significant practical implications.

One of the biggest advantages of AI with LearningML in education is the ability to personalise learning. AI can analyse data from multiple sources, including test results, student behaviour and learning preferences, to tailor content and teaching methodology to the individual needs of each student. This personalisation of learning can increase learning effectiveness, reduce the knowledge gap and improve information retention.

In addition, AI can also help in the assessment of student learning. LearningML algorithms can analyse student responses to test questions and provide immediate and specific feedback on areas where students need improvement. This not only helps students learn more effectively, but also helps educators identify problem areas in teaching and content. AI can also be useful in identifying students at risk of dropping out of school or underachieving.

These implications, both theoretical and practical, can have a direct relationship with the development of the SDGs and, in particular, with SDG 4 aimed at providing quality education. In this sense, both IL and ML promote access to education by overcoming geographical and economic barriers, offering affordable and accessible online educational resources. Moreover, this technology allows personalised learning by adapting content and teaching methods according to the individual needs and preferences of students, detecting learning difficulties in students at an early stage, allowing for personalised and appropriate intervention. Finally, and from an administration and policy point of view, AI and ML offers the possibility to analyse educational data to identify patterns and trends, providing valuable information for decision making and the implementation of effective educational policies. All these actions point to the exceptional potential of this technology to deliver quality education adapted to the context and the specific needs of both teachers and students.

Appendix A

Pre-test and post-test questionnaire where students have to answer one of the following colours; Yellow, blue, green or grey.

1. Tetra break cartons are placed in the container of the colour…
2. The cardboard boxes are placed in the coloured container…
3. Plastic water bottles are deposited in the coloured container…
4. Leftover vegetable trimmings are placed in the coloured container…
5. A glass bottle is deposited in the coloured container…
6. A set of books and notebooks are deposited in the coloured bin…
7. A can of tuna fish is placed in the coloured bin…
8. A glass of water or wine is deposited in the coloured bin…

9. Fish bones are deposited in the coloured bin…
10. Leftover pizzas are placed in the coloured bin…
11. A carton of milk is deposited in the coloured container…
12. Yoghurt cartons are deposited in the coloured container…
13. Egg cartons are deposited in the coloured container…
14. An infusion sachet is deposited in the coloured container…
15. Leftover coffee grounds are placed in the coloured container…
16. Plastic shopping bags are deposited in the coloured bin…

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A Framework for AIoT-Based Smart Sustainable Marketing System

Hamed Nozari, Maryam Rahmaty, and Agnieszka Szmelter-Jarosz

Abstract Marketing management implies planning, organizing, executing, and controlling marketing assets and assembly desires and requests of buyers to realize the objectives of the organization. For marketing administration to be effective, the complete organization must back the advertisement and client introduction. With this definition, it can be said that sustainable marketing management incorporates arranging, organizing, executing, and controlling marketing assets to reply to wants and requests of nowadays and future eras by watching social benchmarks and the normal environment and accomplishing the organization's objectives. It is obvious that the first step to creating a stable marketing environment is targeted and accurate data and transformative technologies are the most important tools for extracting, maintaining, and analyzing data. AIoT technology, which is a combination of Internet of Things technology and artificial intelligence, not only helps to exchange data but also helps to collect and create a customer database and analyze the extracted big data. Smart interactive marketing based on AIoT has included various advantages for marketers, it brings sustainable development in all its dimensions, which affects the user's decision to choose and buy a product. Data-driven marketing helps to develop innovative sustainable products and strengthen innovation based on human health. For these reasons, in this research, after examining the dimensions, components, and key performance indicators of smart sustainable marketing based on AIoT, a conceptual framework is presented to better understand the issue.

Keywords Sustainable marketing · Intelligent marketing · Artificial intelligence of things (AIoT) · AIoT-based marketing

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1 Introduction

Smart marketing is the process of collecting and using information and data related to a company's marketing decisions, which are collected to make accurate decisions. Smart Marketing focuses on actionable insights related to audience analysis, Strengths, Weaknesses, Opportunities, and Threats (SWOT) analysis, competitor analysis, market research, and web analytics. Targeted data is information about target customers, market trends, etc. that are relevant to company decision-making. Smart and creative marketing means using the tools available on the Internet and the digital world to market services and products. Smart marketing decides the data required, collects it by looking at the environment, and conveys it to the marketing supervisors who require it. Intelligent promoting computer program collects information from different information sources such as web analytics, commerce intelligence, and contact center, and deals with information that frequently gives partitioned reports and puts them into a single environment.

From an organizational point of view, intelligent marketing is the name of the department that performs both intelligent retrieval and competitor analysis roles. Measuring market share and setting growth targets, group integration and aggregation to discover new opportunities, research, and development to compare companies' innovation trends, and discover opportunities are all among the functions of intelligent marketing (Nozari et al. 2023a, b).

The existence of the Internet of Things is profitable for digital marketers. Because they can use this huge data set to analyze and analyze consumer behavior in their marketing strategy (Aliahmadi and Nozari 2023). This allows them to even predict consumer behaviors to take a better step to implement their next strategy. With the Internet of Things, access to a wide range of information from different points is obtained for marketers. From a digital marketing perspective, this is extremely useful for creating a better understanding of the starting point of the customer journey from start to finish. On the other hand, AI technology is revolutionizing marketing, with the ability to analyze them, apply them, and then react to them. In fact, it can be said that the use of artificial intelligence in marketing will be more important in the future. Because the amount of information about potential consumers is increasing, artificial intelligence can be a great help to the marketing field due to its high potential in making quick and accurate data-based decisions (Hu et al. 2023).

With the help of artificial intelligence, many basic sales activities are performed automatically, which can have a great effect on saving time and energy (Taylor et al. 2020). Activities such as entering data extracted from the Internet of Things, and organizing communication with representatives and customer support can be done automatically, easily, and with great accuracy. Artificial intelligence integrates data from various sources (obtained using IoT technology) effortlessly and intelligently with the customer relationship (CRM) system. It can also be used to automatically send ordered emails to different people or representatives. On the other hand, considering that the sales process is based on finding and identifying potential buyers, it is difficult for the marketing team to identify all potential buyers 100%. With the help of deep learning, artificial intelligence has made it possible for marketers to easily collect customer contact information and classify their customers' preferences.

Predictive analytics is another area where AI is equipping marketing professionals with new tools and opportunities for business growth. Predictive analytics relies on past data to generate insights to predict future outcomes. Although there is a lot of interest in AI-based predictive analytics solutions, marketing professionals are facing challenges in fully adopting the technology. AI tools can generate content and create ads using your marketing tone and style. They can personalize content for different audiences and make sure it's centered around your users' behavior and what they enjoy.

AI and IoT marketing tools are developing at a rapid pace, prompting marketing professionals to constantly follow trends and learn new skills. Although using AI and IoT tools can seem overwhelming at first, if used wisely, they open up opportunities to save time on repetitive tasks, better understand your customers, and ultimately grow your business (Nozari et al. 2022).

Due to the increasing growth of Internet of Things and artificial intelligence applications in all kinds of business processes, the effects of these technologies on marketing are increasing every day. These technologies also have tremendous effects on the agility of processes, accuracy and environmental factors and sustainability and cost reduction. For this reason, the use of the combined technology of artificial intelligence of things has multiple importance. Considering the practical features of this technology and its effects, in this research, it has been tried to investigate the dimensions and features of this technology and its effects on sustainable marketing. Finally, a conceptual framework is presented to understand the factors affecting this intelligent system. A proper understanding of this framework can be an effective and powerful guide for the implementation of these sustainable intelligent systems.

The structure of this chapter is as follows. In the second part, the concept of artificial intelligence of things (AIoT) is presented. In the third part, the arguments related to sustainable marketing are examined. In the fourth part, the effects of artificial intelligence on the sustainability of marketing are analyzed. In the fifth section, the relationship between the Internet of Things and marketing is presented. In the sixth part, the conceptual framework for the marketing system based on artificial intelligence of things is presented. Finally, in the seventh part, the conclusion is presented.

2 Artificial Intelligence of Things (AIoT)

Businesses in today's world are changing with the progression of transformative innovations such as the Internet of Things (IoT) and manufactured insights. IoT makes a difference in gathering and refining colossal sums of information from different sources. In this case, this huge volume of information collected through endless IoT gadgets makes information handling and examination complicated. Realizing the objectives and full potential of IoT apparatuses and their particular information requires venture into unused and some of the time half-breed advances. The merging of artificial intelligence (AI) and the Internet of Things can rethink how industries, businesses, and economies work and process. Artificial intelligence, alongside the Internet of Things, makes shrewd machines that recreate shrewd behavior, and these gadgets back decision-making with small or no human mediation (Nozari et al. 2021a, b).

To attain all the objectives of Internet of Things instruments, ventures ought to be made with modern and transformative advances. The arrangement of artificial intelligence (AI) and the Internet of Things can change the way industries, businesses, and economies work. Artificial intelligence, together with the Internet of Things, makes intelligent gadgets that recreate intelligent behavior and bolster decision-making with small or no human intercession. The culminated combination of the Internet of Things (IoT) and Artificial Intelligence (AI), known as AIoT, permits companies to appreciate the benefits of both at the same time. In this unused half-breed technology, while the Internet of Things gives information, artificial intelligence takes over the control to gather the answers, giving both inventiveness and set to drive clever activity. Since the information given by the sensor can be analyzed with artificial intelligence, businesses can make educated and exact choices utilizing this explanatory information. This cross-breed innovation is fruitful in accomplishing agile solutions (Ayson et al. 2023).

Artificial intelligence in the Internet of Things breaks the inactive streams of information and recognizes designs that are not beguiling at basic scales. In expansion, machine learning combined with artificial intelligence can foresee operation conditions and adjust parameters that guarantee perfect results (Shen et al. 2023).

The artificial intelligence of things leads to an extent of benefits for companies and consumers, such as personalization of encounters and intelligent mechanization.

- **Increased operational efficiency**: Intelligent automation works better than traditional methods by simplifying organizational processes. Several industries are using these AIoT technologies to save resources.
- **Risk Management**: Superior integration of artificial intelligence with the Internet of Things will offer assistance to businesses get a wide range of dangers and mechanize real-time reactions. This permits them to better control monetary misfortunes, representative security, and cyber dangers.
- **Launching new and advanced products and services**: Without a doubt, the Internet of Things and artificial intelligence together can specifically make unused items or update existing items and administrations to new items through the plausibility of quick information handling and examination.
- **Increased scalability**: IoT devices range from mobile devices and high-end computers to low-end sensors. However, the most common IoT ecosystem consists of low-level sensors that provide massive amounts of data.

The advantages of artificial intelligence of things are shown in Fig. 1.

By combining artificial intelligence and the Internet of Things to create Artificial Intelligence of Things (AIoT), IoT devices are enabled to analyze data collected

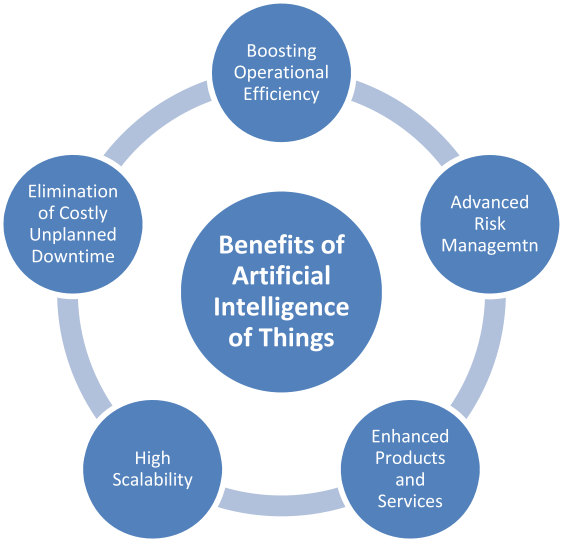

Fig. 1 Advantages of artificial intelligence of things

through equipment or devices and make intelligent decisions without human intervention (Aliahmadi et al. 2022). Ultimately, these devices will become intelligent, connected, and powerful systems that can process data and make decisions faster and more accurately than ever before.

3 Digital and Sustainable Marketing

Sustainability has three environmental, social, and financial measurements, analysts have assessed and analyzed green or environmental marketing methodologies in numerous studies. In expansion, in a few investigations, the promoting methodology has been analyzed from the social viewpoint. However, there are exceptionally few considerations that make the association between supportability and marketing technique. Subsequently, there is an ought to plan a marketing methodology that can bargain with issues related to accomplishing natural, social, and financial objectives and targets in a coordinated way. Be that as it may, planning a compelling marketing technique is exceptionally complex since each trade objective requires a distinctive promoting technique that includes a special set of choices (Denga and Rakshit 2023).

With so numerous transformative marketing innovations accessible, marketing inquiries have entered a modern stage of advancement. The democratization of data and the expanding number of mechanically smart clients have also touched off modern inquiries about patterns within the marketing literature. Digital transformation, in common, may be an alter in which computerized artifacts, frameworks, and images are utilized both inside and around an organization (Gao et al. 2023).

Consumers also engage with sustainable marketing practices primarily because of their functional value, which values sustainable features and environmental protection. If consumers perceive negative consequences (such as reduced product performance, additional cost, or inconvenience) for engaging in sustainable marketing practices, they quickly resort to unsustainable alternatives. Despite many researches that have been done in the field of sustainable marketing, there are gaps in the existing literature in the field of sustainable marketing. First, most previous studies study sustainable marketing alone and neglect the structural relationship between sustainable marketing innovation and specific marketing innovations such as digital marketing. In addition, although extensive studies have investigated consumer perceptions of sustainable marketing, few have attempted to present a sustainable marketing model based on a digital marketing approach, including smart and interactive marketing (Ghahremani-Nahr et al. 2022).

Smart marketing is defined as the process of collecting and implementing data-driven information to formulate effective marketing strategies for businesses in order to optimize the generated leads and conversions from target markets. The said data is information about the target customer, market trends, etc., which is related to the company's decision-making. Smart marketing is actually a combination of creativity, innovation, and knowledge creation and can play an important role in the success of any organization. Using this type of marketing makes an organization successful and creates customer satisfaction.

Smart marketing frameworks are planned to be utilized by marketing supervisors and seen by representatives all through the organization. These frameworks can collect exceptionally point-by-point and valuable information but frequently require suppliers to construct and alter custom reports. The developing impact that innovation has on consumerism has expanded the requirement for smart marketing. Customer interaction with companies is continually changing due to the utilization of innovation and social systems. To keep up with the changes, buyer understanding requires explanatory strategies (Nozari et al. 2023a, b). Marketing research is without a doubt the establishment of any company's commerce arrangement, revealing bits of knowledge approximately customers and producing future deals potential. Since the collection of information and their investigation give unused and valuable data to companies, companies ought to ceaselessly utilize them to move forward with their marketing exercises and embrace modern cleverly showcasing successfully. As information becomes accessible to companies, it creates modern openings and challenges for marketers to memorize their customers (Kumar et al. 2023).

With the increasing use of the Internet and the web, many industries are using intelligent and stable digital advertising tools to advertise products in their marketing, and customer service is done in this way with greater reliability, ease, and efficiency. Knowledge-based companies are one of the most important factors in knowing the factors influencing the success of knowledge-based and technology-oriented businesses. This is while usually, the analysis of criteria of interest in marketing and the recognition of complications is less attention and focus of the owners of knowledge-based companies, and they generally have challenges and weaknesses in this sector (Nozari et al. 2021a, b). These tools allow companies to obtain real customer attitudes and create more communication value for customers. Viewing competitive factors is essential for a company to improve its performance and thus realize its mission, strategic goals, and future vision. Figure 2 shows a framework for sustainable marketing that can be empowered by technology.

Utilizing green marketing, sustainable items and administrations can be presented to the advertise. In spite of the fact that the potential of green marketing endeavors has not been realized, and cross-reactions and the component have made disturbances within the marketing path, the concept is still valuable. Green marketing can give more wonderful and economical choices to the consumer and constrain the antagonistic impacts of marketing movement on supportability. Such endeavors can guarantee that item planning and development, generation, distribution, advancement, and deals are economical and, in this way, optimize utilization and constrain waste.

Another dimension of sustainable marketing is communication and interactive capabilities. This dimension of sustainable marketing, by creating and establishing interaction based on modifying the consumption pattern and improving coordination in service delivery, as well as creating and maintaining a stable relationship with customers, creates a long-term approach to creating relationships with customers. Because the concerns of the customers are identified and evaluated and the products are created with an emphasis on the needs of the audience. Undoubtedly, the

Fig. 2 A framework for sustainable marketing (Gordon et al. 2011)

capabilities of intelligent and transformative technologies, such as the communication capabilities created by the Internet of Things, make this aspect of sustainable marketing more powerful.

4 The Effects of Artificial Intelligence on Marketing and Sustainable Development

Advances in data collection methods, analytics, and the digital economy have enabled marketers to deploy and make advertising personalization tactics more efficient. Despite such wide benefits, a large part of businesses is not familiar with the applications of artificial intelligence in online marketing and do not prioritize the use of this technology, and in many cases create risks for their customers' data and privacy. In recent years, the research on the applications of artificial intelligence in business has increased, and as a result, the research in the field of artificial intelligence in online marketing has also increased. The applications of artificial intelligence in online marketing have created a revolution in this field, which has drawn the attention of many investors and marketing managers to this field. Artificial intelligence, especially machine learning, is growing as an integrated part of many industries. One of these industries is the marketing industry (Zhang et al. 2023). To use AI in marketing, AI typically collects data, learns customer behaviors, and analyzes this information to help the business achieve its goals. Improving targeted advertising is desirable for marketers. The consensus among marketers is that predictive marketing can be defined as: using artificial intelligence to predict the probability of success of existing methods, to make more informed marketing decisions. Marketing data and user data come from many sources. With a lot of information to review and not having a proper understanding of them, as well as the inability to review them in a traditional way, it is necessary to use artificial intelligence to analyze the components of a positive customer experience and predict consumer behaviors. In this area, the application of artificial intelligence in marketing is that it allows marketers to act based on the results extracted from the data, based on the customer's needs at any moment.

Artificial intelligence is used in the marketing industry to help marketers make the sales process easier and provide a more pleasant experience for customers. To optimize costs, customize content and personalize the customer experience, marketers use artificial intelligence tools, which include: data models, algorithms, and machine learning to create a model of customer insight. This set of processes is called artificial intelligence marketing. If we want to mention examples of artificial intelligence marketing, we can mention chatbots, image recognition, personal assistants, content recommendation engines, targeted ads based on your search, and active pricing on e-commerce sites (Ghahremani-Nahr et al. 2021).

Artificial intelligence marketing is used today to increase the performance and return on investment of digital marketing campaigns. It can also bring the following benefits:

- **Makes Ads Smarter**: Artificial Intelligence helps by using big data to accurately analyze and create smarter online ads. AI can also process your data and look at your results to drive targeted advertising.
- **Improves searches**: AI and big data solutions can analyze consumers' digital search patterns to determine key areas on which to focus marketing strategies.
- **Content Personalization**: By combining big data, machine learning, and artificial intelligence, marketers can analyze customer perceptions and personalize content accordingly. Hyper personalization is the latest trend focused on customer preferences, combining digital and non-digital tools.
- **Improved customer service**: Chatting and other means of customer interaction have increasingly become the domain of AI bots, and this trend should continue as AI performance further advances.

The points mentioned above are only a part of the events that have taken place these days, and we will probably face more serious changes as more time passes. The changes in the marketing world will increase every day with the expansion of artificial intelligence and will lead to a better experience for the customer. The artificial intelligence approach in marketing is used for practical guidance and intelligent development of cause-and-effect relationships. Artificial intelligence creates a profile for each user, which is based on data integration. These profiles allow marketers to reach customers' choices. As a result, by using this data, customers' next choices can be controlled and directed.

Organizations should treat each customer as a special person. A customer behavior analysis system can help you provide superior experiences to your customers in all marketing channels. AI marketing tools are developing at a rapid pace, prompting marketing professionals to constantly follow trends and learn new skills. Although AI tools can seem overwhelming at first, when used wisely, they create opportunities to save time on repetitive tasks, better understand customers, and ultimately grow your business.

5 Internet of Things and Marketing

The Internet of Things could be an item of the big data transformation. This technology creates real-time experiences with its ability to associate your data and forms together with your business framework. The Internet of Things could be a driving computerized change innovation because it combines smart gadgets with business analytics to convey arrangements never recently conceivable. All this and more comes from the straightforward thought of utilizing sensors and wearables to monitor processes. The suggestions for digital marketing are total resource upkeep and following the best of broad client insights. As a result, this innovation is changing business through the personalization of client encounters and more noteworthy effectiveness (Abbass and Mehmood 2023). Meanwhile, the quick advancement of communication and versatile computing has given a more reasonable setting and opportunity for this alter and change and has made a modern era of marketing beneath the title of intelligent marketing. The intelligent intuitively promoting approach based on the Internet of Things and other transformative advances certainly brings numerous preferences for marketing activists and impacts the choices and choices of clients and buyers. These smart tools and technologies can provide decision-makers with many solutions for collecting data. Among these tools, we can mention social networks, which, in addition to the power of sharing information among users, can also influence the opinions of users to choose products (Nahr et al. 2021).

With IoT, organizations can expand their marketing reach beyond borders. The Internet of Things enables a channel to share data without the need for human interaction. Predictive analytics helps in learning the market behavior and makes better decision-making accordingly. Using this technology, business owners can get real data about the usage of their products and services to plan their strategies well to enhance the customer experience.

Data-driven marketing approaches can analyze user behavior using web-connected platforms. This makes it possible to reach the target audience directly instead of relying on advertising media to convey the message (Rehman et al. 2023).

At the beginning of the emergence of the Internet of Things and intelligent marketing based on it, many materials were presented about its ability to transform business and its basic activities such as marketing, which were mostly nothing more than fiction. But gradually with the passage of time and conducting various research in this field, its abilities and benefits were realistically identified, which we mention below as examples.

5.1 Increasing Influence in Marketing

The Internet of Things technology can transform the marketing world in such a way that a higher level of data can be achieved. Data that is based on performance and not on the simple level of expression. In today's world, the Internet casts a shadow on all aspects of human life. Since it is always possible to make our choices interactively or by sharing information, the Internet of Things helps us to obtain real and high-quality data more deeply than in the past. The tools that we deal with daily, can produce this reliable data as an information system.

5.2 Interactivity and the Ability to Provide Information at the Same Time

The interactive intelligent marketing approach based on transformative innovations such as the Internet of Things can simultaneously give all the data required by the gathering of people at all hours of the day and night. Usually due to speedy reactions and giving way better administrations to clients. The intuitive apparatuses of the Internet of Things permit marketers to be able to reach the changing needs of customers at all hours of the day and night. As a result, they can give more precise methodologies for the requirements of clients.

One of the most important features of marketing based on smart technologies such as the Internet of Things is collecting audience information with an emphasis on the Internet and online. The advantage of this data is to create specialized marketing according to the characteristics of the customers. Two-way communication with the audience is a valuable solution to increase loyalty. Also, this online communication with the audience provides the possibility of obtaining reliable data due to the lack of face-to-face communication. Because the data is collected anonymously, online, and using Internet of Things tools, and therefore people are not ashamed to provide valid data based on their heart's desire.

5.3 Real-Time Customer Analysis

When it comes to belief and client relationship administration, the Internet of Things takes the lead. The Internet of Things will be able to do more than collect data and organize client data. The Internet of Things can analyze the data of your clients with exceptionally fitting exactness by considering different variables and giving you pertinent and solid information. And this issue can be more important for marketers. Since the chain of demand among customers is often long and their decision-making requires more time, the Internet of Things can minimize this time. Smart devices, by simplifying this process and by providing their functional information, inform marketers about the process of customers' future decisions for repeat purchases. In the same way, marketers provide better shopping opportunities for their customers by measuring the existing conditions.

5.4 Prediction of Social Networks

A long time prior, when Facebook and Twitter were to begin presented to the open, marketers did not indeed envision that one-day social systems would be one of their fundamental objectives. But presently, we all get it this incredible alter exceptionally well.

Currently, the Internet of Things is well integrated with social networks. Smart devices are fully automatic in sharing content and promoting themselves on different social networks. As soon as these devices connect to the Internet for the first time, they join the communities of users of the same common product. Connecting these devices to social networks helps marketers who are looking to predict the buying process and consumption behavior of customers in the future. In this way, marketers can identify their audience and potential customers and plan to attract them (Najafi et al. 2022).

The Internet of Things technology is one of the most important tools for generating big data. This tool brings a deep and wonderful insight into the needs of customers. The data obtained from the Internet of Things helps to optimally understand the daily life of the audience and their needs. Therefore, by using this data, marketers can allocate advertisements for them based on the precise needs of the audience. Providing advertisements based on the tastes and interests of the audience is loyalty. will increase them. This approach will improve the performance of the marketing system. Therefore, as can be seen, the Internet of Things systems affect all the different processes in business and life, and therefore the effective implementation of intelligent marketing systems based on Technology can bring beneficial results for organizations.

Subsequently, the approach of intelligent interactive marketing based on Internet of Things innovation has had different points of interest for marketers, and for this reason, companies are looking to move from conventional promoting and Internet marketing to shrewdly intelligently marketing based on Internet of Things and other transformative innovations.

All of the over appears that understanding IoT development is for marketers who need to remain ahead of the competition in the future. The Internet of Things is always advancing in plan and functionality. Associated gadgets with sensors, processors, and monitors have superior information at their transfer, giving the control of unmatched market experiences. Marketers have to get IoT patterns to remain ahead. The long run of IoT is characterized by its applications in commerce, where e-commerce is booming. Appropriate utilization of IoT in marketing can benefit income and client encounters. For case, companies are as of now utilizing blockchain innovation and cryptocurrency to form internet browsers that store and oversee consumer information for more noteworthy effect, and this itself can be an appropriate stage for marketing.

6 AIoT-Based Marketing

Marketing based on the artificial intelligence of things refers to the use of the Internet of Things and artificial intelligence technologies by businesses to market their products and services. This involves using connected devices, data, and insights to create targeted and personalized marketing strategies that increase customer engagement and improve the overall customer experience. IoT has the potential to revolutionize marketing by providing businesses with valuable insights, enabling them to create more personalized and relevant marketing strategies. As long as marketers are mindful of privacy and security concerns, of course.

Although it seems to be mandatory for marketers, in fact, all the applications and automated systems that are based on artificial intelligence and IoT only dilute the complexity of classic targeting and custom production processes. In many cases, the platforms used for online promotion include algorithms to identify the best combinations. In other situations, companies take the lead in developing and implementing custom systems in-house (Uma 2023). The use of AIoT in marketing allows the marketing team to use this useful technology and examine the audience, collect their information, and analyze the data easily. Companies that use digital marketing for their sales are more likely to use AIoT in marketing, and it can be said that AIoT plays a key role in increasing their sales speed. The use of AIoT in marketing and its useful tools can be the best way to communicate with customers and send messages suitable to target customers at the best time, which will lead to the best performance. Because it makes the team members less tired and can put their energy into smarter work. Most marketing teams use this technology for tasks that have a specific method and do not require human intelligence (Khan et al. 2023).

Without the use of AIoT, all the information related to the company's campaigns and programs must be analyzed manually, but with the use of AIoT in marketing, it is easy to analyze the data, build customer service bots, and customize for the customer. AIoT helps business managers to choose the best strategy for the marketing team and develop their business, using AIoT it is easy to choose the best among several strategies and make decisions. Ever since social and digital media have opened their place among people, businesses have faced a huge influx of data. AIoT has provided an opportunity for the marketing team and business managers to easily review methods and strategies and select more valuable channels. The use of AIoT in marketing allows marketers to select the most valuable information from a wealth of information (Liu et al. 2023).

Using AIoT in marketing can help companies improve their marketing methods and attract customers. By using artificial intelligence algorithms and emphasizing IoT data, companies can accurately identify customer behavior. For example, AI algorithms can predict customers' needs based on their purchase history and provide them with the best offer (Sanyal et al. 2023). The use of AIoT and machine learning algorithms automate marketing processes and help brands improve their performance by increasing efficiency and reducing costs. AIoT analyzes information quickly without tiring team members and extracts important and necessary items from it. Of course, the ability of this technology is not only limited here, AIoT can offer the best things for future digital marketing and save the marketing team's time. One of the focal points of AIoT is that it can give the plausibility to consult and utilize the business of clients, which is of incredible offer assistance to promoting directors. Figure 3 shows the framework for the AIoT-based marketing system.

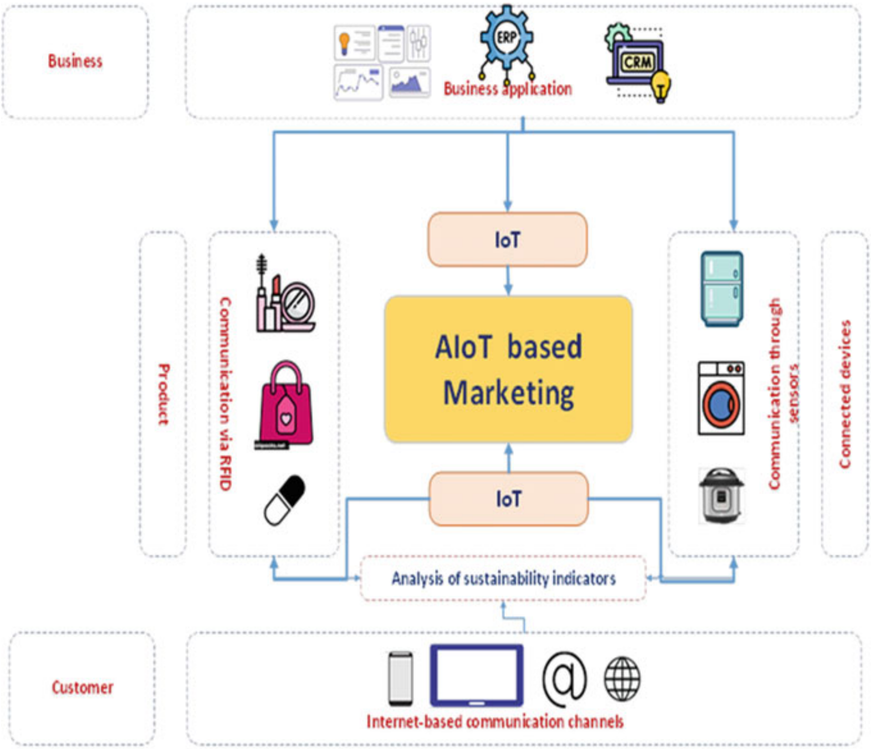

Fig. 3 A framework for AIoT-based sustainable marketing

This framework has been created by using field surveys and literature reviews and reviewing the opinions of active experts in the field of marketing with relevant work records and academic researchers with relevant research records and presented after several refinements. This conceptual framework has also been validated using experts' opinions.

As you can see from the framework, several different things must be done to collect information and use it. These tasks are done by managers or members of the marketing team in certain periods, and the result is used in reports. AIoT-based smart marketing frameworks are planned to be utilized by promoting directors and seen by representatives all through the organization. These frameworks can collect exceptionally detailed and valuable information but regularly require suppliers to construct and alter custom reports. Data-driven marketing pros are enlisted to gather marketing information in arrange to determine the quality of production, the way workers bargain with clients, and the quality of offices given by the company. Retailers and benefit suppliers allude buyers to the company. Companies can also utilize buyers to assess the quality of the client involvement. Nowadays, due to the activities of businesses in virtual space and social networks, the use of data from these platforms has become more necessary to analyze the above cases. Using the data generated around a brand or organization (whether positive, negative, or neutral) to collect information about products, the quality of their presentation, customer satisfaction with them, and much other information makes intelligent marketing fast, accurate, and simple.

7 Conclusion

In today's world, the expanding impact that innovation has on consumerism has expanded the requirement for smart marketing. Buyer interaction with companies is continually changing due to the expanded utilization of innovation and social systems. To keep up with the changes, customer understanding requires explanatory strategies. Marketing research is without a doubt the establishment of any company's commerce arrangement, revealing insights about shoppers and producing future deals potential. Since the collection of data and their analysis provide new and useful information to companies, companies should continuously use them to improve their marketing activities and adopt new intelligent marketing effectively. As more and more data becomes available to companies, it creates new opportunities and challenges for marketers to learn about their consumers. Due to the importance of using big data analysis of social networks for smart marketing, online tools have been created that companies can refer to collect and analyze this data.

Today, with all kinds of transformative technologies, the experiences of users regarding the use of a product have become very important. These experiences are integrated with the information obtained from searches made through internet search engines and affect the user's decision to choose and buy a product. The correct understanding of the data received from customers helps the production and innovative industry based on human health, which itself is one of the pillars of sustainable development. One of the highlights and benefits of AIoT is that it can give the plausibility of two-way interaction and the utilization of customers' business, which is of incredible offer assistance to marketing supervisors and activists in this field. Another advantage of intelligent marketing with the AIoT approach is the capacity to gather and refine data about clients through online surveys. IoT innovation can give a gigantic sum of information that brings more profound and key insights about clients and gatherings of people. Information from keen gadgets based on the Internet of Things is utilized to get the everyday way of life of buyers utilizing manufactured insights of things. This permits computerized marketers to advance items based on collected information and with an accentuation on green and sustainable standards.

By utilizing this extraordinary information from smart technologies, companies can give suitable and fitting notices to each client. This highlight of the communication smart marketing approach encourages the execution of devotion programs. This makes a difference in targeting gatherings of people and clients more precisely makes strides and optimizes the adequacy of marketing campaigns. As you can see, AIoT will not as it were alter technology and other issues, but also encompass a great impact on marketing and its successful usage, and by utilizing it, marketers' dynamic within the field of smart advances can foresee the issues that will alter.

and take fitting measures to bargain with them. In this manner, brilliantly interactive promoting based on AIoT has contained different preferences for marketing activists, and for this reason, companies are looking to move from conventional past-oriented marketing to intelligent interactive promoting based on AIoT and other transformative advances. Concurring with all the specified cases, this investigation, it was attempted to present these profitable innovations and present their measurements and fundamental components, to present a conceptual system to show the cause-and-effect connections of the viable components. This system can give a successful direction for the usage of an intelligent interactive marketing framework based on AIoT with an accentuation on sustainability indicators.

The place of artificial intelligence and the Internet of Things in the future of the marketing world is increasing significantly, but if we want its presence to be positive, it is also necessary to address its warnings. Experts rightly demand full transparency and accountability in the field of artificial intelligence. They point out that the pervasiveness of the development and use of artificial intelligence of things depends on the creation of ethical applications, in a way that does not deprive users of their rights.

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Enabling Sustainable Transportation Through IoT and AIoT Innovations

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Abstract Implementing the SDGs requires political commitment, adequate resources, and effective policies. Governments play a crucial role in setting national priorities, aligning policies with the SDGs, and mobilizing financial resources. This study investigates how the Internet of Things and Artificial Intelligence of Things (AIoT) may improve transportation systems and help the planet. It stresses the significance of environmentally friendly transportation in solving urban and ecological problems. Smart mobility solutions, electric mobility adoption, and AI-enhanced public transit are all made possible by the IoT and artificial intelligence. The importance of environmental monitoring through IoT sensors is emphasized, and the chapter also examines IoT-based intelligent parking systems and safety precautions. The study additionally examines how IoT and AIoT influence urban planning and efficiency, aiming to better organize cities and their transportation systems to reduce traffic and urban sprawl. This chapter explores the potential of these technologies to curb harmful emissions and encourage environmentally friendly modes of transportation. The study uses in-depth analysis of case studies and practical applications to demonstrate their use and potential. It discusses the dangers and problems of using these technologies, as well as the steps that may be taken to make operations more secure and dependable. Smarter choices about the future of transportation may be made with the help of IoT and AIoT by legislators, urban planners, and transportation regulators.

Keywords Sustainable transportation · IoT · AIoT · Smart mobility solutions · Electric mobility

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1 Introduction

Sustainable transportation is a crucial aspect of sustainable development, aiming to reduce greenhouse gas emissions, promote energy efficiency, enhance public health, and ensure equitable access to transportation services (Nozari et al. 2022). With rapid urbanization and population growth, the importance of sustainable transportation has become more pronounced. Traditional transportation systems reliant on fossil fuels significantly contribute to air pollution, traffic congestion, and climate change. Sustainable transportation aims to achieve the following objectives: reduce emissions, enhance energy efficiency, improve public health, and foster equitable access (Çetin et al. 2021). The role of IoT and AIoT technologies in transforming transportation systems is significant. The IoT and AIoT technologies play a transformative role in the transportation sector, integrating IoT devices and sensors with AI capabilities into transportation systems (Seng et al. 2022). These technologies enable real-time data collection and analysis, facilitating the creation of smart mobility solutions such as ride-sharing, dynamic routing, and traffic management systems (Sergi et al. 2020).

The importance of the SDGs lies in their universality and inclusivity. They apply to all countries, regardless of their level of development, and recognize the interconnectedness of global challenges. The goals emphasize the need for collaboration and partnerships among governments, businesses, civil society, and individuals to achieve sustainable development (Erin and Bamigboye 2022; Heydari et al. 2019). By 2030, the SDGs aim to end poverty, hunger, and inequality, ensure access to quality education and healthcare, promote sustainable economic growth, combat climate change, and protect biodiversity. The SDGs offer a transformative vision for a more equitable, prosperous, and environmentally responsible world (Caiado et al. 2022).

Electric Mobility Adoption is further enhanced by IoT, which facilitates the monitoring and managing of electric vehicle (EV) charging stations, optimizing energy consumption and encouraging widespread adoption of EVs (Cliff et al. 2023). Intelligent Public Transportation enhances the performance of public transportation systems by optimizing scheduling, predicting passenger demand, and improving overall efficiency (Saad et al. 2023). IoT-enabled parking systems allow real-time parking space availability updates and efficient management, reducing congestion and emissions. Safety measures are also enhanced through real-time monitoring of road conditions, traffic sign recognition, and collision avoidance systems (Tauseef et al. 2023). This research explores the potential of IoT and AIoT technologies in transforming transportation systems to promote sustainability. The scope of the research includes a comprehensive review of existing literature, examination of case studies and real-world implementations, analysis of challenges and security concerns related to the adoption of IoT and AIoT in transportation, evaluation of the impact of IoT and AIoT on urban planning, congestion reduction, and environmental management, and providing recommendations and policy implications for policymakers, urban planners, and transportation authorities to foster the adoption of IoT and AIoT for sustainable transportation.

2 IoT and AIoT Technologies for Sustainable Transportation

The convergence of IoT and AIoT technologies has completely transformed the transportation industry. The IoT is based on a network of linked devices that gather and exchange data to facilitate effortless communication and informed decision-making (Luzolo and Tchappi 2023). Intelligent and autonomous activities are made possible by AIoT's data processing and analysis algorithms based on artificial intelligence. These innovations have far-reaching consequences for the transportation sector, improving efficiency, sustainability, and accessibility (Brinken et al. 2022). The IoT and the Artificial Intelligence (AI) of Things are changing the world in many ways. Sensors and gadgets enabled by the IoT are installed in cars, roads, traffic lights, and other transportation infrastructure to gather and analyze data in real-time (Huang et al. 2022). Optimizing traffic flow, predicting congestion, and boosting road safety are all possible with this information. Algorithms trained on this data can adjust traffic lights and reroute cars away from clogged streets in real-time (Boulouard et al. 2022).

Battery health monitoring, charging station optimization, and energy consumption management are all critical components of electric mobility, and both IoT and AIoT play important roles in each. As a result, more people will choose electric cars, reducing harmful emissions (Oyebode 2022). IoT and AI technologies are useful in public transit because they enable real-time tracking, smart ticketing systems, and predictive maintenance. Due to the IoT and artificial intelligence in transportation applications, cities may benefit from data-driven insights about traffic patterns, transportation needs, and areas needing infrastructure upgrades (Das 2022). Transportation IoT and AIoT research is extensive, evolving, and promising for many fields. An intelligent, connected, and environmentally friendly future may be achieved via the smart use of IoT and AIoT in transportation, as shown in Fig. 1.

3 Improving Traffic Management and Efficiency

Traffic monitoring and congestion management have been transformed by IoT technology. IoT-based traffic monitoring systems capture real-time data on road conditions, traffic flow, and vehicle movement using sensors, cameras, and other devices (Johnson and Klassen 2022). This data is then examined and processed to reveal traffic patterns and hotspots, helping authorities reduce congestion and enhance traffic management. IoT-based traffic monitoring provides real-time data. Manual counting or loop detectors are time-consuming and may not cover the full road network (Saad et al. 2023). However, correctly placed IoT sensors may provide real-time traffic data. Traffic management authorities can react swiftly to changing traffic conditions and conduct congestion control measures using this real-time data. IoT-based traffic

Fig. 1 Overview of IoT and AIoT technologies for sustainable transportation (Giuffrida et al. 2022)

monitoring allows dynamic traffic control (Giuffrida et al. 2022). Traffic management systems enhance traffic flow by adjusting traffic signal timings, rerouting traffic, and implementing variable speed restrictions based on real-time data. This dynamic strategy optimizes road infrastructure and reduces congestion and travel times (Kemmoe et al. 2022). Traffic management systems are further improved by integrating AIoT in traffic analysis and optimization. AI algorithms can analyze enormous amounts of IoT sensor data, detect traffic trends, and accurately anticipate traffic congestion. This predictive capacity lets authorities design alternative routes or change signal timings depending on projected traffic levels to avoid congestion (Kazmi and Sodangi 2022).

AIoT can optimize routes and smartly navigate. AI algorithms can recommend the best routes for drivers based on historical traffic data and real-time circumstances, including road closures and weather. Drivers save time and gas, and traffic is decongested (Zhao et al. 2022). IoT-based traffic monitoring and AIoT promote sustainable mobility alongside congestion management. Optimizing traffic flow and decreasing congestion reduces carbon emissions and fuel usage, making transportation more ecologically friendly. IoT-based traffic monitoring and AIoT traffic analysis face obstacles. Real-time traffic data collecting raises data privacy and security problems (Hammi et al. 2022). IoT sensors create a lot of data. Therefore, a solid communication infrastructure must accommodate and provide a smooth connection. IoT-based traffic monitoring and congestion management, paired with AIoT's predictive traffic analysis and optimization, may make urban transportation systems smarter, more efficient, and greener (Casini 2022). Traffic management authorities may use real-time data and AI algorithms to reduce congestion and improve passenger experiences. IoT and AIoT in traffic management will continue to improve urban mobility as technology advances (Saad et al. 2023).

3.1 Case Studies of Smart Traffic Management Systems

Intelligent traffic management systems have recently arrived on the scene as cutting-edge approaches to the problem of urban congestion and to enhance overall transportation effectiveness. Several case studies such as (Aloqaily et al. 2018; Hameed et al. 2021; Whaiduzzaman et al. 2022) from different parts of the globe illustrate that these systems were successfully implemented, as well as their positive influence on traffic management. Let us have a look at a few of the most notable case studies of intelligent traffic management systems:

Singapore's Intelligent Transport System (ITS): The Intelligent Transport System (ITS) of Singapore is a leading example of an all-encompassing smart traffic management system. It monitors and manages traffic flow across the city by integrating various technology, such as sensors connected to the IoT, cameras, and data analytics (Carneiro et al. 2019). This enables authorities to make judgments based on accurate information on road conditions, vehicle movements, and traffic volumes, thanks to the system's real-time data collection (Soriano et al. 2018). The implementation of adaptive traffic signal control and dynamic route guiding is being done to improve traffic flow and cut down on congestion. Because of this, Singapore has made major strides in improving its traffic management and has emerged as a model for other cities all over the globe (Prančevičius and Kraujalis 2012).

The Congestion Charge Method Used in London: The congestion charge plan in London is an innovative traffic management system created to lower the traffic congestion in the city center. Vehicles that enter the specified zone during peak hours will be assessed a price by the system, which uses cutting-edge technology (Alama et al. 2021). The program incentivizes the use of public transit as well as cycling, which in turn reduces the number of private automobiles that are driven on the roads. It has been effective in reducing car congestion and air pollution in downtown London while at the same time producing cash that can be invested in the infrastructure of public transportation (Adebayo and Kawu 2022).

System for the Real-Time Management of Traffic in Los Angeles: To monitor traffic conditions around the city, Los Angeles has created a real-time traffic management system that uses IoT sensors and powerful artificial intelligence algorithms. Commuters may get up-to-the-minute traffic information from the system through mobile applications and dynamic message signs (Otuoze et al. 2021). It allows the authorities to react quickly to emergencies, divert traffic, and vary the timing of signal changes to reduce congestion. The system has cut travel times and decreased the number of delays caused by traffic, which has improved the transportation experience for both locals and tourists.

Stockholm's Dynamic Tolling System: A further effective example of intelligent traffic management is shown in Stockholm's dynamic tolling system, which was implemented in 2008. Implementing dynamic congestion pricing on certain roadways during peak hours is made possible by the system via IoT technology (Lilhore et al. 2022). Drivers are subjected to variable toll prices depending on the current volume of traffic, which incentivizes them to use other routes or travel during less busy times of the day. This strategy has resulted in a major decrease in traffic congestion and a move toward more environmentally friendly transportation choices (Olusegun Onifade 2020).

Optimization of Traffic Signals in the City of Toronto: The traffic flow at junctions in Toronto was significantly improved because of the installation of an intelligent traffic signal optimization system. Sensors connected to the IoT and real-time data analytics are used to modify the timing of traffic signals in response to changes in traffic conditions, pedestrian activity, and bus timetables. The system has cut down on travel times and wait periods at junctions, resulting in a more consistent flow of traffic and increased safety for pedestrians (Çetin et al. 2021; Opoku et al. 2022).

The case mentioned above studies illustrates how intelligent traffic management systems have the potential to revolutionize urban transportation and provide solutions to the problems caused by traffic congestion. These systems have produced major advances in traffic management, decreased emissions, and better overall transportation efficiency by leveraging the IoT, AI, and data analytics. Intelligent traffic management systems give cities a possible answer for constructing more sustainable and pleasant urban environments as they continue to tackle the difficulties of urbanization and increased vehicle traffic due to urbanization, as shown in Fig. 2.

4 Enhancing Public Transportation Systems

Smart bus stops, real-time tracking, and scheduling and route optimization applications are just a few ways IoT and AIoT have transformed public transportation. Smart bus stops powered by the IoT help commuters plan their trips more effectively by providing up-to-the-minute information on bus arrival times, route timetables, and service changes (Doshi et al. 2018; Giuffrida et al. 2022). These stations also track weather data, so transportation officials may address passenger complaints about the weather and make the stations more pleasant places to wait. IoT-enabled public transit systems rely heavily on real-time tracking (Pundir et al. 2020). With GPS tracking devices and the IoT, transit agencies can keep tabs on where their buses are at all times, improving service for riders and allowing for more efficient route planning. Bus routes and timetables may be enhanced using AIoT applications by evaluating large volumes of data, such as past traffic patterns, current weather, and passenger demand. Scheduling controlled by AIoT guarantees ideal frequencies, lowering wait times and congestion during peak periods (Murali and Jamalipour 2020).

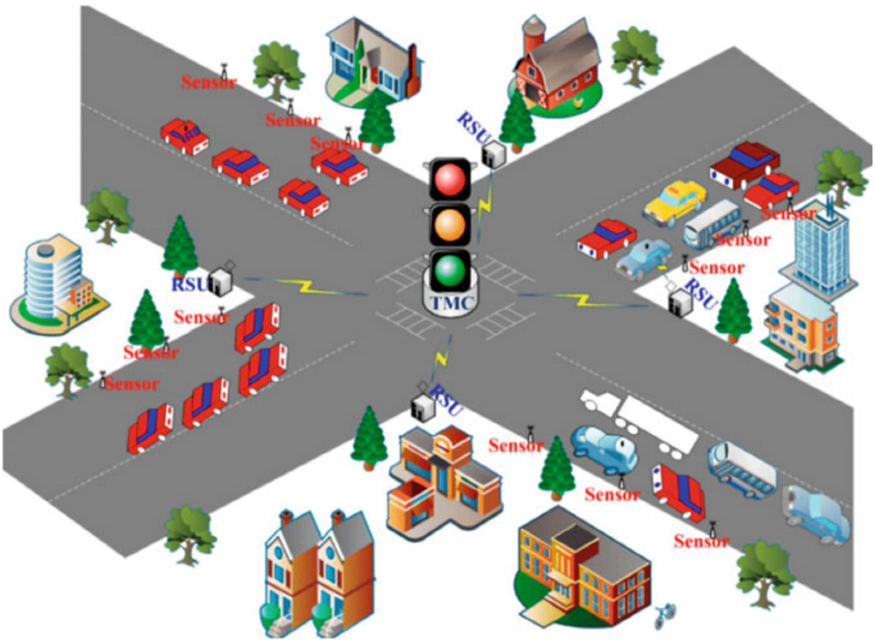

Fig. 2 IoT-based traffic monitoring and congestion control (Giuffrida et al. 2022)

Buses and other transit vehicles may undergo predictive maintenance thanks to AIoT in the public transportation sector. IoT sensors track how well the car is running by recording gas mileage, tire wear, and engine temperature information. Transportation authorities may use the results of these analyses to plan for preventative maintenance, thereby lessening the likelihood of service failures and interruptions (Li et al. 2019). Data security and privacy are only two issues that must be addressed with the public transportation sector's adoption of IoT and AIoT. Protecting passenger data and keeping the public's confidence requires stringent cybersecurity safeguards and data protection regulations. Thus, the IoT has greatly enhanced public transportation systems' efficiency and user experience, making trips more pleasant, predictable, and ecologically sustainable via AIoT applications like smart bus stops and real-time tracking.

4.1 Benefits of Implementing Smart Public Transportation

Integrating IoT and AIoT technologies into public transportation systems offers various advantages that change urban mobility and enhance the passenger experience. AI algorithms evaluate real-time data on transportation systems, such as bus locations, traffic conditions, and passenger demand, to improve planning and efficiency

(Yu et al. 2021). This causes bus schedules to be optimized, leading to shorter wait times and more consistent arrival times. Combining IoT and AIoT in public transportation systems makes better traffic management and congestion control possible. Authorities may better manage traffic flow and encourage sustainable urban mobility with information on current traffic conditions. With real-time monitoring and digital displays at bus stops, travelers can better plan their routes and have a more pleasant experience thanks to smart public transit (A. Kumar 2022).

Smart public transportation can save money and maximize available resources. Algorithms based on artificial intelligence and the IoT may improve fleet management by distributing buses in response to real demand. Predictive maintenance made possible by the IoT sensors may also save costs by preventing costly breakdowns and minimizing downtime (Aliahmadi et al. 2022). Smart public transportation is also crucial in the pursuit of sustainability and the mitigation of negative environmental effects. Smart transportation systems may contribute to cleaner and greener communities by minimizing fuel consumption and greenhouse gas emissions via route and frequency optimization (A. Kumar 2022). More people will utilize public transit because of real-time updates, resulting in fewer car journeys and reduced congestion, which benefit the environment. A more interconnected, efficient, and sustainable future for urban mobility may be achieved via the widespread use of smart public transit (Otuoze et al. 2021).

4.2 Challenges of Implementing Smart Public Transportation

Smart public transportation systems offer numerous benefits but also present challenges that must be addressed for successful deployment. One major challenge is the high upfront cost of implementing smart transportation infrastructure, which requires significant investment and can be costly and time-consuming for cities with limited financial resources (Coelho et al. 2020). To address this, governments and transportation authorities can seek partnerships with private sector companies to share the financial burden and explore innovative financing models. Grants and funding from regional or national governments can also support the initial investment in smart transportation projects. Data security and privacy concerns are another critical challenge in implementing smart public transportation (Gazzeh et al. 2022). IoT devices collect vast amounts of data on passenger movements, preferences, and behaviors, which must be securely stored and protected from cyber threats. Ensuring data privacy and compliance with regulations such as the General Data Protection Regulation (GDPR) is crucial to building public trust and confidence in using smart transportation services. Adopting robust data encryption and authentication measures and conducting regular security audits can help mitigate data security risks (Otuoze et al. 2021).

Interoperability and standardization present a challenge in integrating various smart transportation systems. Developing common standards and protocols for IoT devices and AIoT platforms is essential to foster interoperability and facilitate a smooth integration process. Collaboration between stakeholders, such as transportation authorities, technology providers, and academic institutions, can help develop and promote industry standards for smart transportation (Chiu et al. 2022). Public acceptance and awareness are critical factors influencing the successful adoption of smart public transportation. Educating the public about the advantages of smart transportation and its positive impact on their daily lives can build public support and encourage wider adoption (Ali and Choi 2020). Involving citizens in planning and decision-making through public consultations and feedback mechanisms can foster a sense of ownership and engagement. Regulatory and policy frameworks can also pose hurdles to implementing smart public transportation (Eze et al. 2022). Outdated regulations and bureaucratic procedures may hinder the adoption of innovative technologies and slow down the implementation process. Governments and transportation authorities must proactively review and update existing rules to accommodate emerging smart transportation solutions and foster an environment that encourages innovation. By tackling these challenges head-on, cities can harness the full potential of smart transportation systems to create more efficient, sustainable, and passenger-centric urban mobility networks (Hammi et al. 2022).

5 Intelligent Transportation Systems for Safety and Security

Intelligent Transportation Systems (ITS) are crucial in improving the safety and security of contemporary transportation networks. These technologies incorporate information and communication technology with transportation infrastructure and vehicles, using real-time data, sophisticated sensors, and AI algorithms to deliver intelligent and adaptable transportation solutions (Saraswathi and Rao 2022). By providing smart traffic management, control, and vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, ITS seeks to minimize accidents and deaths. These technologies allow drivers to make more informed judgments and avoid crowded routes, lowering the likelihood of an accident (Zhang et al. 2019). Smart car technologies have demonstrated promising results in improving safety by enabling vehicles to interact with one another and their surroundings, delivering important information about possible risks. These technologies may alert drivers to oncoming emergency vehicles or pedestrian crossings, enhancing road safety and reducing accidents (Habibi et al. 2017).

Furthermore, ITS technologies help improve transportation security by combining modern surveillance systems, such as video cameras and license plate recognition, with AI algorithms to identify suspicious actions or objects, allowing quick reactions to security concerns (Olorunnimbe et al. 2022). Furthermore, ITS allows real-time tracking and monitoring of vehicles and cargo, which is critical for freight transportation security. Transportation businesses may monitor the position and condition of shipments using GPS and RFID technology, decreasing the risk of theft and

Fig. 3 Intelligent transportation systems for safety and security (Ntlotlang 2019)

ensuring timely product delivery (Kumar et al. 2020). However, significant obstacles must be overcome before ITS technology may be widely used. It is critical to ensure the privacy and security of data gathered by ITS to foster public confidence and avoid exploiting personal information. To secure sensitive data from unwanted access, robust cybersecurity safeguards and data protection rules are required (Rathod et al. 2023). Finally, ITS is critical in improving safety and security in contemporary transportation networks via smart traffic management, vehicle communication, and enhanced monitoring. Addressing data privacy, cybersecurity, and cooperation concerns is crucial for reaching the full potential of ITS for transportation safety and security, as illustrated in Fig. 3.

5.1 IoT-Based V2V Communication for Collision Avoidance

The IoT has transformed several sectors, most notably road safety via V2V communication. Road traffic accidents are a worldwide problem, resulting in deaths and injuries. Researchers and the automobile industry have investigated novel approaches to improving road safety, with IoT-based V2V communication emerging as a potential option (Alaba 2021; DADA et al. 2021). IoT technologies, such as Dedicated Short-Range Communication (DSRC) and Cellular-V2X (C-V2X), as well as sensor technologies like radar, lidar, and cameras, play an important role in enabling V2V communication. These technologies let cars recognize and react to possible collision hazards with greater accuracy, lowering the number of accidents and saving lives. Implementing IoT-based V2V communication has significant advantages for road safety, including the ability for cars to communicate important safety information, foresee probable crashes, and take preventative steps (Abdullahi et al. 2022). This real-time teamwork has the potential to minimize accidents and save lives drastically. Furthermore, V2V communication enhances overall traffic flow, reducing congestion and more efficient traffic management.

Data privacy and security concerns, difficulties with standards and interoperability, and practical implementation obstacles threaten the viability of V2V communication that relies on the IoT (Sharma et al. 2022). Case studies and real-world deployments have shown the use and advantages of IoT-based V2V communication in various real-world contexts. Future directions and developments include integrating AI and machine learning, 5G and edge computing technologies, cooperative V2V and V2I communication, and encouraging industry stakeholders to collaborate. Overall, V2V communication based on IoT represents a huge leap in road safety technology, allowing cars to interact and cooperate in real-time, averting accidents and making roads safer for all users. Thus, Fig. 4 shows IoT-Based V2V communication for collision avoidance.

Fig. 4 IoT-based V2V communication for collision avoidance (Batool et al. 2022)

6 Environmental Sustainability and Emission Reduction

In recent years, the IoT and its upgraded form, the AIoT, have emerged as potent instruments for dealing with environmental issues. The environmental effect of sustainable transportation options can be measured, pollution can be tracked, and eco-friendly transportation options can be promoted thanks to these cutting-edge technological advancements (Heydari et al. 2019). Human health and the natural world are both seriously threatened by air pollution, making it a critical worldwide concern. Particulate matter, nitrogen dioxide, ozone, and volatile organic compounds are just some of the pollutants that IoT-enabled air quality monitoring systems can track in real-time thanks to sensors and networked devices (Usmani et al. 2022). Insights gained from analyzing this data by AI algorithms may help politicians and urban planners take effective, targeted steps to reduce air pollution. The transportation sector exacerbates greenhouse gases and air pollution (Raimi et al. 2021). Integrating IoT devices into vehicles and transportation infrastructure can provide useful information on traffic patterns, congestion, and emissions, optimizing traffic flow, reducing idling time, and encouraging environmentally friendly transportation options like electric vehicles, carpooling, and public transit. IoT smart parking systems assist cars in identifying parking places quickly, cutting down on wasted time and gas (Hongxin et al. 2022).

To fine-tune sustainability policies, direct future investments in green infrastructure, and quantify the environmental advantages of adopting cleaner transportation alternatives, impact evaluations of sustainable transportation efforts are needed. Congestion and delays may be mitigated with the help of AIoT-powered traffic management systems, which analyze data from connected vehicles and other IoT devices in real-time (Khandelwal et al. 2022). The IoT may improve the effectiveness and convenience of public transportation. Smart transport vehicles with IoT sensors may reduce fuel consumption and pollution by monitoring passenger occupancy, tracking real-time positions, and optimizing routes (Johnson and Klassen 2022). IoT-enabled smartphone apps may disseminate up-to-the-minute information about bus and train timetables, encouraging people to use public transportation and discouraging them from driving. Finally, using IoT and AIoT for sustainable mobility is a breakthrough in creating environmentally friendly and economically viable cities. The IoT and the AIoT provide novel approaches to environmental problems and the promise of a more sustainable future by using data and cutting-edge algorithms. To successfully adopt these technologies and lead the globe toward a cleaner, healthier, and more sustainable transportation system, policymakers, urban planners, and stakeholders must work together (Panteli et al. 2020).

7 Barriers to IoT and AIoT Implementation in Transportation

The IoT and AIoT can revolutionize the transportation industry by making it more intelligent, efficient, and environmentally friendly. On the other hand, broad acceptance and use of these solutions are hampered by considerable obstacles (Knebel et al. 2022). The high initial investment costs, difficulties in interoperability and standardization, concerns over data privacy and security, inadequate infrastructure support, and reluctance to change are some of the primary problems that hamper the effective integration of the IoT and artificial intelligence-enabled IoT technologies in transportation systems (Yu et al. 2021). The high initial investment costs may be a major obstacle to introducing the IoT and the AIoT since they can cause adoption to be delayed. Governments and other stakeholders may share the financial cost of deploying IoT and AIoT technologies via exploring public–private partnerships, including tax incentives and subsidies to stimulate investment in smart transportation projects (Mishra and Shrivastava 2021).

Developing industry-wide standards and protocols for IoT and AIoT technologies is vital for smooth integration across various devices and platforms (Chiu et al. 2022). Collaborative efforts among industry actors, standardization organizations, and regulatory authorities may facilitate the establishment of common frameworks that encourage smooth integration. Implementing stringent cybersecurity measures, observance of data privacy legislation, and provision of openness about the gathering and use of data may increase the public's trust in the safety of smart transportation systems (Das 2022).

The lack of adequate infrastructure support, especially in developing nations, may hinder the effective implementation and operation of intelligent transportation systems. To make it possible for the IoT and AIoT technologies to operate smoothly, governments and organizations from the private sector may invest in creating and improving necessary infrastructure, such as broadband networks and power supply (Mishra and Shrivastava 2021). Adopting solutions for edge computing may assist in overcoming infrastructure restrictions and show the real advantages of implementing IoT and AIoT, such as greater efficiency, decreased costs, and enhanced safety. This can be accomplished by demonstrating the tangible benefits of IoT and AIoT adoption. The potential of IoT and AIoT to revolutionize the transportation sector has been shown. However, there are still several obstacles that must be overcome before they can be fully implemented. By proactively tackling these hurdles, we can unleash the full potential of IoT and AIoT technologies, which will allow us to create transportation systems that are smarter, more efficient, and more sustainable, hence improving mobility, safety, and environmental outcomes (Chiu et al. 2022).

7.1 Future Trends and Potential Advancements in Sustainable Transportation

Sustainable transportation promotes economic growth and environmental protection. Sustainable transport is promising as technology advances. This section examines sustainable transportation trends that might change how we move people and products while minimizing environmental effects.

Alternative Fuels: Electric vehicles (EVs) and fuels are major sustainable transportation developments. EVs are getting cheaper and more accessible as technology advances and battery storage costs drop. Hydrogen fuel cell technology and biofuels provide viable alternatives to fossil fuels, lowering greenhouse gas emissions and improving the environment (Okanga 2022).

Autonomous Vehicles: Self-driving cars will transform transportation. These self-driving cars employ sensors and AI algorithms. Autonomous vehicles might improve road safety, traffic, and transit efficiency. They can also optimize ride-sharing and public transit networks (Kou et al. 2022).

Mobility-as-a-Service (MaaS): Mobility-as-a-Service (MaaS) promises a single platform for buses, trains, motorcycles, and ride-sharing. Mobile apps provide more efficient and sustainable travel solutions. MaaS may reduce automobile ownership, traffic, and transportation sustainability (Lin et al. 2022).

Intelligent Transportation: IoT and AIoT technologies enable better transportation infrastructure. Smart traffic signals, networked highways, and real-time data processing improve traffic flow and cut pollution. Smart parking systems reduce congestion and optimize parking space utilization. These advances optimize resources and reduce fuel usage, making transportation more sustainable.

Hyperloop/Maglev Technologies: Hyperloop and maglev technologies promise fast, energy-efficient transportation. Hyperloop is a sustainable alternative to air transport for medium-distance travel. Maglev trains employ magnetic levitation to reach high speeds and little friction, saving energy and reducing pollutants (Liu et al. 2021).

Renewable Energy Integration: Sustainable transportation requires renewable energy integration. Transport may employ renewable energy to power EV charging stations, trains, and electric buses. This minimizes transportation's carbon impact and improves energy sustainability (Lin et al. 2022).

Sustainable transportation might revolutionize people and commodities movement. Among the intriguing transportation themes are electrification, driverless cars, Mobility-as-a-Service, smart infrastructure, hyperloop, maglev, and renewable energy integration. By embracing these advances, we can develop a more efficient, environmentally friendly, and equitable transportation system that improves mobility, lowers emissions, and promotes sustainable economic growth. To green transportation, governments, corporations, and society must cooperate and invest in these future trends.

8 Conclusion

This chapter analyzes the revolutionary effect of the IoT and the AIoT on facilitating environmentally friendly modes of transportation. IoT and AIoT have ushered in a new era of sustainable mobility by enabling real-time data analysis, improving connectivity, and optimizing resources. Safer and more environmentally friendly transportation is possible because of IoT and AIoT applications such as smart traffic control systems, V2V communication, and air quality monitoring. Incorporating renewable energy sources, electrification, and alternative fuels drives the shift toward cleaner and greener transportation solutions. The rise of Mobility-as-a-Service (MaaS) platforms is reshaping the transportation industry by eliminating the need for individual automobile ownership and providing convenient, networked mobility choices.

We cannot exaggerate the value of IoT and AIoT in facilitating environmentally friendly modes of transportation. High carbon emissions, traffic congestion, and poor resource usage are only some of the problems that these technologies aim to solve. Increased productivity, resource conservation, security, mobility for everyone, and economic development are just some outcomes of IoT and AIoT's use of real-time data, sophisticated analytics, and autonomous capabilities. More studies and novel approaches are needed to realize their full potential. Smart city connectivity, legislation and regulation, data privacy and security, public awareness and adoption, and collaborative collaborations are all topics that need further research. We can build a future of transportation that is good for people and the earth if we accept these technologies and work together.

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Investigating Key Dimensions and Key Indicators of AIoT-Based Supply Chain in Sustainable Business Development

Hamed Nozari

Abstract One of the most vital parts of the overall organization is supply chain management as a department whose responsibility is coordinating all units from the initial stages such as the supply of materials to the final ones like delivery and after-sales services. Supply chain management aims to find ways to reduce as much as possible the production cycle of the desired product and service, and in this way takes advantage of the latest advances in management science and technology (including the Internet, the global wide network, and information technologies, artificial intelligence, the Internet of Things [IoT], etc.). Today, guaranteeing the sustainable development of any country depends on its preservation and optimal use of limited and irreplaceable resources. In the meantime, the Internet of Things is embedded in physical objects using activating sensors and data communication technology, therefore, it provides the possibility of tracking, coordinating, or controlling objects through the Internet. In addition, the combination of this Internet of Things technology with artificial intelligence technology, known as artificial intelligence of things (AIoT), also adds the power of analysis and learning to the key capabilities of the Internet of Things. In this research, the dimensions as well as components, and key indicators of an AIoT-based supply chain have been investigated and a framework has been proposed for evaluating the intelligent supply chain to meet the requirements of sustainable development. The conceptual framework model is compiled from five important concepts of supply chain management, including business strategy, technology, sustainable development, cooperation, and management.

Keywords Artificial intelligence of things (AIoT) · AIoT-based supply chain · Smart supply chain · Sustainable development · Sustainable supply chain

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1 Introduction

Nowadays, supply chain management is considered as one of the most important infrastructure resources to implement process-oriented and regular businesses in the world. One of the foremost topics discussed in supply chain management is regular activities and integrated and coordinated control of these activities. Supply chain management is a comprehensive approach to the regular management of goods and information flow. This flow of goods and information starts from suppliers and ends with final customers and consumers (Fallah and Nozari 2021). Supply chain management combines inventory management with a focus on operations management with communication analysis in industrial organizations. This field has become very important in recent years. The supply chain comprises all exercises related to the stream and change of merchandise from the raw material's arrangement or extraction to conveyance to the ultimate shopper, as well as the relative data flows. For the most part, the supply chain incorporates all exercises related to merchandise and the transformation of materials, from the raw material planning stage to the conveyance of the ultimate item to shoppers (Nahr et al. 2021). About the flow of goods, there are two other flows, one is the flow of information and the other is the flow of financial resources and credits (Aliahmadi and Nozari 2022).

Compared to the last decade, different headways in data technology have quickly changed the confront of the industry. The securing and usage of data technology presented a strategy to apply a unmistakable forceful identity to companies and the supply chain. The appropriation and effective usage of data innovation can improve the participation between individuals of the supply chain, through the fast exchange and conveyance of precise data and the utilization of data systems as well as expanding the effectiveness of the supply chain (Nozari et al. 2021a). The conducted ponders illustrate the impact that data innovation has on progressing responsiveness, dissemination, and transmission of data and the effectiveness of the chain. As a result, the advancement of participation in both inside and outside measurements leads to anticipating the rise of the leather whip impact and creating deals channels (Liu et al. 2016). Moreover, data technology applications in supply chain management with innovative approaches and data systems are exceptionally critical. In expansion, studies have illustrated that a few components such as the organization's measure, success rate, uncertainty, and weight from other chain accomplices can play a critical part in the acknowledgment of data innovation (Nozari et al. 2019).

Currently, transformative technologies such as Artificial Intelligence and the IoT are rapidly growing. These technologies include different layers such as sensors, communication networks, middleware and applications, and intelligent and learning analytical systems (Sim and Jeong 2021). The applications of these technologies are used in various fields such as homes, smart cities, industries, education, energy, transportation, business, etc. Artificial Intelligence and its subsets such as machine learning and deep learning in addition to the IoT play a significant role in industries, supply chains, and other fields (Najafi et al. 2022).

Recent evolutions in electronics and wireless communication have given the potential to design and manufacture sensors with lower power consumption, smaller sizes, reasonable prices, and various applications. The small sensors, capable of receiving different environmental information based on their type, and then processing and sending that information, have led to the emergence of an idea to create and expand networks known as WSN or Wireless Sensor Networks (Yang et al. 2021). The implementation of Internet of Things technology based on information clouds, using accurate and real-time information coverage, facilitates forecasting and planning processes, procurement and supply of resources, logistics and support, management of services and spare parts, and many sub-processes of the supply chain. These transformative technologies let organizations invest more in functional and production processes instead of high costs in software production, and this can lead to more and faster development and lower costs (Maryniak et al. 2021).

Organizations are now embracing and using AI and machine learning to refine core strategies for various items such as warehouse location optimization and periodic activities like availability, costs, inventory, transportation, suppliers, and staffing. As the demand for different products increases, transportation companies receive more demand and this makes artificial intelligence more useful. Utilizing artificial intelligence technology in the supply chain reduces implementation costs. These benefits include increased productivity, faster response times, greater visibility throughout the value chain, fewer errors in product delivery, higher quality at lower costs, plus the ability to anticipate customer needs (Hsiao and Sung 2022).

Numerous businesses have embraced artificial intelligence and the Internet of Things as a portion of their forms and items. Later surveys state that these two are the foremost well-known advances in utilization nowadays. It was also found that they are the pre-eminent innovations that companies contribute to expanding proficiency and making a competitive advantage. Combining these two advances makes a modern innovation called Artificial Intelligence of Things or AIoT (Rahchamani et al. 2022). Utilizing Artificial Intelligence, the IoT can make keen innovations that mirror intelligent behavior and can make choices with negligible or indeed no human intercession. While the IoT is around contraptions that interface with each other over the Internet, AI centers on gadgets that contraptions that learn from their experiences and information (Ghahremani-Nahr et al. 2022).

There are assorted sees on transformative advancements and their potential impact on sustainable development. The AIoT has exceptional potential to help in unraveling complex and interconnected challenges of sustainable improvement such as climate change, get to to health care, and dissimilarity. Numerous innovations and imagination within the field of the Internet of Things in expansion to Artificial Intelligence and other transformative innovations guarantee exceptional and alluring improvements in different businesses such as generation, benefit, horticulture, and supply chain. By merging these two smart innovations, we are going witness an insurgency in all divisions of society and businesses. The combination of artificial intelligence and the Internet of Things can redefine the way industries, businesses, and the economy work. The utilization of artificial intelligence in conjunction with the Internet of Things technology makes clever machines and frameworks that plan and mimic intelligent behaviors and empower capable decision-making with negligible human mediation. In other words, you can envision gadgets prepared with the combined innovation of the IoT and AI as a comprehensive computerized anxious framework that performs capacities through the commands of the system's brain (Hangl et al. 2022). AIoT will bring fundamental changes in the supply chain by improving efficiency in operations increasing profitability opportunities and reducing related costs. In today's market, the supply chain is not only used for product tracking. Rather, it is a way to gain a competitive advantage and even create a brand name.

In the rest of this chapter, we will examine the key features of these transformative technologies, as well as describe AIoT-based supply chains. A conceptual framework for this intelligent system will be presented and the effects of this intelligent supply chain system on the sustainable development of businesses will be analyzed.

2 Artificial Intelligence of Things (AIoT)

Devices equipped with the Internet of Things include wearable devices, refrigerators and freezers, smart assistants, sensors, and other equipment that are connected to the Internet. They can be identified by other devices and can collect and process data. Furthermore, when a system can perform a set of tasks or learn from data intelligently, it is known as artificial intelligence. Hence, when artificial intelligence is included in the Internet of Things, it implies that these gadgets can analyze information make choices, and act on that data without human mediation (Nozari et al. 2022).

The productivity and viability of a smart framework increase in combination with other inventive innovations such as machine learning (ML). The terms AI and ML are presently utilized to imply the concept of making intelligent computer programs. This intelligence engages them to study information and make choices as the human brain does. IoT gadgets point to gather and utilize data, machine learning, and artificial intelligence let us get it and make strides in the information collected from physical gadgets. As a gathering of related contraptions collect and total raw data, programs with machine insights capabilities analyze the data (Fig. 1). After an exhaustive survey, the extreme result contains valuable data (Chen et al. 2021).

The utilization of artificial intelligence of Things gives a wide run of central focuses on businesses and customers, checking personalization of the client encounter and intelligent mechanization. Manufactured insights within the IoT crunch ceaseless streams of information and find plans that cannot be recognized and found by routine estimations. In extension, machine learning merged with AI can expect operational conditions and recognize parameters that have to be changed to realize the needed outcomes. The artificial intelligence of Things can have tremendous volumes of data sent and gotten through gadgets. Since the total procedure is based on machines and computer programs, it can be completed without human interventions, arranging the botches caused by human botches and making strides in precision (Wang et al. 2021).

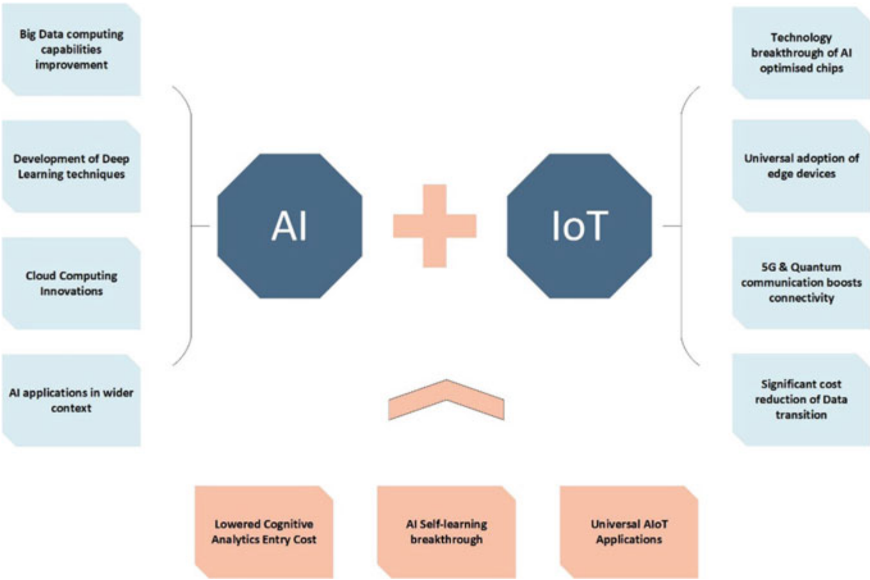

Fig. 1 AIoT combining the IoT and AI (Zhu 2021)

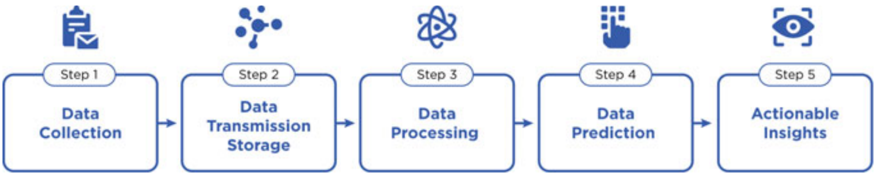

Fig. 2 Workflow diagram of AIoT-enabled devices (Takyar 2022)

The preeminent common IoT environment comprises sensors that make colossal entireties of information. Sometimes by transferring data between two gadgets, the AIoT environment analyzes it. The sequential steps of any AIoT-enabled solution are shown in Fig. 2.

Hence, it compresses huge sums of information into a sensible estimate, empowering the association of a huge number of IoT gadgets. In general, the features of AIoT can be described as follows:

- AIoT acts as a brain that controls the apprehensive framework to create optimal business decisions.
- AIoT, which enables intelligent decision-making in business processes, requires professional software codes composed by software engineers to perform different errands.
- AIoT is the advanced, advanced, and advanced era of the IoT, and its essential objective is to form autonomous operations without human bolster utilizing

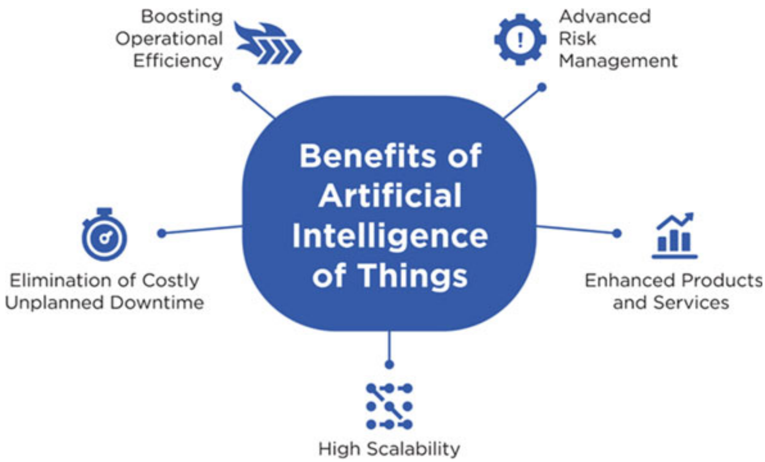

Fig. 3 The benefits of artificial intelligence of things (Takyar 2022)

artificial intelligence calculations and prescient support and repairs in one-stop forms.

- In AIoT, self-correcting IoT gadgets are made by analyzing information to make better decisions.

The advantages of artificial intelligence of things are shown in Fig. 3.

AloT makes a difference in foresee forms and this leads to more correct comes around inside the long term. One of the compelling works of AIoT's keen innovation and analytics is robotized robots that are utilized to convey products. These robots have user-defined sensors that collect and store data obtained from contraptions related to the Internet of Things. By having this smart and clever crossover innovation, businesses can better and more recognize the needs of clients and plan and supply their things in line with these needs. Along these lines, AloT advancement has various inclinations not only because it is for commerce but also conclusion clients. Artificial intelligence of Things is successful in achieving the following agile solutions:

- Manage, analyze, and gain meaningful insights from the data
- Fast assurance and accurate analysis
- Balance requirements for local and centralized intelligence
- Balance personalization with confidentiality and data privacy
- Maintaining security against cyber attacks

In a long time, the edge computing worldview has picked up impressive ubiquity. It serves as a key enabler for numerous future innovations such as the IoT, 5G, and AI. Thus, edge computing is the biggest driver of AIoT. By abusing the unused worldview of edge intelligence, emerging AIoT resource-intensive and computationally serious applications can be viably backed at the edge of the arrange. Hence, Edge Computing is basic to attain the quick preparation capacity and moo idleness required in smart IoT applications (Aliahmadi and Nozari 2022).

Afterward impels in equipment and machine learning have quickened the arrangement of billions of associated, intelligent, and adaptive gadgets in basic frameworks such as health, environmental control, logistics, coordination, transportation, and cultivating. Moving AI preparation from the Cloud to associated and disseminated edge gadgets offers an arrangement to overcome the bottlenecks, inactivity, and protection issues of cloud-based AI applications. Compared to low-power IoT gadgets, AIoT requires edge gadgets with satisfactory computing resources to perform on-device machine learning assignments. In any case, the asset capacity and control budget of edge gadgets are normally restricted. Along these lines, AIoT applications are based on an optimization challenge to alter.

In general, the IoT combined with AI technology has the potential to provide the best solution for advanced system functional experience. Business can be improved by integrating artificial intelligence and data received from IoT devices. The integration of two advanced technologies leads to intelligent devices that help companies make strategic decisions with zero error (Nozari et al. 2022).

3 IoT and Sustainable Development of the Supply Chain

In today's world, with the increasing use of the Internet in people's daily lives, various life processes and businesses have been greatly affected by Internet-related technologies. By using the connection of product audiences through technologies related to the Internet network, two-way communication between audiences and business marketers has been established at any time and in any place. The IoT technology has many useful tools that make marketing processes powerful (Kian 2022). This growing technology, in addition to causing fundamental changes in society, can be a smart solution to create sustainable development in societies. Having up-to-date and growing technology, along with other key indicators such as the growth of specialized employees and the investment of countries in the field of technology-based industries, are other important factors in the industrial and social development of countries (Obaid and Nozari 2022). Hence, due to the significance of choosing the proper innovation for the victory of improvement and financial development of society, there are systems for actualizing the Internet of Things in creating sustainability (Nozari et al. 2021b).

Supply chains have a coordinated and tremendous effect on society, the environment, and budgetary execution. With the suitable utilization of later advances, supply chains have more prominent potential to make and encourage a sustainable world. Better driving routes can be found utilizing a coordinated IoT arrangement with the assistance of other advances. Subsequently, it is conceivable to diminish the utilization of diesel and gasoline by cargo vehicles, which are one of the biggest buyers of vitality and contribute to the emanation of nursery gasses. Another benefit of the Internet of Things about sustainability is the reduction and elimination of waste. By

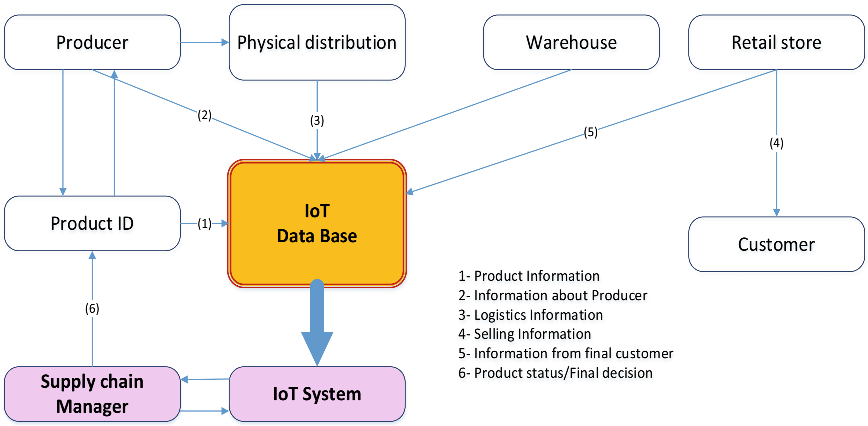

Fig. 4 IoT-based Supply chain (Končar et al. 2020)

using Internet of Things technology, we are going to be able to track all merchandise from root to goal, and we can even see the movement path. Therefore, the possibility of any fraud, damage, and theft will be reduced (Nozari et al. 2022).

One of the foremost imperative challenges of production and logistics organizations is the security challenges that the Internet of Things can help to increase and improve safety in this organization. For example, sensors connected to the Internet can be placed everywhere in a business environment and used to monitor processes. The data obtained from behaviors and activities in all processes are practical data that can be used to analyze risky behavior. Figure 4 shows a supply chain based on the IoT.

In Fig. 4, arrows show the flow of information. Internet of Things tools act as the foremost sources of data collection and extraction, refine, and maintain data from all active elements in the supply chain. The addition of analytical tools to these transformative systems can increase the operational power of the supply chain and the active actors in it.

Knowing where products and materials are at any given time can help companies maintain appropriate inventory levels. By forecasting supply and demand; and ensuring the supply of resources from stable partners; To save energy, fewer, shorter, and more direct delivery routes can be created, reducing waste throughout the supply chain. This in turn can help minimize the carbon footprint of the supply chain. The delivery and procurement process has potential quick wins for reducing greenhouse gas emissions and increasing sustainability, whether through increased use of technology to improve efficiency or by ensuring partners adhere to more sustainable practices (Nozari et al. 2021a).

By imbuing everything in the supply chain with digital intelligence, companies can truly revolutionize the way products are manufactured, distributed, sold, consumed, and reused. But more importantly, such efforts don't just translate into healthier profits, they may save the planet (Valero et al. 2021).

As mentioned earlier, using sensors embedded in the IoT provides valuable insight into products. Not only can you track purchasing patterns, but you can also monitor the condition of products such as heat and humidity to detect if they are defective. Preventing defective products before they leave the warehouse is critical to maintaining customer satisfaction. Unfortunately, transporting goods between processes contributes to global greenhouse emissions in warehouses. To reduce the effects of emissions, smart technology such as the Internet of Things identifies the best direct route for your goods during the logistics process. As for the last-mile delivery phase, autonomous vehicles are about to dramatically change supply chains across all industries. Big companies like Amazon are already channeling resources into testing self-driving and delivery robots. High quality is a universal goal that companies should strive for! Automation enables consistent results that aid in precise quality control by eliminating human error. For example, IoT technology increases efficiency by automatically collecting data at a granular level for management use.

The digital transformation of the supply chain that integrates the Internet of Things is revolutionizing logistics processes. This technology will only continue to evolve with time, and thus, will create stronger capabilities to create a resilient and sustainable supply chain. With the real-time tracking functions of the Internet of Things, it is possible to ensure that the supply chain is on track for optimal management of inventory/warehouses, transportation, and delivery.

4 Artificial Intelligence and Sustainable Development of the Supply Chain

Artificial intelligence is an umbrella term for a set of technological algorithms and approaches that allow machines to simulate human cognitive functions such as reasoning and learning. Since the development of digital computers in the 1940s, it has become clear that computers can be programmed to perform complex operations such as proving mathematical equations, problem-solving, decision-making, thinking and reasoning, and exhibiting human-like reactions. Artificial intelligence can be used to solve the challenges of sustainable development, such as methods of diagnosing various diseases, combating illegal hunting of wildlife, improving the performance of crops, etc. (Maryniak et al. 2021). Technology can use all available data capacity. In this way, it can inform businesses of existing risks and provide solutions to existing problems. This capability allows organizations to make better decisions and use resources optimally. Artificial intelligence can do all these equations much faster and more accurately than before. This is the reason for more use of artificial intelligence in the supply chain.

Artificial intelligence (AI) has many wonderful applications. One of its applications is in all parts of the supply chain. In addition to artificial intelligence, machine learning is also used in the field of transportation. Organizations are presently grasping and using machine learning to refine center procedures for issues such as warehouse location optimization and day-to-day exercises such as accessibility, costs, stock, transportation, providers, and staffing. As the demand for different products increases, transportation companies receive more demand and this makes artificial intelligence more useful (Nahr et al. 2021). Smart transportation has numerous arrangements for numerous issues. Some artificial intelligence solutions for transportation are:

- Resource management
- Forecasting variances in worldwide transport volumes recently happen
- Optimization of shipping courses and quicker conveyance
- Better customer service
- Advanced image recognition capability that distinguishes the status of items and shipments
- The capacity to foresee and screen parameters such as activity, climate, and socioeconomic issues for more exact cargo estimating

Utilization of artificial intelligence technology in the supply chain reduces implementation costs. These benefits include increased productivity, faster response times, greater visibility throughout the value chain, fewer errors in product delivery, higher quality at lower costs, and the ability to anticipate customer needs (Nahr et al. 2021).

Artificial intelligence is used in warehousing to predict demand, modify orders, and reroute products. For example, you will be able to alter your orders agreeing to these figures and, if necessary, deliver the requested goods to local warehouses. On the off chance that there are different distribution centers within the supply chain, AI can connect them to discover the leading shipping choice. Anticipating demand for certain products and planning will improve service, reduce shipping costs, and save a lot of money. Computer vision innovation utilized in distribution centers permits the distinguishing proof and organization of distinctive things. This sort of innovation will offer assistance with quality control in the future and kill the requirement for human supervision (Nozari et al. 2021a). By using intelligent algorithms, it is possible to accurately predict warehouse stocks, and by using smart solutions, a lot of improvement in warehouse management and reduction of costs related to inappropriate stocks can be obtained. The use of artificial intelligence can help reduce costs and improve productivity in delivery and distribution processes. By using smart solutions, delivery and distribution processes can be improved and productivity can be increased by reducing costs. With the use of artificial intelligence, it is possible to better analyze the purchase patterns and demand of customers and identify problems that may cause product returns. By improving quality control and inspection processes, shipments that have caused product returns can be avoided. Also, by improving the processes of after-sales service and communication with customers, it is possible to better manage customer needs and avoid sending inappropriate goods. Therefore, the use of artificial intelligence in supply chain management can help reduce the costs related to the payment of returns and after-sales services, and also improve the quality of goods and products, customer satisfaction, and improve their shopping experience.

Artificial intelligence has the possibility of providing algorithms to predict these trends. Different tests have shown that artificial intelligence tools provide even better predictions than human experts. Another advantage of using artificial intelligence is improving the experience of customers and buyers. By using artificial intelligence, we will always have the possibility of personalizing data based on customers' tastes and interests, and this can help improve customer experiences. Clients appreciate a more personalized involvement and are more steadfast to the company. Combining artificial intelligence with robotic process automation (RPA) has made an innovation called cognitive computerization. Artificial intelligence combined with robotic process automation helps employees improve their performance by increasing productivity and accuracy. For illustration, a few monotonous assignments related to information can be done consequently with the assistance of AI. In this way, office robotization makes a difference in supply chain companies to spare both time and cash. Some employees such as accountants and HR professionals can be replaced using this type of technology. As a result, the possibility of human error will decrease.

Artificial intelligence can be used to analyze chemical and biological systems and increase efficiency in plant breeding, biotechnology, and agricultural chemistry research. With the ever-increasing amount of data on farms, artificial intelligence is essential for farmers to use this data to make better decisions. The objectives of maintainable improvement have a complex structure. Sustainable development includes various topics and topics such as environmental and climatic conditions, and social and cultural structures, and includes all elements of society from industry to culture. Comprehensive coordination is necessary to achieve these goals. Therefore, it can be seen that artificial intelligence as a solution-creating and analytical technology can provide many facilities to different departments and increase the capabilities of organizations for sustainable development. These capabilities include forecasting demand, improving production and distribution performance, reducing costs, and increasing productivity. Considering these issues, it seems that the use of artificial intelligence in supply chain supply management is necessary and very effective. The use of artificial intelligence technology in the field of supply chain supply management can lead to better performance, increase customer satisfaction, and improve competitiveness. The use of AI can help managers improve the sustainability and performance of the supply network by applying intelligent algorithms. By analyzing the available data, it is possible to identify the patterns of customers, suppliers, and different processes, and by applying smart solutions, a lot of improvement in the performance of the supply network can be achieved.

5 AIoT-Based Supply Chain in Sustainable Business Development

Supply chain management in today's era includes parts of e-commerce that seek ways to reduce product production time and improve services. In this way, it employments the most recent propels in administration science and innovation, including the Internet, the World Wide Web, and the data advances of the Internet of Things. Supply chain management in today's mechanical environment could be a modern administration strategy that has a direct impact on the success of organizations in today's highly competitive business environment. In recent years, supply chain management, with its new approach to management issues, has been able to bring about a change in the reduction of implementation costs the correct implementation of management issues, and the production of quality products in organizations. However, the implementation of supply chain management can be useful in organizations when it can show itself well in interaction with the goals and components of the organization.

On the other hand, with the rise of transformative advancements such as the Internet of Things and artificial intelligence and their combined advancement such as AIoT, the world has changed certainly; Through the use of AIoT, assorted programs and contraptions can communicate with each other through the Web affiliation. The reason for AIoT is to arrange the separation between commerce shapes inside the honest-to-goodness world and their representation in data frameworks. Data organization is considered one of the first basic competitive resources for any organization, as various acknowledge that companies that can get data as quickly as conceivable and bring it to the down-to-earth arrange will be more fruitful in competitive promoting. Considering the changes in the approach inside the field of supply chain organization and AIoT learning, it is imperative to arrange an exhibit for the supply chain based on the Internet of Things and utilize information administration approaches in an organization. These innovations allow supply chain companies to diminish costs, truncate thing movement times, decrease negative normal impacts and finish remarkable levels of mechanization. A critical point almost the relationship between AIoT and the supply chain that gives rise to a shrewd supply chain is that such a supply chain may be a self-improving and completely adaptable framework that can perform well in an unusual environment. A keen supply chain will moreover incorporate consistent data sharing and, of course, persistent optimization of workflows based on real-time information. To better understand what a keen supply chain is, you ought to know that such a framework can handle numerous things, counting deals history, climate conditions, and the sorts of information it gets from its sensors, hence giving much superior execution in coordination and supply chain.

As mentioned earlier, AIoT is at the intersection of AI and IoT. The term particularly reflects the integration of computer program capabilities such as ML and AI with the framework perspectives of the IoT. Considering the huge potential for AIoT to reduce costs, increase productivity, and improve quality, there are many applications for this technology in businesses. One of the most important parts of the production business is the organization's supply chain, which can be made more

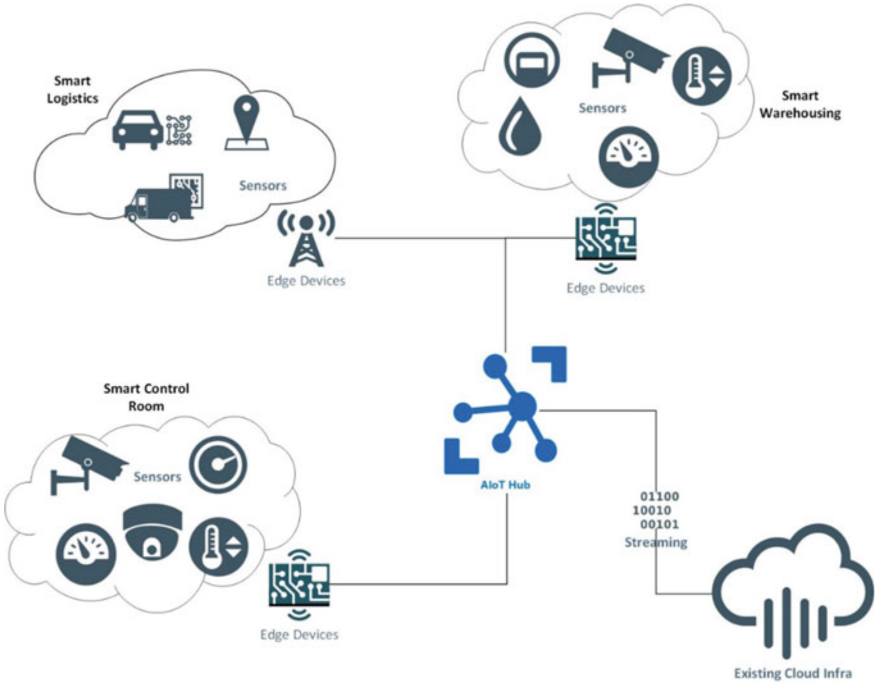

Fig. 5 Basic applications of AIoT in the supply chain (Zhu 2021)

powerful by using AIoT and taking fundamental steps in the direction of sustainable development. Figure 5 shows the basic applications of AIoT in the smart supply chain (Nahr et al. 2021).

The way companies organize acquirement nowadays is not feasible. Supply chains are not continuously environmentally inviting, and it is troublesome for organizations to strike a balance between the leading speed, adaptability, taking a toll, and carbon impression when it comes to transporting and conveying their products. In a perfect world, organizations would have a sustainable, cost-effective, and efficient supply chain for their items—in any case, this can be not continuously conceivable utilizing right now accessible strategies of transportation. Nevertheless, new technologies such as big data analytics from the Internet of Things and artificial intelligence can help companies make positive changes and ensure that their supply chains are as efficient and sustainable as possible. The utilization of AIoT can have a noteworthy effect on supply chains, making a difference in organizations taking advantage of the fastest, cheapest, and most feasible courses for transportation and combining these seamlessly.

For a supply chain manager, this level of complexity provides too many variables for people to calculate. It is impossible for the human brain to quickly adapt to the changing information received from hundreds of suppliers and other stakeholders in a typical supply chain. The list of data sets is endless: operational capacity, past performance, availability of green transportation modes, carrier prices, estimated transit times, and the likelihood of route disruption are just a few. The AIoT is a way that a business can effectively extract, analyze, and manage this volume of data.

The role of AIoT in supply chain management is a key and very important role that can help reduce energy consumption, optimize various processes, reduce costs, etc. AIoT and supply chain are very closely related to each other today, which can undoubtedly affect the future of industries, businesses, and many different organizations.

Using this data set from the Internet of Things, AI technology can rank and identify the biggest levers to decrease the carbon impression. One of the most important and perhaps most surprising capabilities of AIoT is the place of realization. The right choice can reduce the carbon footprint of a business by almost 30% and has a huge impact on other factors as well. Keeping the right products or services close to end-users means that vehicles to deliver goods and services travel less distance and loads are lighter. Both of which are effective factors in reducing carbon effects. However, this is one of the applications of AIoT in the supply chain for sustainable development. For shipments, AIoT can also help calculate the route with the least miles traveled in heavy transport modes and times with the least possible delay by accurately receiving IoT-based big data and AI-based analysis. Businesses can also adopt a multi-carrier strategy, where the artificial intelligence of things automatically selects the operator with the greenest fleet and can automate carrier switching in case of problems. This in itself is a way to develop sustainable supply chains (Aliahmadi and Nozari 2022).

The transparency afforded by IoT technologies in AIoT-based supply chain processes provides great insights into the status of your inventory, customers, and the market. For example, products with built-in sensors can inform you of your current shopping pattern. Therefore, this technology provides valuable information on how to adjust production volumes to accurately reflect the real-time market situation. Even if it does not have a complete view of the supply chain, that transparency would not be valuable if the technology does not provide you with actionable insight. AIoT provides predictive power to identify potential growth opportunities based on real-time supply chain data (Khan et al. 2023).

By introducing AIoT technology in the warehouse, employees can prevent work-related accidents. For example, computer systems can perform repetitive tasks that are potentially dangerous for warehouse workers, or wearable technology that can detect and warn workers of dangerous conditions. Risk diminishment is one outline of the feasible improvement of smart supply chains. Diminishing risk, reducing disturbances in operational forms of the supply chain, and expanding the responsiveness of the supply chain are noticeable highlights of a maintainable Smart supply chain framework based on AIoT (Nahr et al. 2021). Figure 6 shows the framework for this intelligent and sustainable supply chain based on AIoT.

Due to the importance of sustainable development, this concept is examined by macro-indicators of sustainable management and considering ecosystem, economic, and social considerations. In addition to this, current supply chains are exposed to a wide range of risks, which can put the execution of providers and the complete supply chain at risk. For these reasons, understanding the cause-and-effect connections of

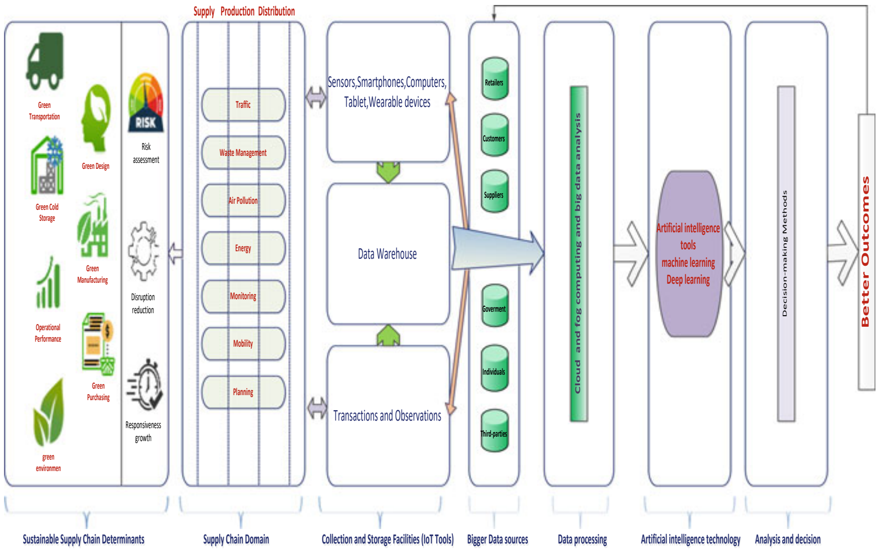

Fig. 6 AIoT-based smart and sustainable supply chain framework

the components that play a part in these supply chains and the part of transformative technologies is essential.

The framework presented in Fig. 6 is a cause-and-effect framework that shows the elements influencing the smart supply chain based on the Internet of Things with an emphasis on sustainability indicators. The effective ranges of each tool are shown. Understanding this system can be an important direct for actualizing these capable and steady systems.

6 Conclusion

Considering the importance of information flow and its role in the supply chain, it can be said that information technology causes improvement in an organization. Goals such as reducing organizational costs, employee satisfaction, and creating a business brand can be considered. Moving organizations towards the AIoT system has been a great development in this field and has created productive and functional infrastructure. The development of a powerful database facilitates the processes of planning, forecasting, and resource support. On the other hand, the role of knowledge management is more visible in this approach. The required information should be communicated to users at the right time and place so that users can access product information, inventory levels, customer information, and information related to the supply chain. It also helps to know other information available in this field, including the appropriate marketing approaches, customer orientation, and the required products. IoT builds up communication between individuals and things with the assistance of apparatuses such as sensors, controllers, and other different gadgets such as RFID labels and indeed portable gadgets. Intelligent logistics frameworks are built on IoT stages and can control and analyze a huge sum of information automatically. Whereas within the conventional mode, the forms of filtering things and entering information were frequently done physically. Big data investigation apparatuses can oversee expansive volumes of information produced by IoT gadgets. IoT totals data collected from different sensors and big data analytics apparatuses can utilize this data to store and create experiences. Big data investigation instruments can oversee expansive volumes of information produced by IoT gadgets. IoT totals information collected from different sensors and big data analytics instruments can utilize this data to store and produce experiences. Artificial intelligence solutions are available for organizations to achieve better performance in supply chain management. These solutions have different features: demand forecasting models, transparency throughout the supply chain, integrated business planning, dynamic planning optimization, and physical flow automation, all based on determining models and relationship investigation to better get it causes and impacts in supply chains, including these are features. Sustainability is one of the increasing concerns of supply chain managers because most of the indirect problems of an organization are caused by its supply chain. The concurrent utilization of artificial intelligence and the Internet of Things can offer assistance to make strides in supply chain operations to make them greener and more economical. AIoT-enabled gadgets can offer assistance to optimize transportation courses by taking into account variables such as traffic, road closures, and climate to diminish the number of miles traveled. As AIoT-based expectations can offer assistance in keeping up ideal stock levels, carbon outflows caused by putting away and moving overabundance of stock can be decreased. Smart energy utilization arrangements can moreover decrease carbon emissions related to warehouse vitality utilization. AIoT combined with big data can offer assistance to the supply chain to become not as it were economical but moreover adaptable.

The mentioned items are some of the most important and up-to-date applications of artificial intelligence in the supply chain and logistics that businesses can use to improve their profitability. The speed of technological progress makes these applications increase day by day and it is likely that shortly, it will affect all parts of this field. The mentioned items are some of the most important and up-to-date applications of artificial intelligence in the supply chain and logistics that businesses can use to improve their profitability. The speed of technological progress makes these applications increase day by day and it is likely that soon, it will affect all parts of this field.

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AIoT and Its Trust Models to Enhance Societal Applications Using Intelligent Technologies

Kousik Barik, Sanjay Misra, Raghini Mohan, and Biswajeeban Mishra

Abstract Artificial Intelligence (AI) remain evolved as a central focus on international terrain, whereas the Internet of Things (IoT) is balanced to convey transformative changes in diverse disciplines. The anticipated revolution of sustainable future growth is likely compelled by the integration of Artificial Intelligence and the Internet of Things (AIoT) owing to this technology's comprehensive coverage of applications. The AIoT application fields are extensive and diverse. It is imperative to emphasize the Sustainable Development Goals (SDGs) of technical evolution. This chapter aims to identify the significance of artificial intelligence in IoT and the trust models in integrating AI with IoT. The impacts of SDGs on digitization are emphasized, and security measures for AIoT are outlined. The strategies and drivers for SDGs toward digitization are emphasized in the context of AIoT. The chapter further outlined the existing challenges and future research directions.

Keywords AIoT · Artificial intelligent · SDGs · Digitization · Security

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1 Introduction

Industry directors must monitor societal and environmental balances and per-form satisfactory returns to achieve long-term company conquest and endorsement. This is especially correct during times of rapid technical evolution. Artificial Intelligence (AI) is a precious breakthrough technology helping drive this transition (Bronner et al. 2021). AI is classified into two types, each further classified according to its capabilities and applicability. This study analyses how Artificial Intelligence of Things (AIoT) based on the SDG can help extend the digital revolution.

The applications built for the Internet of Things (IoT) have profoundly influenced our energy, providing new significance to how people and businesses go about their everyday practices. Billions of commonplace items feature cutting-edge computing capabilities, wireless networks, and sensors (Sestino et al. 2020). This outbreak includes wearables, home applications, healthcare systems, and smart cities. The IoT reminds us of the growth of the most interconnected physical devices, which can process and forward data in real-time (Firouzi et al. 2022). Integrating advances in AI with IoT data streams can help better comprehend how things work, build more productive relationships between humans and machines, and strengthen da-ta communities and analytics. Using AI, IoT data enables the conversion into helpful information for improved valuable insights, applying the foundation for cutting-edge inventions (Hong Yun et al. 2022). AI contributes to the IoT with machine learning capabilities. IoT contributes to AI with connectivity, motioning, and communication replacement and AIoT is a transformative invention. With the accumulation of IoT systems among the most successful businesses, the im-portance of shapeless data generated by humans and machines has become inevitable (Awotunde et al. 2022). AIoT may assist in clarifying data analytics that can emanate intentions from this IoT-created information. Through AIoT, which is invariant to IoT systems, artificial intelligence is entrenched in communication agents, such as workshops, processors, and edge analysis. The classification of AI is shown in Table 1.

Table 1 Classification of AI

Type-1					Type-2	
Narrow AI	General AI	Strong AI	Reactive machines	Limited memory	Theory of mind	Self-awareness
A common type of AI that performs a specific task	General AI performs intellectually similar to the human brain	Strong AI performs more than human intelligence in a better cognitive aspect	Machines that do not store past activities are reactive. They perform in real-time	Machines store past activities in a limited manner and perform accordingly	Machines understand human emotions, and such machines are under research	Machines are the future of AI, and such machines are more powerful than humans

Application programming interfaces are then utilized to improve the interoperability between the hardware, software, and platform layers. These elements focus on facilitating the framework and process approach by deemphasizing data. Although AIoT is unaltered and novel, numerous prospects exist for enhancing enterprise sectors such as business, commerce, and consumer development (Wu et al. 2022). They continued throughout their development. The cost is associated with the unpredictability of the adjustable chains and transportation processes. AIoT can help businesses and consumers in several ways (Ghoreishi et al. 2022). These include functional involvement, data reinterpretation, and insightful automation. Artificial intelligence in IoT utilizes a constant flow of data and deter-mines the strategies that need to be revised for primary assessments.

Furthermore, machine learning correlated with AI may forecast functional prerequisites and confine constraints to be adjusted to ensure optimal outcomes (Bustillo et al. 2021). Therefore, the intelligent IoT recommends determining which tasks can be adjusted to improve productivity. Integrating AI with the IoT enables companies to discover and predict diverse threats. It allows for handling economic adversity, expected protection, and digital hazards (Chang et al. 2022). This chapter explores the role of artificial intelligence in the Internet of Things. The different types of trust models used to integrate AI with IoT. There are different types of security measures used in digitizing AIoT. This chapter aspires to ad-dress the following research questions.

- RQ1: What is artificial intelligence's significance in the IoT context?
- RQ2: What are the trust models used in integrating AI with IoT?
- RQ3: What are the impacts of digitization on sustainable development?
- RQ4: What are the strategies and challenges in security measures for digitizing AIoT?
- RQ5: What are strategies for enhancing security capabilities for SDG?

The major contributions of the chapter are under:

1. A taxonomy is presented for the classification of trust models for integrating AI and AIoT in Sect. 1.
2. A taxonomy of security measures of AIoT is demonstrated in Sect. 2.
3. The common security IoT architecture is pictured in Sect. 3.
4. The strategies and challenges for enhancing security capabilities for SDG are illustrated in Sect. 4

The remaining chapter is formulated as follows: Sect. 2 concerns the role of artificial intelligence in the Internet of Things and the trust models used in integrating AI with IoT. The impacts of digitization on sustainable development and the security benefits of digitizing AIoT are conferred in Sect. 3. The strategies and challenges for enhancing security capabilities for SDG are demonstrated in Sect. 4. The discussion is presented in Sect. 5. Finally, the chapter is concluded in Sect. 6.

2 Role of AI in IoT and Trust Model Integration

The present research focuses on enabling the widespread deployment of billions of IoT gadgets across various applications on a global scale. These network devices are linked via the internet interaction data and enable efficient communication. After the splendid existence of the sensor arena, IoT plays a tremendous role in multiple applications like home automation, environmental monitoring, the defense sector, and vehicle automation. Resource-constrained devices and variable fluctuations within wireless devices lead to frequent disconnection issues. Such is-sues lead to crucial downstream nodes disconnecting from the network (Bagchi et al. 2020). Due to this, consequential effects include authentication failure, inappropriate access, disclosed data, and resource damage. Aaqib et al. (2023) presented a study on trust management models for maximizing these connecting de-vices' working nature. These devices must be smart enough to connect and collect data.

Ghosh et al. (2018) discussed AI, which replaces human smartness in an era of machine-made intelligence to enable the future with such intelligent devices. AI pronounces zero risk capabilities, avoidance of biased decisions, and intelligent applications. When AI and IoT are integrated, both depend on each other to practice and pronounce technological innovations in the future. Ozdemir and Hekim (2018) analyzed IoT devices connected via the internet, which will generate vast amounts of data that must be analyzed appropriately. AI places its illustration here, where AI algorithms can support IoT devices to handle vast data. Thus, IoT device depends on AI algorithms to get the outcome of analytical reports. AI depends on IoT devices to obtain real-time data for any application. AI integrated with IoT builds the era of AIoT (Chang et al. 2021). This prompt rise of AI, IoT, and 5G networks paved a vast space in intelligent business applications. The information provided by IoT widgets is being integrated and interpreted for automatic data and image analytics.

Figure 1 depicts how the IoT devices are connected to integrate with Artificial Intelligence, and thereby, AIoT outcomes and their corresponding analytical result are obtained for innovative applications. IoT devices such as mobile, sensors, and smart TVs are connected through the internet to the IoT cloud and integrated AI for analysis and prediction. AIoT plays a significant role in intelligent agriculture; choosing fertilizers has been automated to analyze the reaction of fertilizers according to the external environmental condition. Harvest control and usage of land levelers for different types of lands are also automated using AIoT (Pan and Zhang 2021). AIoT steps into other significant applications such as Healthcare, Intelligent Surveillance Systems, Plant Monitoring, and Environmental Sensing. Vinuesa et al. (2020) reviewed pertinent proof that AI may serve as an enabler on 134 targets (79%) across all SDGs, typically via technical advancement, that may enable overwhelming particular current constraints. AIoT devices can analyze da-ta to discover patterns and understandings, adapting system operations to enhance efficiency. This adaptability allows for real-time adjustments to be made. Data can be generated and analyzed to identify failure instances, allowing the system to make necessary adjustments. The significance of AI in the context of IoT is delectated in the section (RQ1).

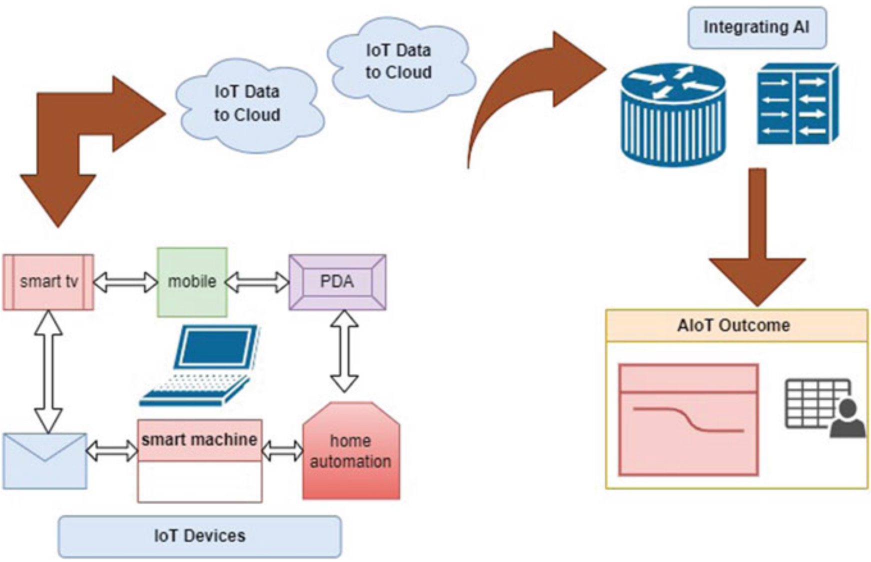

Fig. 1 Integration of AI with IoT

Traditional trust models could be more efficient in solving the challenges; hence, studying AI-based Trust Models is necessary to implement a trustworthy environment. There are many trust models based on knowledge information about trustors and trustees. There are many challenges in the traditional trust models, such as calculating trust factors and ensuring accuracy in trust calculations. Thus, a detailed analysis and research contribution toward an artificial intelligence-based trust model is needed to overcome the discussed challenges. The literature of several articles results in a broad taxonomy of trust models (Najib and Sulistyo 2019). The two main classifications are Trust Management and Artificial Intelligence. The two main classifications of trust management-based trust models are Decision and Evaluation (Papakostas et al. 2016).

Al-Shamaileh et al. (2022) presented a study on the decision model based on policy-making decisions. The adopted policy should be suitable for any environment with complex devices. The decision model is further divided into propagation, behavior, and hybrid. Each node generates trust outcomes with all other nodes. Chen et al. (2014) analyzed that the node point is where the individual nodes or devices will propagate trust scores unassisted without the help of the cluster head. In the cluster point, the head controls all the node connections. With this information, a node can compute the trust values. Sometimes, direct observations are more vital to evaluate trustworthiness.

When such trust computation is done, a node that predicts other nodes becomes authentic, and the malicious node's score becomes negative. The behavior node works perfectly against on–off attacks (OOA). During such attacks, the malicious nodes are identified either by the node's position or the density of the malicious node. Further, this model is being enhanced as predictability trust, which enforces predicting future trust values based on the previous behavior. A Dynamic Trust Management Model (DTMM) was proposed to speed up the process, where the nodes will evaluate nearby nodes individually. This evaluating node will reward the trust nodes and punish the malicious nodes. Gao et al. (2021) studied the hybrid model; recommendation-based trust calculations declare a node's trustworthiness. Hybrid works differently for different types of networks.

Boucetti et al. (2022) studied the evaluation model focusing on Quality of Ser-vice (QoS) parameters: energy consumption, computation, throughput, and bandwidth. The two types of trust assessment are direct trust value evaluation and indirect trust value evaluation. Direct trust value evaluation is based on collecting the history of information from transmission among instruments. Indirect trust value evaluation is complex since direct proof or history of communicating entities is not focused. Indirect trust value is often computed based on recommendations and feedback.

The evaluation model is classified into statistical, probabilistic, fuzzy, belief theory, entropy, and Bayesian inference models. Rafey et al. (2016) analyzed that statistical evaluation is based on mathematical computations from the feedback obtained from node interactions. The trust calculation is based on the parameters such as computation power, response, and context awareness. This statistical approach gains benefits by avoiding spoofing attacks. This model is established on the Probability Distribution Function to compute the trust value of a node. The probabilistic model is classified into Belief Theory and Bayesian Assessment Method. Arisdakessian et al. (2022) presented a novel methodology for belief theory that classifies trusted and untrusted nodes through a belief method that avoids several attacks. The Bayesian assessment method is based on a node's direct and indirect trust values.

By correlating both values, specific knowledge will be gained to make secure da-ta delivery. This model ensures avoidance of malicious nodes, but a change in trust value is not done and demonstrates a node's trustworthiness towards the fuzzy concept. Fuzzy models are based on the Fuzzy Set Theory (FST), from which data efficiency is obtained by enforcing trust computation on IoT devices (Soleymani et al. 2017). The variables considered for trust computation are recommendations, experience, and knowledge. Krishankumar and Ecer (2023) presented a study on including trust, which could increase the number of devices without affecting the productivity of all nodes Krishankumar and Ecer (2023). Alowaidi (2022) proposed a fuzzy model approach that uses a grid-based environment to evaluate trust based on on–off attacks and secure messaging schemes within all nodes. The graph Theory model is based on social interactions between IoT nodes.

Kumar et al. (2015) presented how nodes will propose the opinions of all other nodes through paths to reach a particular node. By comparing the iterative recommendations and observations among the nodes, a graph can be predicted to outline the trust among nodes. Initially, challenge-response trust evaluation was developed, which resulted in less overhead and strong cooperativeness among nodes. Subsequently, a novel trust model incorporating entropy was introduced, referred to as the entropy weight method. This model quantifies the trustworthiness of entities and classifies nodes based on their degree. Wang et al. (2020) showed that this approach regularly updates a node's trustworthiness. This model identifies only malicious nodes but fails to detect internal attacks. Herewith, basic trust models used for trust management have been studied. Al Batayneh et al. (2021) studied to integrate AI with IoT, AI-based trust models are necessary by which intelligent solutions are implemented to existing IoT devices. The influence of AI algorithms with IoT generates future trends toward intelligent applications. AI-based models are classified into data mining and deep learning models.

2.1 Data Mining-Based Model

Savaglio and Fortino (2021) proposed a study on Machine Learning (ML) techniques and IoT platforms combined to develop an intelligent environment and accumulate various features like analysis, decision-making, acting, learning from action, and interacting with the environment. Figure 2 shows how the real-time dataset obtained from IoT devices is processed by ML algorithms and trained by AI techniques. This ML-based model is further classified into the Direct Trust Evaluation and Assisting Trust Evaluation Model (Muzammal et al. 2020).

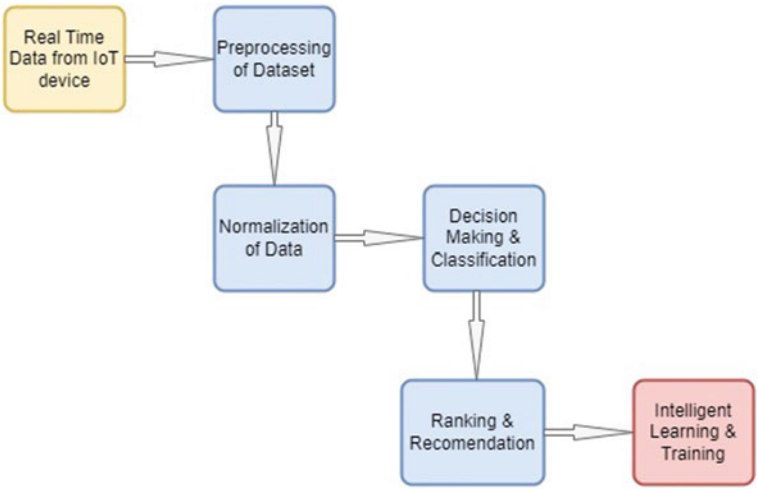

Fig. 2 Combining AI and ML with IoT data

2.2 Direct Trust Evaluation Model

ML algorithms use trust features by which evaluation is done to notify whether the node is trustworthy or not. Al Ridhawi et al. (2020) study some ML techniques, such as binary, numeral, and hybrid rating, and will use learning granularity to measure trust. The binary is based on two values over the trustworthy and non-trustworthy of a node. Logistic regression is one of the ML techniques that use binary rating, mainly used for routing protocols to identify the trustworthiness of nodes forming the path toward the destination. Lopez and Maag (2015) pronounce numeral rating in terms of value for the trust, like 0 means neutral, 1 means trusted node, and -1 means non-trusted node. Also, the trust factor based on the Naïve Bayes Classifier is used to achieve a robust decision-making process. The Apriori algorithm is supported for pattern analysis, and a naïve classifier makes final decisions to declare whether the nodes are trusted. Hybrid achieves both discrete and binary ratings. The ML techniques in (Abderrahim et al. 2017), which use hybrid rating, are K-Nearest Neighbor (KNN), Decision Tree (DT), and Random Forest (RF). KNN compares query context with the past query and finds social similarities and service importance for the application. DT identifies and classifies the behavior of the node. RF combines several DTs and gives an accurate result for high-dimensional applications where the missing data is easily found. Kalinić et al. (2021) presented a study on an Artificial Neural Network (ANN) that represents an intelligent trust management system that standardizes a node by giving suggestions about its trustworthiness. Q-learning is a technique that uses a hybrid trust model combining fuzzy logic and Q-learning.

2.3 Assisting Trust Evaluation Model

Liu et al. (2021) proposed evaluation models where the data is executed to select the trust of the nodes. K-Means classifier is given to find out the insider attack. Each node is assigned fewer performance metric values, so the initial attack is easily identified. Further, classifiers and regression are used to detect whether or not the node is trusted. Saeedi Emadi and Mazinani (2018) presented the DBSCAN algorithm, a highly complex computation algorithm operating on some input parameters. DBSCAN operates on the entire dataset, but it could be more efficient for massive high-dimensional data applications. When the data becomes enormous and uneven, the clusters formed become far from each other resulting in inefficient execution. The chameleon technique builds a trust layer for IoT devices due to its methodology of creating hash parameters. The security issues faced by the centralized system are solved by the distributed chameleon method. Malicious nodes are easily avoided in this scenario (Zhang et al. 2021). The study outcomes shown by the above Ml algorithms to integrate with IoT are satisfied, but the potential impact still needs to be accomplished for many services. Parameters such as trust evidence, computational overhead, and secure protection are only partially analyzed (Puliafito et al. 2019).

The performance of the algorithms could be analyzed more in terms of metrics such as delay, throughput, and overhead variations. Naïve Bayes, Deep Learning, and ANN show performance in terms of accuracy. Still, SVM and Q-Learning concentrate more on trust computation and evaluation but fails to detect most malicious nodes. Algorithms such as Naïve Bayes, SVM, and DT focus on computational overhead, a much-needed security-analysis parameter. Thus, these techniques are slightly behind in computational complexity, precision, and robustness, which are the essential parameters for re-source-constrained IoT devices. There are two types of IoT trust models, i.e., trust-based management and AI-based. The trust-based model is further classified as a decision-based and evaluation-based model. The decision-based model consists of three classes, i.e., propagation, behaviour, and hybrid-based. The evaluation-based model is also categorized into five categories, i.e., statistical, fuzzy, entropy, graph theory, and probabilistic model. The AI-based model is organized into two types, i.e., data mining and deep learning-based. Figure 3 presents the broad classification of Trust Models. The different types to trust models for the integration of AI with IoT are presented in this section (RQ2).

2.4 Deep Learning-Based Trust Management

Recent research and studies show Deep Learning in IoT as an emerging trend for many industrial and business applications. The most favorable applicability of deep Learning is to perform efficiently with colossal datasets. Deep Learning executes better efficiency with such datasets than standard ML algorithms (Kalinin and Krundyshev 2023). The protocols available with deep learning algorithms enable IoT de-vices to be automated without human interactions. The core architecture of deep Learning is to operate similarly to the human brain. This section is followed by a few deep learning techniques that ensure IoT devices' trustworthiness. Sumathi et al. (2022) presented a study on the Recurrent Neural Network (RNN), a reinforcement learning-based trust model that computes a node's trustworthiness using a reinforcement manager. Based on the distance vector calculated by the manager, the node is declared as trusted or not. Awais et al. (2020) studied Long Short-Term Memory (LSTM) as a deep learning technique that has emerged to solve complex problems and obtain efficient outcomes in various applications. LSTM holds its benefits in applications such as text generation, language interpretation, and cryptography. The above-discussed deep learning algorithms are efficient in terms of outcomes but possess very high memory utilization to handle massive datasets. Table 2 shows the applicability of the advantages of the above-discussed algorithms for various real-time IoT applications.

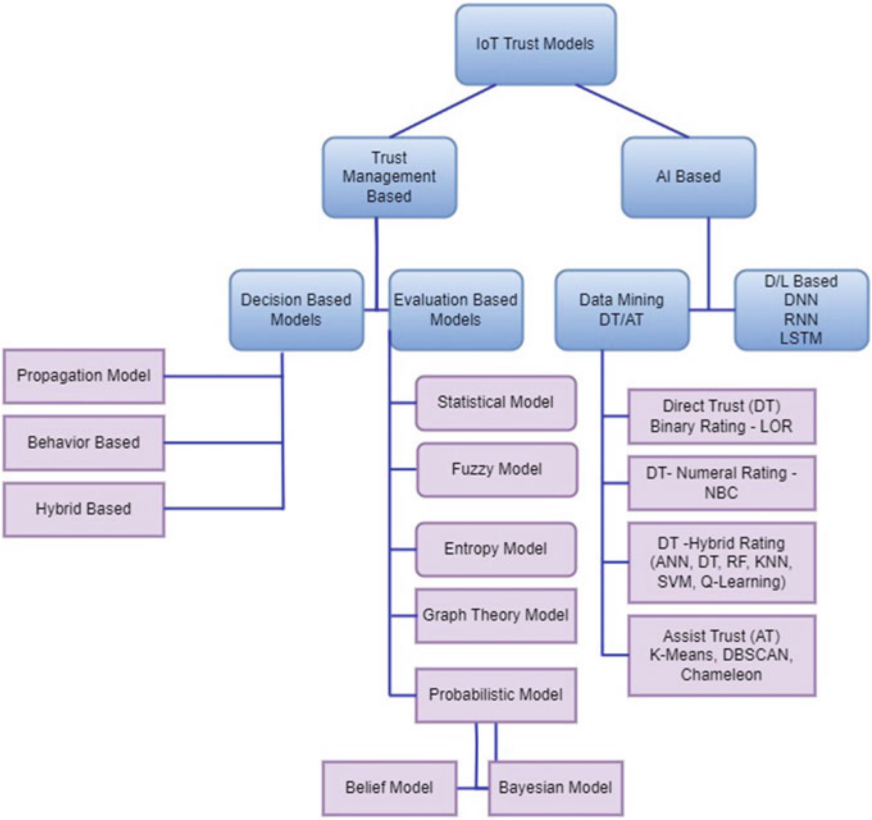

Fig. 3 The classification of trust models

Table 2 ML algorithms for IoT applications

IoT applications	Algorithm	Advantages
Agriculture monitoring and data analytics	Naïve Bayes classification	Easy to execute
		No need of huge dataset
Air control monitoring	K-means clustering	Perform seamlessly with huge data with organized clusters
Automatic lameness detection	KNN classifier	Detect in noisy environment too
Environmental monitoring	Feature extraction	Complexity and redundancy are reduced
Energy monitoring	Neural network-regression	Easy prediction
Healthcare	Neural network-classification	Easy to execute

3 The Impacts of Digitization on SDG and Security Measures in AIoT

Considerable innovations and automation in the digital environment to society are bringing potential and sustainable development. The era of an intelligent environment has a technological impact on every individual. This impact will make urban and rural people combine their day-to-day activities to be automated—digitization results in an automated environment, a clean society, and active living conditions. People with a digital environment will benefit from educational growth and career growth. Karnik et al. (2022) presented a study on digital economy development results in Industry 4.0 with technological growth in augmented reality, simulations, cloud computing, IoT, system integration, big data analytics, and AI techniques. Zhang et al. (2022) examined the AIOT prominent role in transforming the digital environment even more into a smart, equipped environment. At the same time, the digital environment also faces some challenges to implement seamlessly. AI influences IoT and cloud computing technology to im-pact the digital world towards sustainable development. Figure 4 presents the major environmental impacts due to digitalization.

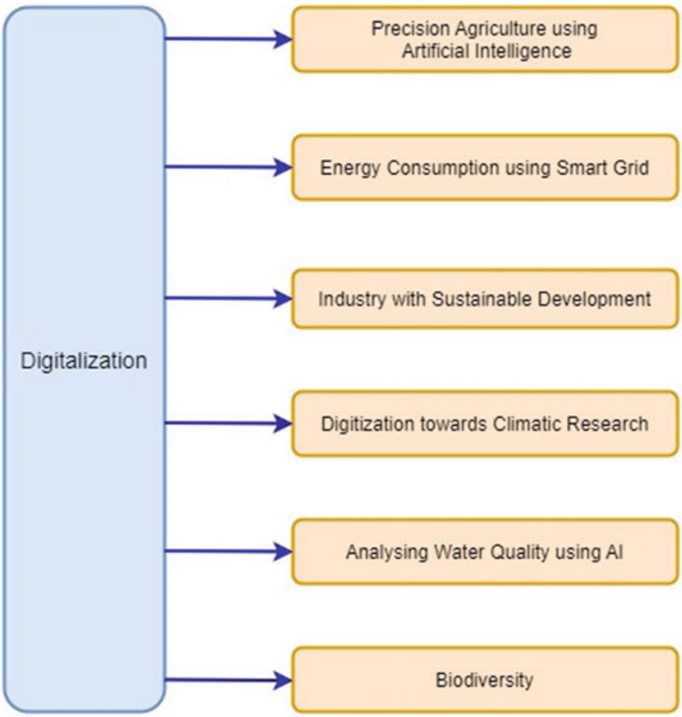

Fig. 4 Environmental impacts of digitalization

3.1 Energy Consumption

Energy is the primary resource employed in diverse sectors of society; AI algorithms predict the consumption of energy using intelligent grids. Cheng et al. (2022) presented an analysis of a smart grid that maintains the usage of energy consumption, supply, and demand. Sectors like manufacturing, industries, transportation, and laboratories are being adequately monitored for energy usage. The benefits of AI integration with these applications lead to proper refilling of demands, less energy wastage, and decreased greenhouse gas emissions.

3.2 Smart Agriculture

Jadon and Singh (2022) presented a study on agriculture enriched by many emerging technologies such as drones, remote sensing equipment, laser equipment, crop predictive analysis, fertilizer optimization, and crop disease prediction.

3.3 Healthcare System

Kishor and Chakraborty (2022) presented a study on healthcare systems, which is a prominent field acquired aided by AI. Much research continues on drugs, diagnosis, patient monitoring, and treatment monitoring. Deep Learning algorithms influence healthcare applications with an accurate prediction of drug combinations (Kwekha-Rashid et al. 2023). World Health Organization (WHO) introduced Ethics and Governance of AI for Health to ensure that innovations in healthcare should undergo proper ethics and rights in their research (Galetsi et al. 2023).

3.4 Environmental Monitoring

Environmental monitoring plays a vital role in society's human welfare. Kashid et al. (2022) studied AI technologies to step its path in environmental monitoring by creating innovative applications for checking air quality and measuring the amount of pollution. Environment Programme (UNEP) has introduced a digital platform called World Environment Situation Room (WESR), which makes AI algorithms work on massive datasets and gives real-time predictions on environ-mental issues (Green et al. 2023). Deep learning algorithms analyze, predict, and identify trends for natural disasters. Common Alerting Protocol (CAP) is developed to make fatal alarms before a natural disaster (Nautiyal and Mishra 2022).

Implementing security measures in IoT techniques is challenging due to the wide range of devices and transmission protocols and the diverse types of assistance provided. This complexity makes it challenging to rely solely on traditional IT network keys for ensuring security. The security benchmarks involved in a traditional network may require to be adjusted. All three IoT layers must be involved with security (Mahmoud et al. 2015). For illustration, the connection between the machine and the Cloud or the machine and the gateway is without transport encryption.

Insufficient authentication and authorization methods make a preferred vector for accessing IoT devices. MQTT, DDS, Zigbee, and Zwave are present IoT proto-cols permitting authentication (Al-Fuqaha et al. 2015). In addition, if network services are not sufficiently shielded, the immoral individual can fumble the technique and distribute malware. Authentication is the most widely employed security approach for securing secure transmission at the network layer Lv et al. (2022). Continuous studies have presented deploying Internet Protocol Security (IPSec) in an IoT background via the adaptation layer, even though accomplishing so offers some problems due to the constraints of the devices. Hardcoded credentials are continually employed in IoT devices, defining security configurability. Multiple instruments utilize the exact password, making it straightforward to compromise hardcoded credentials Streit et al. (2021). Insufficient physical security is another access point for faultfinders due to hardware imperfections. The inherent simplicity of devices like sensors presents the most significant challenge when encrypting them. Also, the product's functionality may be at odds with one another (Jiang et al. 2020). However, lightweight device encryption may be necessary to protect users' privacy and safety. The common IoT security is demonstrated in Fig. 5 and consists of three broad areas, i.e., IoT application, Network layer, and Perception layer. The IoT application includes smart home security, traffic security, healthcare security, agriculture security, logistic security, etc. The network layer consists of Wi-Fi security, 5G security, GPRS security, LAN security, Internet security, etc. The perception layer consists of RFID security, infrared sensor security, neural sensor security, environmental security, medical sensor security, etc. This section concerns some of the impacts of digitization (RQ3).

The information must be protected and only accessible by authorized parties. Users can be humans, different AIoT gadgets, or even non-networked devices. It is crucial to confirm that the data accumulated by the detectors in a given node is not available to other nodes in the network. A Radio-Frequency Identification (RFID) electronic tag must not expose confidential data to undesirable readers. It should be apparent to a user whether or not data was acquired from an original electronic label, and authentication is crucial in AIoT (Jia et al. 2012). Detector nodes must authenticate themselves to control denial-of-service attacks at the perception layer. Authentication is a vital security effort that must occur at each layer. Wi-Fi authentication procedures for Internet access can confirm that user information is maintained securely (Liang et al. 2023). OpenID is a standardized framework for authentication purposes.

A device's access rights across the network are managed by authorization. Connected appliances in the AIoT construct a trustworthy connection through authentication and authorization. OAuth is a standard framework used across the industry

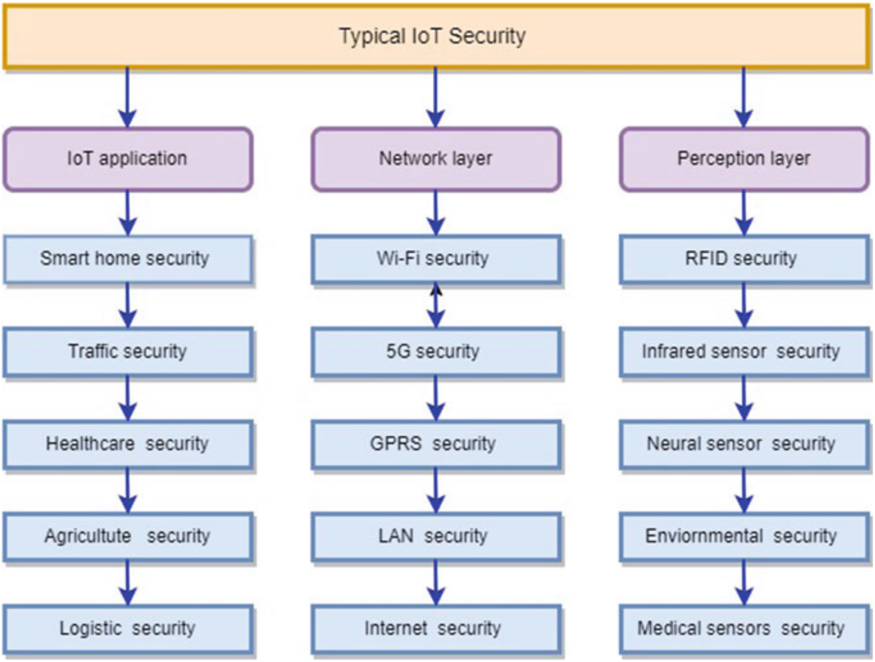

Fig. 5 Common IoT security architecture

for authorization (Aliahmadi and Nozari 2023). Certification is a process of verifying the authenticity of both commodities transmitting. Robust authentication is accomplished by two-way public key certification in an IoT design protected with Public Key Infrastructure (PKI) (Hoglund et al. 2020). Security is provided by access control in the form of encrypted credentials for unauthorized access to protected resources.

Recently, there has been a compass on two distinct types of newly designed technology. Popular new technologies such as software-defined networks (SDN) and blockchain combine with AIoT security designs (Javanmardi et al. 2023). The primary goal of SDN is to partition the network and data control functions. It is feasible to find workable solutions to some of the issues plaguing the Internet of Things, such as reliability, security, scalability, and quality of service. Blockchain technology is essential to the operation of cryptocurrency. Applications based on the Internet of Things will take advantage of the network's private and secure transactions and the decentralization of its transmissions and procedures. Its ap-plication has been met with significant success in financial applications Abed et al. (2023). The Internet of Things can benefit from blockchain technology in several ways, including decentralization and secure transactions (Akrami et al. 2023). The primary considerations for securing AIoT architecture emanated from this study are illustrated in Fig. 6, which includes security analysis, control of the IoT network, the solution to attacks, protection mechanism, the recovery process, PKI mechanism, encryption,

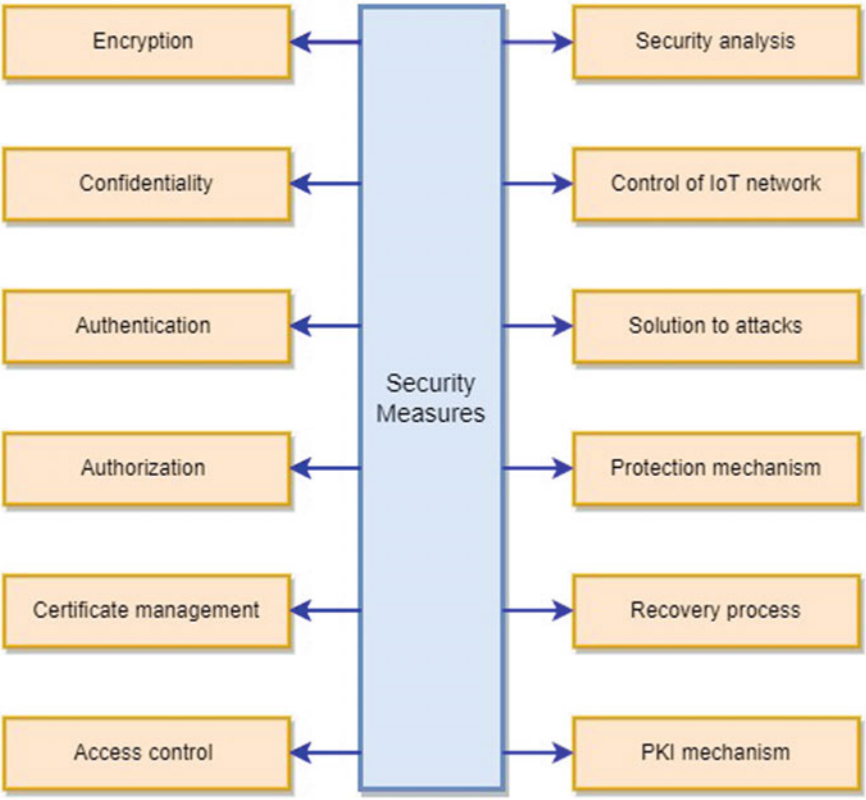

Fig. 6 Security measure for AIoT

confidentiality, authentication, authorization, certificate management access control. The section discussed the security measures for digitalizing AIoT (RQ4).

4 Strategies and Challenges for Enhancing Security Capabilities for SDG Toward Digitalization

This section discusses the strategies and challenges for enhancing the security capabilities of sustainable development towards digitization. Healthcare data breaches are considered an increasing threat to the sector, endangering lives and resulting in data loss, financial fraud, and assaults on medical infrastructure and equipment Safa et al. (2015). Company-wide efforts are needed to create risk prevention and mitigation measures because of the rising number and changing types of cyberattacks directed at clinical and healthcare environments. Rajan et al. (2021) presented a study on the effects of cooperation, training, capacities, technological awareness, and technological infrastructure. They also illustrate how the discovered elements of the M-TISM model interact with each other. Cheng and Wang (2022) presented a study to fill this inside emptiness and provide institutional cybersecurity solutions. The study highlighted the significance of enhancing HEI cybersecurity capabilities by analyzing historical patterns and con-temporary adjustments. Carayannis et al. (2019) examined that these competencies depend on a complex, multimodal, and multilevel collection of skills and capacities of various organizational, technical, and cultural competencies. They explained the structure of the AMBI-CYBER architecture using a 7Ps stage-gate model, a balanced scorecard method, and a multi-stage approach.

Jalali et al. (2019) presented a framework for future research on exposing cognitive biases concerning the complexity of cybersecurity. They emphasized the value of educating decision-makers and systems thinking abilities. Zeadally et al. (2020) examined how an AI can enhance the performance of cybersecurity solutions by examining an AI's advantages and disadvantages. They further dis-cussed the prospects of future research in the realm of security related to the development of AI approaches across multiple domains toward sustainable development growth. Kott and Linkov (2019) presented a study that integrates the human feature is necessary for cyber assets' technical resilience. Indeed, there is widespread agreement among security professionals that humans, acting as users, consumers, administrators, and managers, are the most vulnerable connections in the security chain. Technological advancement can be driven step-by-step by the advancement of users, operators' abilities, routines, and resilience.

Tonhauser and Ristvej (2019) proposed that actors who pose a threat are distinguished from those who do not. Actors have access to material, information, skills, and equipment. They make choices that affect their own and other players' cyber resilience. Franchina et al. (2021) presented a study on a substantial com-promise between the two that has been shown to best suit workers' demands and produce the appropriate degree of awareness. The most effective strategy for increasing security awareness is to use a balanced combination of engagement-based and less interactive approaches. Giacomello and Pescaroli (2019) studied how integrating the human feature is necessary for cyber assets' technical resilience. Indeed, there is widespread agreement among security professionals that humans, acting as users, consumers, administrators, or managers, are the most vulnerable connection in the security chain. Technological advancement can be driven step by step with the advancement of users, operators' abilities, routines, and resilience. The driving factors for SDG included customers, technologies, employee awareness, organizations, policy, stakeholders, regulators, and competitors, presented in Fig. 7.

An ecosystem in which new threats have evolved has been formed through increased connectivity between various ports and the degree of integration of various devices, agents, and activities toward sustainable growth. To ensure that these critical infrastructures are adequately safeguarded and to support the development of new technologies that have usually lagged behind others in changing environments for sustainable growth towards digitization.

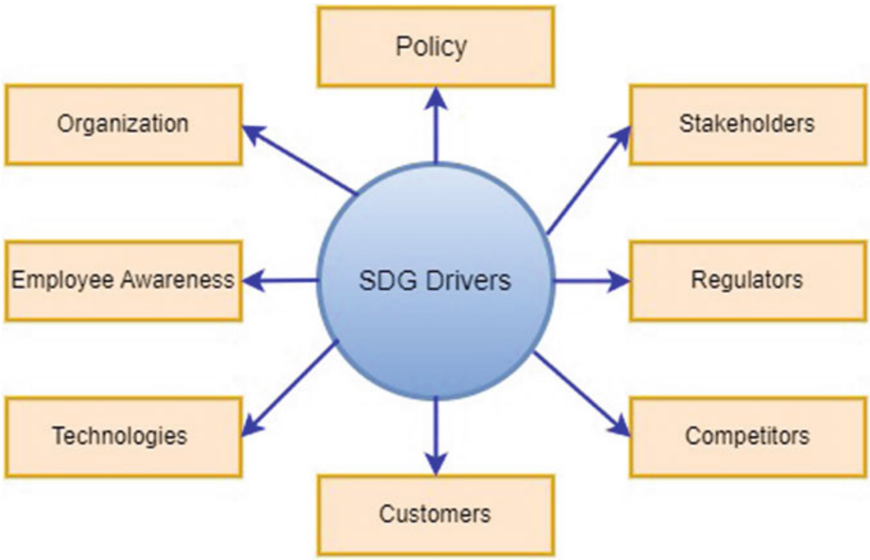

Fig. 7 The SDG drivers

IoT and AIoT have expanded the surface area that criminals may exploit with billions of connected devices, requiring quick and accurate threat detection. Over the past decade, mobile computing, communications, and mass storage technologies have advanced to the point where big data have become a reality. With this comes an immense collection of usable information that can be generated rapidly (Ahmed et al. 2017). This information can be used to recognize more frequent system faults and attacks and to develop suitable security solutions. Given the need for immediate processing of immense amounts of information from multiple sources to identify potential threats and mitigate damage, data analytics as a security strategy will be critical for success. This method enables businesses to swiftly spot anomalies or attack patterns while reinforcing their defense systems and enhancing their strength against future assaults (Rathore et al. 2018). As security becomes more vital to organizations for sustainable development growth, various factors must be addressed to strengthen protection. Tools needed to detect and respond to threats have evolved. Unified data representation, interconnectivity between risk identification systems, online investigation capabilities, samples, methods for dealing with restricted resources while processing data, and anomaly detection with time-series analysis are all essential (Dey et al. 2018). Together, these tactics create a comprehensive approach to security for sustainable development towards digitization.

Vassakis et al. (2018) analyzed that data science is the body of essential directions that encourage acquiring knowledge and information from data. Through the analysis of vital data, the techniques and technologies employed help businesses better understand their surroundings and make timely and educated decisions. Gupta and George (2016) presented a study on organizations across all sec-tors aggressively investing in big data projects since an extensive data strategy. Organizations should invest in formidable aptitudes for competitors to emulate and gain a competitive edge. Choi et al. (2018) reviewed primary big data analytics methods, relative forces, defects, and capabilities. Several techniques have been evaluated to handle the everyday challenges associated with enormous amounts of data processing and repository owing for AIoT. Ahmed et al. (2017) studied to ensure successful analytics and contemporary refinements in big data analytics for IoT systems. This section demonstrated the strategies for enhancing security capabilities for SDG (RQ5).

5 Discussion

Present directions imply that AI-enabled IoT will be approvingly applicable across diverse enterprises. AIoT versatility drives it a powerful prospect for a wide range of services across multiple domains. Data is predicted to evolve into the world's most beneficial resource and organizations that cannot capitalize on this trend risk extinction (Balaji et al. 2019). Issues encountered when incorporating data-intensive AI with IoT devices are the associates' recollection restraint and small computational management. Artificial intelligence (AI) schemes are generally complicated and need extensive memory elements, but IoT devices must obtain these abilities unaided. AI-facilitated IoT can only endure with IoT gadgets. One proposed solution is cloud computing, typically utilized for different AI applications. The Cloud's across-the-board availability and extending popularity have created the natural choice to overcome these obstacles (Nair et al. 2022). This will initially conquer the purpose of enforcing an IoT architecture: quick processing and scalability.

This chapter concerns AI's role and integration with IoT, as demonstrated in Fig. 1. Figure 2 depicts the process flow of combining AI and ML with IoT data. The trust model of integrating AI with IoT is outlined in Fig. 3, which includes data mining-based, direct trust evaluation, assisting trust evaluation, and deep learning-based trust management model. The impacts of digitization on SDG are emphasized. The common security architecture is pictured in Fig. 3, and the major environmental impacts due to digitization are shown in Fig. 4.

The security measures for digitizing AIoT are exhibited in Fig. 5. The strategies and challenges for enhancing security capabilities for SDG toward digitalization are discussed, and the driving factors for drivers are exemplified in Fig. 6. The drivers for SDG are demonstrated in Fig. 7. The classification of AI is shown in Table 1, and the ML algorithms for AIoT are highlighted in Table 2. The artificial intelligence's significance in the IoT context (RQ1) is demonstrated in Sect. 2. The trust models used in integrating AI with IoT (RQ2) are illustrated in Sect. 2. The impacts of digitization on sustainable development (RQ3) are presented in Sect. 3. The strategies and challenges in security measures for digitizing AIoT (RQ4) are demonstrated in Sect. 3. The strategies for enhancing security capabilities for SDG (RQ5) are depicted in Sect. 4.

The enterprise is experiencing a gradual transition toward the future, including the application flank. One of the enterprises that has experienced the most extreme transformation is healthcare. Before the across-the-board adoption of AIoT, healthcare technology was limited to basic facilitative robots and decision-aid procedures; however, wearable gadgets and personal care techniques are acquiring rage. Smaller, more versatile wearable systems are expected to soon be on the market. Smart automobile designs are another place that has experienced surprising conversion due to the Internet of Things. Auto navigation techniques have extended, so automobiles can now be operated without human intake (Xiong and Chen 2020). This contemporary analysis proffers the state of the art by conducting the technology significantly less conditional on human intervention. The agricultural sector is also a substantial adopter of AIoT technologies (da Silveira et al. 2021). Currently, such technologies are limited to confined spaces; added evolution is needed before they can be employed in open agribusiness settings. A comprehensive study is being accomplished on AIoT because of a developing paradigm. It has a promising future, but a full assessment can only be constructed once adequate studies are available to researchers. Deep learning techniques can be extensively used to address the security-related issues of AIoT (Barik et al. 2022). Strazzullo et al. (2023) presented a study on text-mining approaches that can be effectively used between SDS and industry. Barik et al. (2023) presented a comprehensive study on text mining and showed how it could effectively address security issues, highlighting different techniques for SDG of society. Future technology's spread will be partly correlated to its capability to yield sustainable development technological advancements, so this characteristic of the system should also be studied.

6 Conclusion

AIoT refers to integrating complex artificial intelligence techniques into small IoT gadgets, enabling them to possess the full capacities of classic AI systems. This system enables individuals to efficiently access comparable artificial intelligence capabilities in a more streamlined and enhanced manner. Despite the revealed importance of AI and IoT in sustainable development, researchers remain actively committed to seeking enhanced technologies with more effective prospects to accomplish Sustainable Development Goals effectively. This study explored the applicability of AIoT to SDG for digitization. The chapter exemplified the role of AI in IoT, and trust models have utilized AI with IoT. The security measures for AIoT are outlined, and strategies and challenges are exhibited for the SDG. However, the findings of our study emphasize that the leverage of AIoT applications in SDG is in a state of ongoing development. The influence of robotics and intelligent technologies can be observed in various sectors, from medicine to transportation and robotics to developing smart cities. However, the complexities represent a significant challenge within the AIoT industry ecosystem. The concept of AIoT emerges from a complex system encompassing many devices, an extensive supply chain, diverse types of equipment, and a wide range of ser-vice standards. The potential of the AIoT to evolve in the future is extensive and endless. The advancement of the industrial internet will be expedited by enhanced network agility, the integration of AI, and the capability to efficiently execute, automate, coordinate, and protect various points on a large scale towards SDG.

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Advancing Democratic Governance with AIoT-Enabled E-Voting: A Case Study of Covenant University's Departmental Associations in Alignment with SDG 16

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Abstract Voting is a cornerstone of democratic societies, ensuring active participation and representation in decision-making processes. However, traditional voting systems face challenges like inefficiencies, security vulnerabilities, and a lack of transparency. In response, electronic voting has emerged as a promising solution. This project aims to create an intuitive and secure e-voting web application tailored for Covenant University's Departmental Associations, fostering a fair and transparent democratic process, aligned with SDG 16: "Peace, Justice, and Strong Institutions". By following the waterfall model for software development, effective planning, requirement gathering, design, implementation, testing, and deployment ensure a reliable and efficient e-voting platform. Skillfully built with Next.js and CSS for the front-end and Node.js for the back-end, the application enhances user accessibility. Adopting a schema-based approach with MongoDB streamlines database management. The application is securely deployed on a cloud hosting service, utilizing a virtual machine for seamless operation. With the addition of AIoT, the IoT-enabled I-voting system gains new capabilities and functionalities. Furthermore, AI algorithms can aid in voter authentication, fraud detection, and result prediction, making the voting system even more efficient and reliable. The results obtained, including a remarkable response time of 97%, throughput of 95%, F1score of 99%, precision of 99%, and recall of 99%, validate the creation of a secure, accessible, and efficient platform for conducting elections. The implementation of two-factor authentication

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and real-time results has further heightened transparency while minimizing the risk of fraud. In conclusion, this project empowers democratic governance within Covenant University's Departmental Associations, supporting Sustainable Development Goals 16 (SDG 16) vision of strong institutions and just governance. By embracing AIoT-enabled electronic voting, we actively contribute to advancing peace and transparency in our democratic society. The integration of AIoT technology further enhances the system's efficiency, security, and accuracy, making it a robust solution for conducting elections in line with SDG 16 principles.

Keywords AIoT · IoT · CSS · Database · E-voting · MongoDB · SDG-16 · Waterfall model

1 Introduction

In most universities around the world, electronic voting methods are being considered as a replacement for the current paper-based voting procedures (Shahzad and Crowcroft 2019).Voting is an election process done to make collective decisions or express opinions among a group or electorates. It ensures the survival of democracy in any civilized society and has been in use since the seventeenth century (Ch et al. 2022). In many developing nations, where the people are in charge and elect their leaders through elections, democracy is essential (Widayanti et al. 2021) and elections are thought to be the fundamental building blocks of democracy. Electing leaders electronically through a web-based application is called online or internet voting (Khanpara et al. 2022). The benefit of internet voting over the traditional voting method is that voters can vote whenever they want and there is less traffic on voting days and at voting sites. Additionally, it reduces result computation mistakes (Ibrahim et al. 2021; Jafar and Aziz 2021; Varaprasada Rao and Panda 2023). The primary focus of this project is to develop a web-based application for remote internet voting, specifically designed to enhance transparency in Covenant University's voting system and align with Sustainable Development Goals 16 (SDG 16): "Peace, Justice, and Strong Institutions." This application empowers students to conveniently cast their votes from any location, ensuring accessibility and convenience with the help of Internet of Things (IoT) devices.

Information and Communication Technology (ICT) is naturally used in the election process due to the pervasive presence of the Internet and the availability of remote services provided by different organizations. ICT tools are utilized to simplify the election of representatives and decision-making processes. Among these tools, electronic voting stands out as a crucial component in political and administrative settings. Internet voting, also known as I-voting, represents the cutting-edge technology in electronic voting. It encompasses both on-site voting at designated polling stations under the supervision of electoral officials or remote voting from the voter's choice of location (Farhan Rafat 2022). To varying levels, administrative bodies assess and incorporate Internet voting to different extents for local elections (Ganesan et al.

2023). This system provides a more efficient and secure way of voting (Patel et al. 2022). It is cheaper, less time consuming and easier to use compared to the other types of voting systems (Singh 2023). The cast votes are recorded in a database, facilitating the ability to query and identify the candidate who has garnered the highest number of votes for a specific position. Voting is not open to everyone, though. One must meet the criteria to take part in the elections. For instance, he or she must be enrolled in the Electrical and Electronic Engineering Department of covenant university. To prevent data modification, registration must be completed before the election. It offers a framework for streamlining the voting process for any institutions that use voting to make decisions. This internet voting system is specifically designed to enhance the participation rate within the university community (Benabdallah et al. 2022; Eady et al. 2023; Ehin et al. 2022; Kumar and Dwivedi 2023; Poniszewska-Maranda et al. 2022).

The students I-voting system is expected to meet four criteria which are security, accessibility, efficiency, and reliability (Faruk et al. 2022). Hence, the system has been developed with the aim of streamlining the organization of student elections in universities, ensuring simplicity and convenience for students to cast their votes remotely using a variety of devices such as personal hand-held devices, laptops, and computers in computer labs or at home. Throughout the design process, careful consideration has been given to the specified criteria and the implementation of quality assurance measures (Hsiao et al. 2018; Qadah and Taha 2007). To enhance the I-voting system's security and reliability, this project utilizes a computer-generated one-time password. This password provides an additional layer of protection, ensuring that only authorized individuals can access and participate in the voting process. Its inclusion aims to instill confidence among voters and prevent unauthorized access or tampering. Upon registration the user is provided with a uniquely generated password which is sent via the student's mail (Abdullah and Haji Ahmad 2017).

Voting has advanced significantly over centuries, from hand raising to use of electronic gadgets for casting votes (Omolara et al. 2022). In the 1800s, paper ballots were introduced; however, they lacked standardization. There were instances where voters had the ability to add names to the ballots and this practice posed a challenge as there was no reliable way to authenticate a voter's identity, they may vote more than once. Despite seeing the need for a uniform ballot in 1880, the United States did not adopt Australia's White Paper Ballots until 1888. It's worth noting that although there was no paper audit trail for vote recounts during that period, voters were required to confirm identification and provide their signatures in a registration book. However, significant changes have occurred since then, with the development of technology, voting machines have changed from being mechanical to being electronic which provides better efficiency, security, credibility and transparency (Thürwächter et al. 2022). The effectiveness of an election system relies on the fulfillment of all its goals, and compromising any one of them undermines its overall effectiveness (Park et al. 2021). The utilization of technology, including touchscreen voting machines, as well as experiments with internet voting methods on the web using personal computers or hand-held devices are examples of advancements. Some authorities have allowed the use of personal computers and mobile devices with internet access by voters to cast their ballots on the web from their various locations, otherwise known as mobile internet voting. In several of these jurisdictions, people have been able to cast their votes from the comfort of their different locations and devices thereby enabling everyone concerned to easily partake in the election process. Online voting systems demonstrate how the internet can be used to simplify voting processes, removing the requirement for students to physically be present on campus to take advantage of their right to vote. Students may safely connect into the system and take part in the voting process remotely by using a web application during election season and vote online there. Therefore, the major focus of this project is on the use of web-based voting system in a higher institution.

In the next section, Sect. 2, an exploration of relevant literature is undertaken. Moving forward to Sect. 3, a detailed discussion ensues concerning the systematic analysis and design of the system. This inclusive phase encompasses the initial gathering of requirements, followed by successive stages of system analysis and design implementation, ultimately concluding with the evaluation and deployment of the model. In the ensuing Sect. 4, an elucidation of the outcomes achieved by the system is presented, accompanied by an in-depth discussion. In Sect. 5, a detailed discussion of the result analyzed based on the performance metrics. The conclusive Sect. 6 provides the final remarks for this study.

2 Related Works

Much research has been done and on-going in the field of E-voting. Kaushik et al. (2022) developed a web framework for E-voting system. The online application is made to facilitate electoral, organizational, and voter processes. The electoral head (EH), who is the trusted party under the system as it is now implemented, oversees the voting procedure. The code is written using open-source technologies like the Django web framework, MySQL database, and Python language. Paillier homomorphic algorithm produces voting anonymity. The Paillier algorithm and its web application were satisfactorily modelled and evaluated. Peter et al. (2022) proposed a privacy preserving E-voting cloud system. A 3-step security procedure was established before voting to prevent phishing attempt. A mobile application was created that is user-friendly for students with three levels of security, ensuring practicality and reliability in the voting process. The application is built and hosted with Android Studio. This project creates the voting application while adhering to the software development life cycle.

Aniche et al. (2021) proposes data encryption and decryption methods for cyber security and artificial intelligence (AI) pattern recognition were both modified for this study. The created Biometric E-Voting system (BIO-EVS) has the power to stop fraud opportunities and safeguard voters' privacy. The voting protocol created for this system combined all the advantages of the already-used approaches and protocols while also reducing the majority of its known drawbacks and negative effects. The result shows that given that the Independent National Electoral Commission, State electoral authorities in charge of local government elections, and educational institutions can adopt and promote this voting system, the BIO-EVS (Biometric Electronic Voting System) had a significant impact on the voting process.

Shankar et al. (2021) proposes a E-voting cloud system (ECS) made up of three stages. The registration process comes first, vote polling comes next, and result releases come third. With the suggested method, the Indian Election Commission can use cloud computing to check for and validate vote data. The performance analysis demonstrates unequivocally that, when compared to the current system, our proposed approach is extremely secure. The suggested approach enables fast and secure data transport for web-based e-voting applications. Salleh et al. (2021) develop an e-voting system using the 'reCAPTCHA' security feature and test/evaluate the system. The authors used the waterfall model, and the functional testing was done with students. The designed method proved to be effective, trustworthy, and transparent in the use of electronic voting.

Abayomi-Zannu et al. (2020) proposes a mobile voting system that uses blockchain technology to collect and store the votes and two-factor authentication for voter verification was created. The ISO 9241-11 usability paradigm was used to assess the system after that. The proposed system received a good usability rating, according to results, indicating that it can be used in a voting process. Arun et al. (2022) developed a This voting system is made up of fingerprint-based Android application voting software. Following logging in, a voter must authenticate his or her fingerprint imprint, and after successful verification, the voter will receive a list of all the candidates. In the first stage, a scanner uses software to scan the voter's impression. Then the fingerprint impression will be fed into an Arduino that has been designed to receive the impression as a digital piece of information. This is an advanced, modern, and robust system that allows the students to cast their vote over the internet without any limitation. Real time results are illustrated using web views and graphs.

Pawar et al. (2020) implemented an application for online voting system using android devices front-end and back-end design using technologies such as HTML, CSS, JS, J QUERY. REST API, BOOTSTRAP, AJAX, MYSQL, APACHE HTTP server. The system employs the MYSQL database to store and manage all voting data and related information. This database is hosted on the Apache HTTP Server. The process includes voter registration and online vote capturing. Votes are tallied and results computed on the web-based platform. Front-end and back-end design. The application is designed for students and verifies their identity using a unique ID code, such as their matriculation number. This allows students to cast their votes remotely from any location.

Singh and Chatterjee (2019) proposed to achieve a decentralized, immutable, and secure e-voting system to promote a higher level of participation. Decentralization was done using blockchain Composer REST server API serves this purpose by bridging the gap between a client application and Blockchain. Result shows a blockchain implementation of an electronic voting system for annual elections during in an educational institution. Suprianto and Affandi (2020) carried out a qualitative approach with case study focused on student participation with e-voting in the digital era. The results show the implementation of the e-voting method in the election of the student council president is the outcome of students' innovation, leveraging laptops and internet connectivity as the medium, along with the support and encouragement from the educational institution to further enhance its development. Bharti et al. (2020) proposes a simple and interactive GUI for voting system was created and firebase database to store student's information was also developed. Election results are calculated automatically and declared immediately thereby significantly reducing the need for manual effort and the potential for human errors. Furthermore, the system promotes environmental sustainability as it eliminates the reliance on paper-based processes.

Vennila and Varuna (2019) carried out a result for department association. A centralized database is maintained by department associations where student's information is maintained whenever a student is using online voting system his/her information is authenticated with the data present in database if user is not in the list, he/she cannot use online voting system. Users are required to complete an online registration form before they can participate in the voting process. The information provided in the form is cross-checked with the data stored in the system's database. If the provided details match the records, the user is granted a unique username and password. These credentials enable the user to log in to the system and exercise their voting rights. However, if the conditions for eligibility are not met or if the provided information is incorrect, the registration process is terminated. To ensure the legitimacy of the voting process, students are required to provide their Matric number and student email during registration. These details are used for verification purposes, and upon successful validation, the students are granted access to vote through the web application in a secure manner. A web application developed to provide easy solution for colleges and universities to conduct elections in a fair and easy manner. It will have all the basic modules and it makes voting fully computerized which is very fast and efficient.

3 System Analysis and Design

This section provides a detailed overview of the designed e-voting system, elucidating its diverse features and functionalities. The paper will adhere to a standard system analysis and design methodology, commencing with the requirements gathering phase, followed by the system analysis and design implementation phase, and concluding with evaluation and deployment of the model. The design specifications of the system, framework, employed design tools, and a step-by-step procedure for its development are thoroughly elucidated in this section.

Table 1 Breakdown of voting processes by department

Department	Voting process
EIE	Online voting via Google forms
Civil	Manual paper ballots
Mechanical	Online voting via Google forms
Chemical	Poll voting
Building technology	In-person voting with ballot boxes
Architecture	Manual paper ballots
International relations	Hybrid voting (combination of paper and online)
Computer Science	Online voting via Google forms

3.1 Feasibility Study

The research involved conducting interviews with 8 department heads to gain valuable insights into their current voting procedures and identify areas for improvement. The selection of department heads was based on their roles and responsibilities within the University, ensuring a comprehensive understanding of the voting practices. Semi-structured interviews were conducted, employing a predetermined set of questions to maintain consistency. The interviews were carried out in person, creating a conducive environment for participants to freely share their experiences and perspectives.

Upon careful analysis of the findings, it becomes evident that there is a pressing need for an enhanced voting system within the associations. The current manual paper-based approach lacks transparency and leads to unnecessary delays. To address these issues effectively, the implementation of an electronic voting system is imperative. This would ensure secure and efficient voting processes across all departments. A breakdown of the voting processes for each department is presented in Table 1.

3.2 Design of the System

In Fig. 1, we present a comprehensive framework of the voting web application system, composed of four key components represented by rectangles. The User Interface component is responsible for handling user interactions, providing a user-friendly interface for voters, candidates, and system administrators to engage with the system. The Application Logic component plays a crucial role in managing and processing the voting functionalities, ensuring smooth and efficient operations throughout the voting process. The Database component serves as a central repository, storing and retrieving all necessary data related to voters, candidates, and election details. This efficient data management system enables seamless access to information, facilitating a well-organized voting system. Ensuring the security and

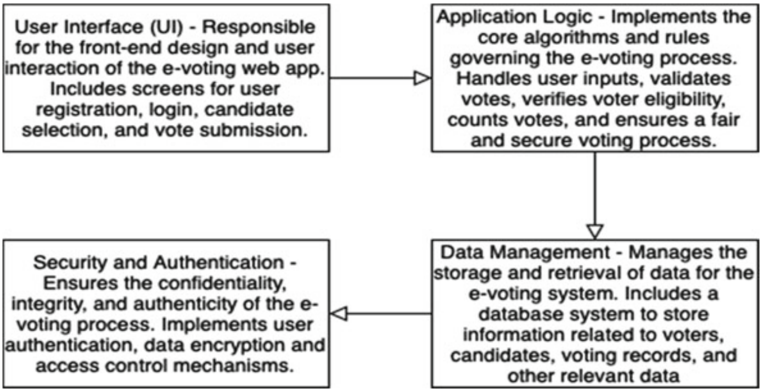


Fig. 1 Dataflow diagram for online voting

integrity of the system, the Security and Authentication component, enhanced by the capabilities of AIoT, plays a vital role in safeguarding sensitive data and validating user identities. It employs robust security measures and authentication protocols, leveraging AIoT to detect and prevent potential threats and unauthorized access in real-time, further reinforcing SDG 16 vision of promoting peace, justice, and strong institutions.

The proposed internet-based voting system is meticulously designed to cater to three distinct categories of users: voters, candidates, and system administrators, as demonstrated in Fig. 1. By harnessing the capabilities of information technology and AIoT, the system aims to revolutionize the voting experience by enhancing convenience, efficiency, performance, and security. Leveraging advanced features and functionalities empowered by AIoT, the system seeks to simplify the electoral process and streamline tasks that were previously handled manually. This includes reducing the workload associated with manual record-keeping and automating various administrative tasks to expedite the voting process. Moreover, the proposed system, backed by AIoT intelligence, is specifically designed to minimize the error rate encountered in traditional ballot elections. AIoT algorithms continuously monitor and analyze voting data, identifying patterns, and ensuring the utmost accuracy and reliability throughout the voting process. By embracing cutting-edge technology and AIoT, the proposed voting system actively contributes to advancing democratic governance and strengthening the institution's democratic processes, in alignment with SDG 16 vision.

For the implementation of the e-voting application, we utilized Next.js and CSS for the front-end, providing a seamless and dynamic user interface for voters and candidates. Next.js, being a popular React framework, facilitated an aesthetically pleasing and responsive design, ensuring a satisfying user experience. On the back-end, we opted for Node.js, a robust and efficient runtime environment, enabled by AIoT capabilities, ensuring smooth data processing and handling, essential for efficient voting operations.

To effectively manage the vast amount of data associated with the voting process, we meticulously designed a well-structured schema. This schema includes collections dedicated to users, candidates, votes, and election details, ensuring systematic organization and easy retrieval of data. The decision to use MongoDB as the database management system ensured seamless and flexible data storage, accommodating the dynamic nature of the e-voting application, with AIoT analyzing data in real-time to detect anomalies or potential security breaches.

In order to ensure optimal performance and accessibility, the application was deployed on a cloud hosting service. Leveraging the capabilities of a virtual machine, the hosting service provided a scalable and reliable environment for the e-voting application to operate smoothly. Additionally, the implementation of SSL encryption during transmission ensured the security and privacy of sensitive data, effectively preventing unauthorized access, while AIoT continuously monitored network activity for potential threats. By employing this comprehensive approach to implementation, the e-voting application achieved a high level of security, accessibility, and efficiency. The seamless integration of cutting-edge technologies and secure hosting practices ensured a user-friendly and reliable platform for voters, candidates, and administrators alike.

The security aspect of the system was strengthened by implementing a two-factor authentication method, reinforced by AIoT-driven behavioral analysis for user identity validation. These include a matching name and matriculation number along with a one-time password sent to their email address. This multi-layered authentication process significantly reduces the risk of unauthorized access, ensuring the confidentiality and integrity of the e-voting system. By incorporating such security measures, the system aligns with SDG 16 goal of promoting peace, justice, and strong institutions by safeguarding the voting process from potential security threats and unauthorized manipulation.

To enhance user experience and usability, the front-end design of the system was carefully crafted using Next JavaScript and Cascading Style Sheets (CSS). These technologies allowed for the creation of an intuitive and user-friendly interface, promoting ease of use and accessibility for all voters, candidates, and system administrators. By providing a user-friendly platform, the system encourages active participation in the democratic process, further reinforcing SDG 16 emphasis on effective and inclusive institutions.

Ensuring accuracy and reliability, a sophisticated vote counting algorithm was developed, leveraging the capabilities of the Mongo Database. This algorithm meticulously processes and records votes, guaranteeing precise and accurate results. By promoting fair and reliable election outcomes, the system aligns with SDG 16 vision of strong institutions and just governance.

For efficient and secure deployment, the web application was hosted on the Vercel cloud platform, a reliable and scalable hosting service. The cloud hosting environment offers numerous advantages, such as high availability, automatic scaling, and data redundancy, which contribute to a seamless and stable voting experience. The adoption of cloud technology further supports the achievement of SDG 16, as it fosters efficient and accountable institutions.

3.3 Design Performance Evaluation

To comprehensively evaluate the system's performance, various mathematical and statistical techniques were employed (Kumar and Sharma 2023):

a. **Simulation:** The system was subjected to a range of simulated scenarios, varying the number of users and transaction volumes. This thorough testing under diverse conditions ensured the system's robustness and efficiency, contributing to the establishment of effective and accountable institutions.
b. **Benchmarking:** A comparative analysis of the system's performance against other similar e-voting systems was conducted. By identifying best practices and areas for improvement, this analysis reinforced the pursuit of transparent and reliable institutions.
c. **Load Testing:** The system underwent rigorous load testing, exposing it to heavy transaction volumes to assess its capacity and identify potential performance bottlenecks. Ensuring the system's ability to handle peak voting periods aligned with Sustainable Development Goals 16.7 (SDG 16.7) aim of promoting resilient and inclusive institutions.
d. **Statistical Analysis:** Data collected from the system underwent detailed statistical analysis, enabling the identification of trends and patterns in its performance. This data-driven approach empowered institutions to make informed decisions, further supporting SDG 16 emphasis on effective and transparent decision-making processes.

The evaluation of performance metrics included (Ojewumi et al. 2022):

i. **Response Time (RT):** The average time taken to respond to user requests was measured. Achieving efficient and accountable institutions relied on optimizing this metric. It can be mathematically represented in Eq. (1).

$$T = (t1 + t2 + t3 + \cdots + tn)/n \tag{1}$$

where $t1, t2, t3, \ldots,$ are the response times for n user requests

ii. **Throughput (TP):** The number of transactions processed per unit time was calculated, indicating the system's ability to handle voting operations efficiently. It can be mathematically represented in Eq. (2).

$$TP = number\ of\ transactions/times \tag{2}$$

iii. **Availability (A):** The ratio of total operational and available time (Ta) to the total time (T) provided insights into the system's reliability and continuous service provision. It can be mathematically represented in Eq. (3).

$$A = Ta/T \tag{3}$$

iv. **Reliability:** The probability that the system operates without failure for a specified time (t) underscored the importance of reliable and resilient institutions Sustainable Development Goals 16.7 (SDG 16.7). It can be mathematically represented in Eq. (4).

$$R = e^{-(\lambda t)} \tag{4}$$

where λ is the failure rate of the system

In terms of security, the system's performance was assessed using metrics such as the number and severity of security incidents. The system's ability to protect sensitive data and ensure the confidentiality of the voting process was evaluated. Scalability, a critical factor for the success of any e-voting system, was determined by assessing the system's capacity to handle increasing numbers of users and transactions without performance degradation. A scalable system contributes to the establishment of inclusive and responsive institutions.

Statistical analysis is also an important approach to evaluating the e-voting system's performance. Some common statistical metrics that can be used include (Ojewumi et al. 2022):

1. **Accuracy:** The accuracy of the e-voting application can be calculated by comparing the system's output to the actual results. For example, the number of votes counted by the system can be compared to the number of eligible voters who cast their vote.
2. **Precision:** Precision measures how well the system avoids false positives, i.e., instances where the system identifies a vote as valid even though it is not. Precision can be computed as the proportion of true positives divided by the sum of true positives and false positives.
3. **Recall:** Recall measures how well the system detects all valid votes, i.e., avoids false negatives, i.e., instances where the system identifies a valid vote as invalid. Recall can be calculated as the ratio of true positives to the total number of actual positives.
4. **F1 Score:** A balanced metric combining precision and recall providing a comprehensive evaluation of the system's performance, aligning with the goal of fostering fair and just institutions.
5. **Error Rate:** The error rate measures the percentage of errors in the system's output. It is calculated by dividing the total number of errors by the total number of votes cast.
6. **Confidence Interval:** The confidence interval is a statistical measure that provides an estimated range of values within which the true results of the e-voting system are likely to fall. It represents the level of certainty or confidence associated with the estimated outcome. The calculation of the confidence interval involves applying various statistical techniques such as hypothesis testing and regression analysis to the collected data.

3.4 Design Tools

To effectively develop the proposed internet-based voting web application, the utilization of various design tools, such as use case diagrams, data flow diagrams, flow charts, and database design, is crucial. These tools play a significant role in visually representing the system's functionalities, data flow, and interactions between different components, enabling a comprehensive understanding and ensuring the successful implementation of the application. Use case diagrams are essential for illustrating how different actors, including voters, candidates, and election officials, interact with the system. These diagrams present a visual representation of various scenarios and user interactions, allowing stakeholders to understand the system's functionalities and the roles different users play in the voting process. Use case diagrams help identify potential user interactions and system behavior, ensuring that the application addresses the needs of all relevant parties. Data flow diagrams provide valuable insights into the flow of data within the system and how it is processed. These diagrams illustrate the path of data through different components of the application, facilitating a clear understanding of data inputs, outputs, and transformations. Data flow diagrams are instrumental in ensuring that data is efficiently managed and shared between different modules, promoting seamless communication within the system. Flowcharts are instrumental in visually depicting the sequential steps involved in the voting process. These charts offer a clear and intuitive representation of the system's operations, outlining the sequence of activities from the user's perspective. Flowcharts help identify potential bottlenecks or inefficiencies in the voting process, enabling the development team to streamline and optimize the user experience. Database design is a critical aspect of the development process, particularly in the context of an internet-based voting application. Effective database design involves establishing a well-structured data model and defining relationships between different entities, such as voters, candidates, and election officials. A robust database design ensures efficient data storage, retrieval, and manipulation, facilitating the seamless functioning of the application.

3.4.1 Use Case Diagram

Figure 2 shows the use case diagram that describes the system and Table 2 describes the use case diagram.

3.4.2 Use Case Diagram

The dataflow diagram can be visualized in Fig. 3. They describe the flow of data.

i. **User Authentication**: In the initial step, users are required to provide their unique username and password to authenticate themselves within the system securely.

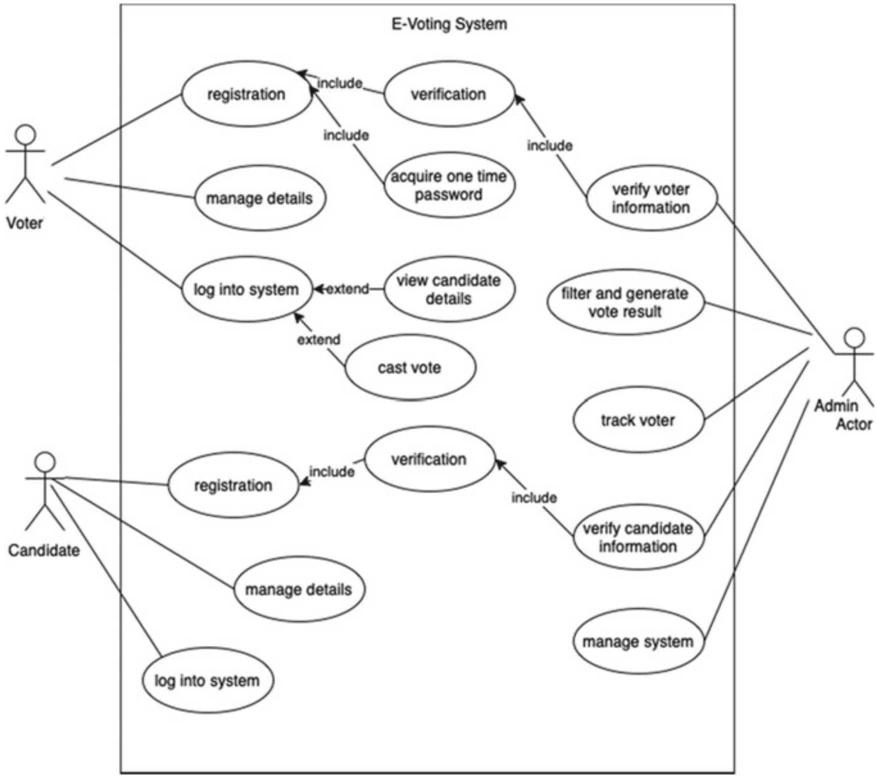


Fig. 2 A dataflow diagram for online voting

ii. **Verification Process:** The entered username and password undergo a verification process to ensure the user's identity and validate their access rights.
iii. **Accessing the Voting Process**: After successful authentication, users gain access to the voting process, granting them the ability to cast their votes and engage in other voting-related activities.
iv. **Voting Status Update**: Throughout the voting process, the system continuously updates the status, capturing essential information about the user's progress, choices, and any relevant details pertaining to the ongoing voting session.
v. **Logging Out**: Upon completing their voting or desiring to end their session, users can initiate the logout process. This action terminates the user's current session and effectively logs them out of the system, ensuring their privacy and data security.

Table 2 Use case description

Registration	This use case illustrates the process of voter and candidate registration for the election
Login into system	This use case focuses on the login functionality for both voters and candidates in the system
Cast vote	This use case describes the process of voters casting their votes in the election
View candidate details	This use case focuses on providing voters with the ability to view the details of all the candidates participating in the election
Verify candidates information	This use case focuses on the verification process of election candidate information by the administrator
Filter and generate result	This use case describes the process of filtering and generating voting results and reports by the admin
Manage profile	This use case focuses on the admin's ability to view and manage user profiles and manifestos in the system
Track voter	This use case focuses on the admin's ability to track and sort the list of voters based on the registered list in the voting system
Manage system	This use case focuses on the admin's responsibility to manage and maintain the voting system effectively
Add new students	This use case highlights the admin's ability to add new students to the system
View current vote result	This use case enables users to access/observe the current vote results in the system

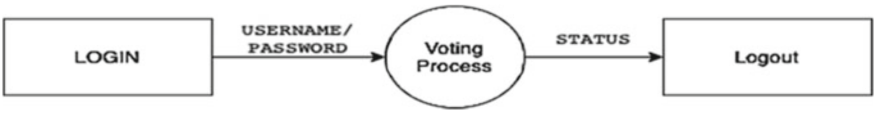


Fig. 3 Dataflow diagram for online voting

3.4.3 Flow Chart

Figure 4 depicts the flowchart diagram utilized in the application. The step-by-step algorithm for the e-voting application is outlined as follows:

Step 1: Start.
Step 2: Initialize necessary variables and data structures.
Step 3: User Authentication (Login Process):

i. Prompt the user to enter their email address, matriculation number, and password.
ii. Validate the provided credentials against the database.
iii. If the credentials are valid, proceed to the next step; otherwise, display an error message and return to the login screen.

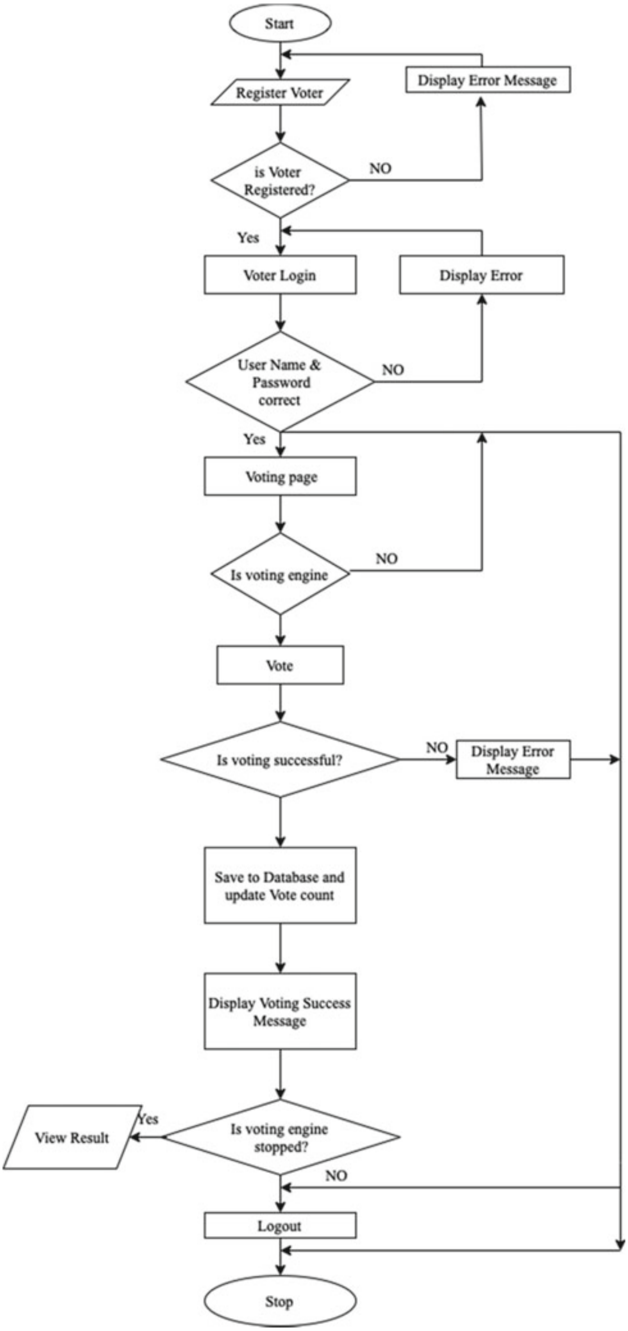


Fig. 4 Flowchart of the application

Step 4: Display the Voting Page:

i. Present additional options, such as "View Results" or "Logout."
ii. Display the list of available candidates or voting options.
iii. Allow the user to select their preferred option(s).
iv. Securely store the vote(s) in the database.
v. Display a confirmation message for the successful vote.

Step 5: If the user selects "View Results":

i. Retrieve the voting results from the database.
ii. Present the results in a clear and easily understandable format.

Step 6: If the user selects "Logout":

i. Terminate the current session.
ii. Return to the login screen for subsequent user authentication.

Step 7: Repeat steps 4 to 7 until the user chooses to logout.
Step 8: End.

3.4.4 Database Design

The e-voting system makes use of a database known as MongoDB which is used to store the student's information. It consists of 3 tables as illustrated in Figs. 5, 6, and 7.

Fig. 5 Student details

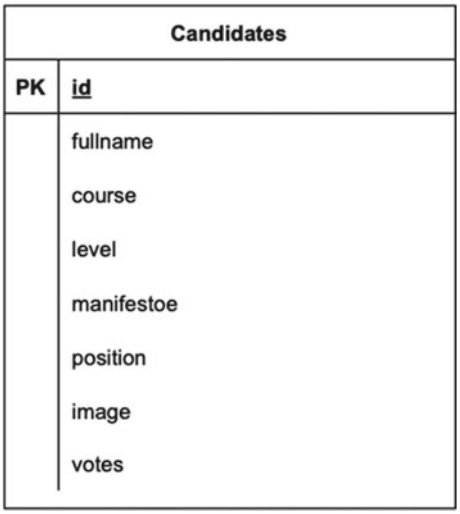


Fig. 6 Candidates details

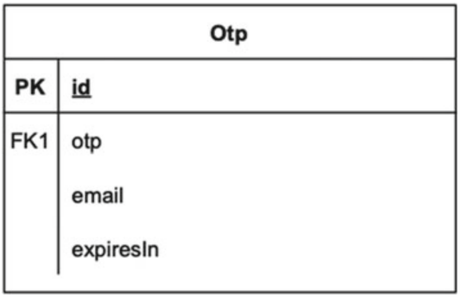


Fig. 7 Dataflow diagram for online voting

4 Result Analysis

This section delves into the findings and discussion stemming from the development and testing of the innovative e-voting application tailored for departmental association elections. The primary focus of this chapter lies in the comprehensive evaluation of the application's performance metrics, with a special emphasis on its security measures, user-friendliness, and accessibility. Furthermore, valuable feedback collected from users during the testing phase is meticulously analyzed, followed by a meticulous comparison between the advantages and limitations of the e-voting application and traditional voting systems. Additionally, this section explores and assesses the constraints and limitations faced during the implementation of the web-based e-voting application. By examining and discussing the results in this chapter, significant insights are gleaned into the efficacy of the e-voting application in enhancing departmental association elections. Furthermore, it highlights the application's potential to significantly enhance the overall voting process in alignment with SDG 16, leveraging the transformative power of AIoT technologies.

4.1 System Implementation

In this section, the user's viewpoint is analyzed regarding the implementation of the web application. Figure 8 illustrate the landing page when accessing the e-voting system. The user's initial interaction occurs on the landing page. which contains the register and sign in option. To use the web voting system, you will need to register as a user. Fill out the registration form on the sign-up page with your personal information, such as your name, email address and matriculation number. Once you have submitted the registration form, you can now access the login page. The registration page is shown in Fig. 9. On the login page the user fills in his/her email address and matriculation number and on confirmation receives a one-time password as shown in Figs. 10 and 11 respectively after which the user is signed into the system and accesses the voting page.

After logging in, you will be directed to the Voting page, where you can view the list of candidates and the positions they are running for as shown in Fig. 12. To vote for a candidate, simply click on the candidate's card containing their name and position, and then click on the "Vote" button at the bottom of the page to cast your vote. After submitting your vote, you will receive a confirmation message on the screen as shown in Fig. 13 each time a vote is done confirming that your vote has been recorded. Note that once you have submitted a vote to a particular position, you cannot go back and make changes. There are two results pages each which have real time updates; the top candidates result page shown in Fig. 14 that contains result

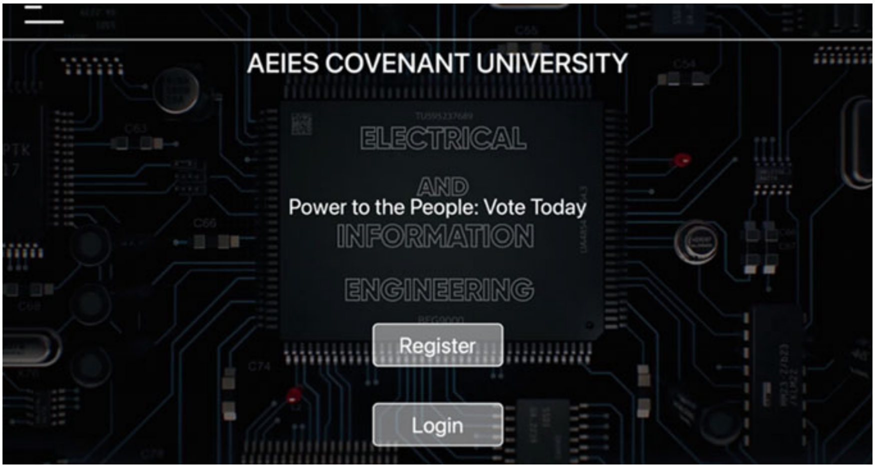


Fig. 8 Landing page

Fig. 9 Registration page

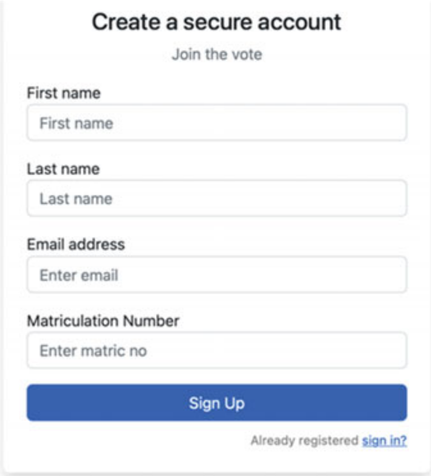


Fig. 10 Login page

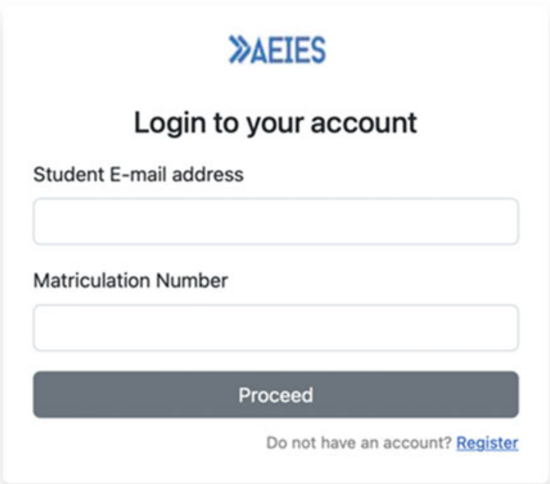
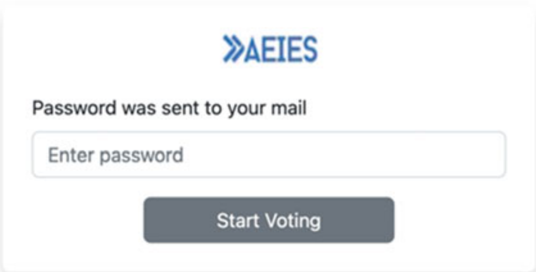


Fig. 11 Authentication page



upload of the candidates with the highest votes for each position and all candidates result page shown in Fig. 15 contains result uploads of all candidates. After casting your final vote, the user can access all candidates result page to logout after which he/she is redirected to the landing page.

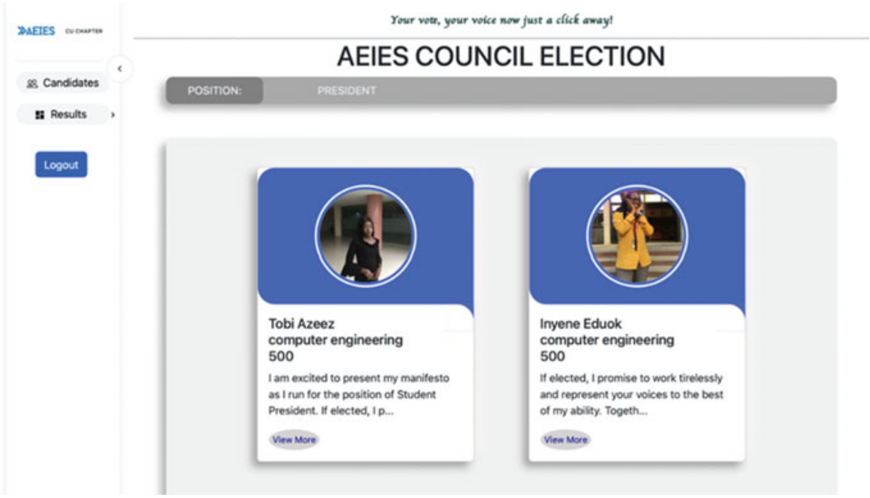


Fig. 12 Voting page

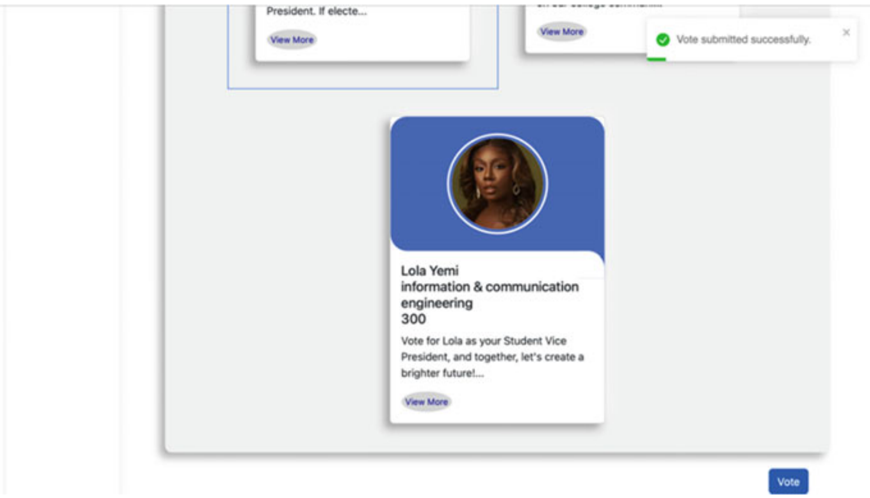


Fig. 13 Confirmation page

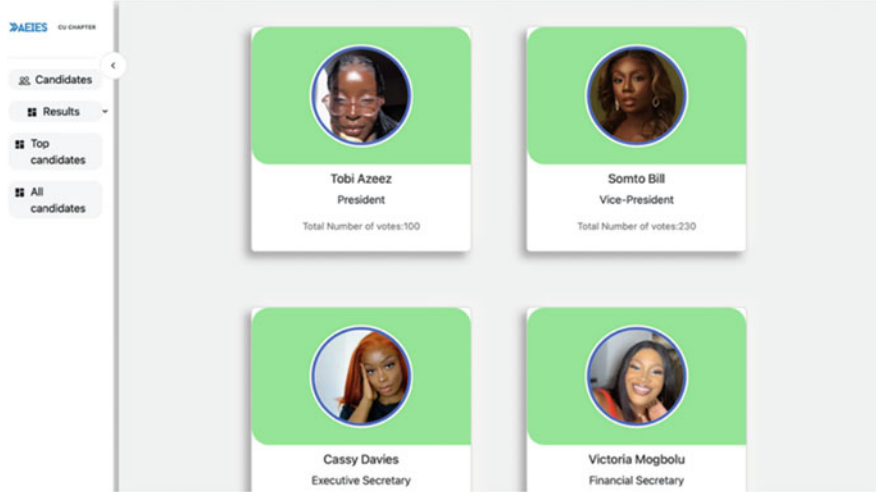


Fig. 14 Top candidates results page

Fig. 15 All candidates results page

5 Discussion

This section discusses the analyzed result based on the performance evaluation. Table 3 presents the performance metrics used to evaluate the effectiveness and reliability of the voting web application. These metrics provide insights into the accuracy and precision of the voting system, allowing us to assess its performance in terms of reliability and overall effectiveness.

Table 3 Performance metrics for the voting web app

Metric	Percentage (%)
Response time	97
Throughput	95
F1 score	99
Availability	99
Precision	99
Recall	99
Reliability	99

5.1 Comparison

By performing a comprehensive analysis of the current and proposed systems, we have identified specific criteria that allow us to discern and contrast these solutions effectively. By referring to the comparison table in Table 4, we can gain valuable insights into the merits and limitations of each system, while considering the integration of AIoT technologies and aligning with the principles of SDG 16.

Through this comparative analysis, the proposed system, with the integration of AIoT technologies, holds significant advantages over the existing system. With its implementation of two-factor authentication, user-friendly interface, enhanced remote accessibility, and automated vote counting, the proposed system addresses several limitations of the existing approach. Moreover, its emphasis on transparency and alignment with SDG 16 vision of promoting peace, justice, and strong institutions showcases its potential in advancing democratic governance within the organization. By leveraging AIoT innovations, the proposed system further demonstrates a commitment to cutting-edge solutions, ultimately contributing to the development of efficient and sustainable institutions.

Table 4 Comparison of existing and proposed systems with AIoT and SDG 16 considerations

System criteria	Existing system	Proposed system with AIoT	Alignment with SDG 16
Security	Basic authentication	Two-factor authentication	Promotes strong institutions and just governance by safeguarding the voting process and ensuring data integrity
User-friendliness	Limited functionality	Intuitive and user-friendly	Fosters accessible and inclusive institutions by enabling all users to actively participate in the voting process
Accessibility	Limited remote access	Enhanced remote accessibility	Contributes to resilient institutions by accommodating users
Efficiency	Manual vote counting	Automated vote counting	Advances efficient and accountable institutions by expediting the voting process and minimizing errors
Transparency	Limited visibility	Transparent and auditable	Reinforces transparent institutions through traceable and verifiable voting processes
Innovation	N/A	AIoT integration	Demonstrates commitment to innovative solutions, enhancing the voting experience and system performance
SDG 16 impact	Limited contribution	Positive impact on SDG 16	Actively contributes to the pursuit of peace, justice, and strong institutions through improved democratic governance

6 Conclusion

Based on the study's findings, it can be firmly concluded that the e-voting application presents a highly effective and viable alternative to traditional voting systems. The successful implementation of the application has resulted in a secure, easily accessible, and efficient platform for conducting elections. The inclusion of two-factor authentication and real-time result reporting has significantly enhanced transparency and curtailed the risk of fraudulent activities. Valuable feedback gathered from users during the testing phase highlights that the application streamlines the voting process, offering increased efficiency and user-friendliness.

To further advance the application's impact, several recommendations have been put forth. These include continuous security enhancements, usability improvements, scalability optimization, and potential blockchain integration for heightened transparency.

While acknowledging the presence of some limitations and challenges, the e-voting application exhibits substantial potential to bring about remarkable improvements to the overall voting experience, ultimately encouraging higher voter turnout.

This project represents a noteworthy contribution to the domain of electronic voting technology, emphasizing the significance of continued research and innovation in this field.

The positive outcomes of this study demonstrate that embracing technology, like the e-voting application, can play a pivotal role in advancing democratic governance and achieving the objectives outlined in SDG 16. By promoting secure, transparent, and efficient voting processes, the application contributes to the establishment of robust institutions and reinforces just governance. This project serves as a compelling call for further exploration and development of electronic voting systems, as they hold the potential to revolutionize democratic practices and foster inclusive and accountable institutions.

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Cyber Resilience for SDG Towards the Digitization: An Imperial Study

Kousik Barik, Sanjay Misra, Biswajeeban Mishra, Clara Maathuis, and Sabarathinam Chockalingama

Abstract With the digitization and evolution of Internet technology, the prevalence of most cyber-attacks is increasing. As society adopts digitalization, the need for cyber resilience in enterprises has become paramount because of the escalating threat of cyberattacks. Despite initial efforts, the world must still be on track to meet most Sustainable Development Goals (SDG) targets. This chapter reviews the significance of cyber resilience for SDG. The chapter identifies essential areas relevant to the sustainable development growth of society towards digitization, such as the Internet of Things (IoT), Artificial Intelligence (AI), Blockchain, Cloud computing, etc. This chapter emphasized the recommendations to become cyber resilient. The chapter highlighted the strategies for adopting cyber resilience for SDG. We have proposed a taxonomy based on techniques and methods for SDG. This chapter also emphasizes open challenges for future research directions.

Keywords Cyber resilience · Digitalization · SDG · IoT · Artificial intelligence · Blockchain · Cyber security

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1 Introduction

Information and communication technologies (ICTs) are evolving increasingly in governments, businesses, and people as digitalization outstretches quickly in both the public and commercial sectors. Digitalization can boost the economy, aid businesses, and enhance public service (Guo et al. 2020). However, an in-crease in information security concerns can limit this potential. Information security events can significantly negatively impact individuals and organizations by causing loss of income, sensitive data, personal data leaks, denial-of-service at-tacks, network outages, etc. Security and privacy issues continue to be barriers to the digitalization of enterprises and e-government services, and cyber security breaches, both intentional and unintentional, are already impacting the global economy (Ziyadin et al. 2020). The frequency of cyberattacks and, consequently, the yearly expenses of cybercrime are predicted to rise sharply in the following years as society continues to digitize. Organizations frequently lack comprehensive incident response strategies and cannot handle or recover from cyberattacks. Recent developments have increased the requirement for cyber resilience, as security failures are becoming costlier to organizations (Matt et al. 2015).

Digitalization refers to the widespread adoption of digital technologies by being transformed into actionable insights using diverse AI methods in interconnected systems such as IoT. The Artificial Internet of Things (AIoT) is an extensive network of interconnected devices, automobiles, buildings, and other interconnected items that exchange data via the Internet using embedded sensors, software, and other technologies (Mondejar et al. 2021). The full potential of these massive information sets has yet to be realized. Nevertheless, it creates novel openings for accelerating innovative, efficient, and sustainable growth development.

Risk analysis has attracted considerable attention, particularly concerning physical infrastructure. Learning in more developed study domains becomes ingrained in practices, legislation, regulations, practitioner education, etc. (Schwanen et al. 2011). Therefore, it is necessary to improve our understanding of cyber resilience. An analysis of the pertinent elements is crucial. The idea that businesses need to be cyber-resilient is gaining popularity as the number of cyber-attacks is anticipated to increase (Zaoui and Souissi 2020) momentarily. Other viewpoints from other disciplines, such as systems engineering, auditing, and risk assessment, have advanced this concept. The primary notion is that it is safer to expect thieves to get past the organization's defenses and develop cyber resilience to lessen the damage rather than putting energy into preventing them from accessing firm net-works. Owing to digitalization, companies are increasingly vulnerable to cyber threats because they produce many opportunities and a more complicated cyber landscape (Schallmo and Williams 2018). Thus, cyber resilience, or an organization's capacity to anticipate, respond to, recover from, and adapt to a cyberattack, is becoming increasingly important.

The cutting-edge technology with physical and digital systems is known as digital transformation. Innovative business strategies, production techniques, and the development of knowledge-based goods and services are all demanded (Gray and Rumpe

2017). Although digitization is not new, its benefits and difficulties are constantly evolving. Before the COVID-19 epidemic, the fourth industrial revolution, as symbolized by the ideas of Industry 4.0, the Internet of Things (IoT), and Web 4.0, was the primary source of digital transformation's challenges (Turkyilmaz et al. 2021). Industry 4.0 consists of 9 pillars that may assist any company in becoming linked, autonomous, and optimized business processes (Oztemel and Gursev 2020). This is particularly factual for SMEs when implementing new technologies since these 9 pillars are essential for comprehending technical needs, integrating into Industry 4.0, and implementing new technologies. The issues are the disruption of concepts and technology and the speed at which this digital shift occurred (Möller 2023). Due to digitization, there has been an increase in cyber security threats across organizations over time (Paul et al. 2023). Figure 1 depicts the trends of global cyber security attacks vs. cyber resilience for the one last year.

Organizations are concerned about cybersecurity resilience, especially as people become more privacy-conscious (Almeida et al. 2020). Therefore, cybersecurity education is necessary to develop resilient and cyber-secure societies and enterprises. Cybersecurity enables technical growth and improvement, creates competitive marketplaces, and eventually leads to efficient and wealthier societies. How-ever, many current cybersecurity education methodologies and methods have limitations (Elsisi et al. 2021). The spread of port digitalization may provide a workable answer to the problems encountered by the more significant marine transport business and associated port infrastructure in managing higher quantities of commodities and larger

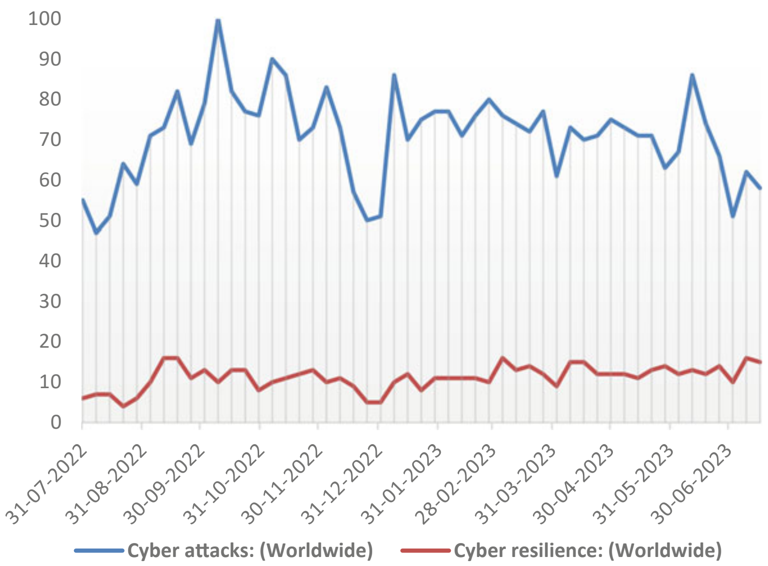


Fig. 1 Google trend for cyber-attacks vs. cyber resilience for the last one year

cargo capacities (Zhu and Liyanage 2021). Adopting state-of-the-art digital solutions, such as the IoT, AI, and blockchain, is essential. Increasing digital technologies in ports may boost profitability and enhance operational effectiveness (Progoulakis et al. 2023).

This chapter examines how digitalization capabilities influence cyber resilience for sustainable development growth. It reviews the literature on cybersecurity, strategies, and frameworks for cyber resilience, digitalization capabilities, and their connections to SDG. This chapter aimed to address the following research questions:

RQ1: How is cyber resilience significant in cybersecurity?
RQ2: What are recommendations to become cyber resilient?
RQ3: What are the cyber resilience strategies for the SDG?
RQ4: What are the tools, techniques, and methods available for cyber resilience towards the SDG?
RQ5: What is the role of AIoT towards SDG?

We collected relevant information from the selected papers to provide helpful content to the scientific community and answers to the research questions. To illustrate cyber resilience towards digitization, we explored various sources. The contributions of this chapter are as follows.

1. A holistic view of cybersecurity and resilience is presented in Sect. 2.
2. The recommendations to become cyber resilient towards SDG are outlined in Sect. 3.
3. The cyber resilience strategies towards SDG are demonstrated in Sect. 4.
4. A taxonomy based on the technologies and methods used in cyber resilience toward SDG is illustrated in Sect. 5.

The remaining chapter is formulated as follows. Section 2 concerns the chapter's background and presents the holistic view of cyber security and resilience. Section 3 highlights the recommendations for cyber resilience in cyber security. The cyber resilience strategies toward SDG are demonstrated in Sect. 4. The technologies and methods used in cyber resilience toward the SDG of society are demonstrated in Sect. 5. The usage of AIoT for SDG is demonstrated in Sect. 6. Section 7 il-lustrates the discussion and the open challenges of cyber resilience toward sustainable development growth and digitization. Finally, the paper is concluded in Sect. 8 with the future research direction.

2 Background of the Chapter

The importance of cyberinfrastructure and cyber resilience stems from the expanded dependency on digitally driven, connected networked systems, raising concerns about the vulnerability of critical cyber infrastructure. The operation of contemporary society depends on these infrastructures, which span industries, including energy, banking, healthcare, and transportation. More than traditional cybersecurity methods are needed for protection as cyberattacks become more complicated and widespread. Building resilience in these infrastructures is necessary to resist and recover from cyberattacks successfully. This section discusses cyber security, cyber resilience, and digitization.

2.1 Cyber Security

Tissir et al. (2021) presented a study on cybersecurity as protection in cyber-space. ISO 270.32 defines cyberspace as complicated conditions associated with individuals and services over the Internet linked via appliances and networks that do not exist physically. Based on ISO connotations, it is conceivable that cyber-security safeguards against virtual or cyber threats. Georgiadou et al. (2022) studied that cybersecurity shields individuals; data should also be shielded because disinformation can impact the social context, affecting connections among individuals, societies, or governments. Mindsets communicated in cyberspace can also affect individuals.

Cybersecurity should defend against established and emerging cyber threats by providing information about which threats pose a risk to particular businesses. Tounsi and Rais (2018) presented a study on Cyber threat intelligence to prevent cyberattacks by identifying risks. Velasco (2022) studied admirably skilled and sponsored cybercriminals who operate in a coordinated and managed manner to launch cyberattacks to maximize profit. Huang et al. (2019) analyzed that the cybercrime ecosystem also has technological resources and training to support further cybercriminals in cyberattack strategies. Barik et al. (2022a, b, c) reviewed text mining approaches for cyber security applications. The latest technologies, such as the IoT and cloud computing, have extended the attacking character and enabled communities to be more exposed to cyberattacks.

Cybersecurity caters to a wide range, which includes a network security protection against possible network disruptors, such as outside threats, malicious activity, and crackers. Zerlang (2017) presented a study on tools that allow companies to maintain secure computer networks for day-to-day operations, including detection, prevention, and monitoring. Sołtysik-Piorunkiewicz and Krysiak (2020) analyzed application security; the system is protected from external threats that can impede applications by utilizing hardware and software, namely Web Application Firewall, Encryption, and Antivirus. Solms and Niekerk (2013) presented a study on information security safeguards digital and physical data against abuse, unauthorized access, exposure, tampering, and erasure. Agyepong et al. (2023) studied operational security, including methods and possibilities for data security, management, and daily operations. Takahashi et al. (2010) presented a study on the cloud security shield data in a cloud environment and continuous monitoring. Tiirmaa-Klaar (2016) offered a study on user training that refers to individuals' variable nature of cybersecurity. The broad aspects of cyber security are presented in Fig. 2.

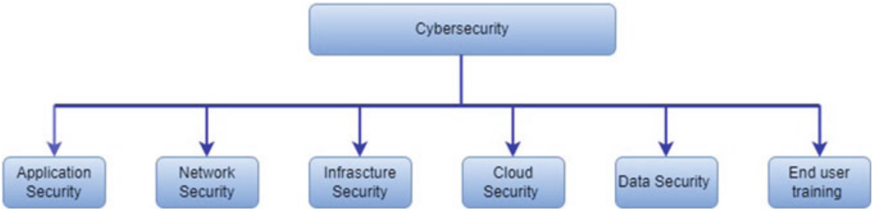


Fig. 2 Different aspects of cyber security

2.2 Cyber Resilient

Linkov and Kott (2019) analyzed cyber resilience using complicated cognitive, social, physical, and informational methods. Cyber resilience ensures system recovery by considering interrelated hardware, software, and cyberinfrastructure com-ponents.

Bellini and Marrone (2020) presented a study that resilience originates from how the system reacts and recovers to normal operations. For instance, resilience engineering is the ability of systems to anticipate and adapt to the potential for surprise and failure, and it has been linked to a change in the safety paradigm that acknowledges the significance of system coping when prevention is not feasible. Ecological resilience refers to a system's capacity to absorb and sustain shocks by focusing on persistence. Watkins and Marsick (1992) presented a study on resilience that is described less abstractly, distancing the metaphor from science and de-scribing how systems respond to shocks. The National Academies of Science (NAS) definition of resilience as the capability to organize and prepare for, interest, recuperate from, and acclimate to damaging circumstances is evolving into one of the terms institutions and controlling bodies. Suhail et al. (2022) presented that the capability of a system to immerse in shocks depends on thresholds, determining whether alternate stable states or recovery time matters more. The recovery time after a disruption in which a threshold is not exceeded is crucial for evaluating the system's resilience. Teng et al. (2021) presented that memory characterizes a system's capacity for adaptive management and offers a method for securely organizing and discovering a system's resilience possibilities and boundaries. A holistic view of cybersecurity and cyber resilience is demonstrated in Fig. 3.

2.3 Digitization

Digital operations and business process automation combine simplicity and efficiency to create operational models that delight consumers and increase productivity. Lallie et al. (2021) presented that a corporation's most crucial business pro-cesses are governed, revamped, and removed via digital operations to save operating expenses, enhance user satisfaction, provide more valuable outcomes, and boost development.

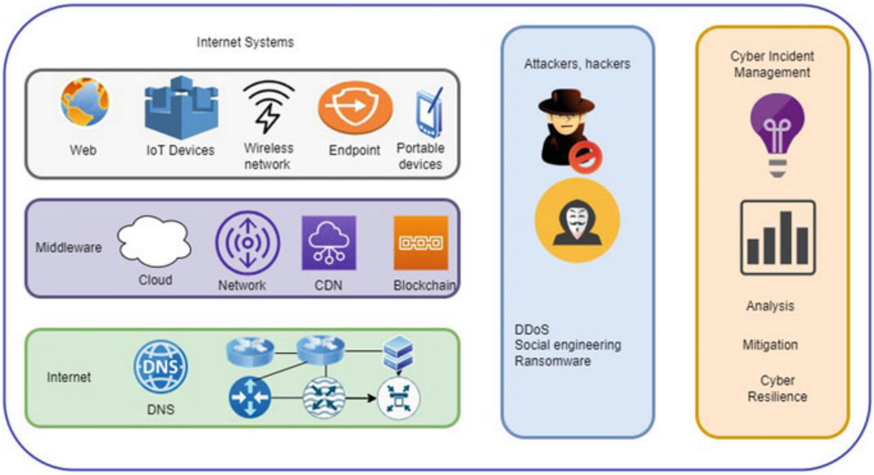


Fig. 3 A holistic view of cyber security and cyber resilience

Küsters et al. (2017) presented a study on organizations that can achieve method excellence and more accurate operational models by forming automatic data-centric outlets and business utilities. A designated person is responsible for the resilience and availability to facilitate the highest level of digital interaction.

Boute et al. (2022) proposed a study that the digital economy offers a new possibility to research and design new interests, usefulness, and process customization according to client expectations. However, a company's attempts at transition must be improved by out-of-date operating models, making meeting consumer and demand requirements more challenging. Companies producing elastic, net-worked, and intelligent strategies can deliver more humanized interactions and procedures that exceed customer demands. Digital processes can support companies in evaluating and establishing digital solutions to enhance enactment and bridge the gaps among clients, vendors, and associates by utilizing strategy out-lets, mechanization, and data.

2.4 *Sustainable Development Goals*

United Nations (2018) presented a report for equity and sustainable development by 2030. George et al. (2021) presented SDGs and emphasized 17 pressing issues. Developing and deploying intelligent technologies to ensure sustainable economic development while considering and integrating the SDGs is digital sustainability. To this end, Magistretti et al. (2019) presented a study with advanced developments like AI, the AIoT, and more traditional tools like creating, using, transmitting, securing, and sourcing electronic data for organizational activities.

3 Cyber Resilient of Sustainable Development Growth in Digitization Contexts

Hillmann and Guenther (2021) presented a study on resilience, which describes a system's capacity to design, interest, recuperate from, or acclimate to actual or possible negative possibilities. It is a metric used in organizational, social, and engineering systems. Duchek (2020) presented a study on resilience, which is the recovery of service levels after a disruption, and the restoration of the service level can be accompanied by modifications to the system's structure and components, which may be either temporary or permanent. Regardless of the definition's domain of origin, resilience's overriding piece is the ability to reduce the size and length of adverse events and incorporate a system's capacity for shock absorption, adaptation, and recovery.

White and O'Hare (2014) studied risk and vulnerability, two concepts intimately connected to resilience. The following are some of the modelling and simulation techniques mentioned in the study: the detection of systematic and necessary failure practices, the quantification of interdependency-related indicators, empirical risk analyses, the use of multi-agent systems, the application of system dynamics, the use of economic theory, and the use of network science techniques. Two types of resilience measures are found: (a) equilibrium resilience achieves the required state owing to the system's resilience mechanisms, and no additional corrective measures are required. Bouska et al. (2019) presented a study on the system decreases performance without falling below the minimum acceptable state and returns to the general area of the required state within an acceptable duration (b) Sterbenz et al. (2010) presented a study on the general resilience means that falling below the minimum acceptable state is necessary for the system to maintain its performance and, after an acceptable amount of time, reach an improved state, which is sometimes the required state. If the improved state produced by the system resilience mechanisms is not close to the required state, additional corrective actions are required to return to the required state.

Carias et al. (2020) presented a study on SMEs can benefit from a cyber-resilience, or a more all-encompassing approach to cybersecurity, which they help to identify, withstand, recover from, and adapt after cyber events. Hausken (2020) analyzed by attempting to identify the elemental details of cyber resilience. Threat actors are separated from non-threat actors and have access to re-sources, knowledge, expertise, and tools. Babiceanu and Seker (2019) proposed an integrated modelling environment that addresses the security and resilience of Software Defined Networks (SDN) applications for virtual manufacturing systems. The study suggests using an SDN-based manufacturing testbed and a cybersecurity-resilience ontology to capture needs during the design stages of virtual manufacturing networks. Kleij and Leukfeldt (2020) presented a study of a frame-work for cyber resilience that combines resilience engineering concepts with human behaviour models. This study, based on a pilot study involving approximately 60 small- and medium-sized businesses (SMEs) in the Netherlands, demonstrates the potential of the proposed framework for improving the growth of organizational human components of cyber resilience. Chaves et al. (2017) presented that an active defence approach is part of a resilience plan for industrial control systems to lessen, if not eliminate, the possibility of a common cause failure by a cyberattack. The active defense implementation is contrasted with a conventional industrial control system resilience solution using a partially simulated wastewater treatment plant subjected to a cyber-attack.

Linkov and Kott (2019) presented a study on cyber resilience, a critical concept in digitization that supports the safe and effective conversion of conventional processes and systems into digital representations. Organizations should inevitably expose themselves to higher cyber risks and assaults to boost efficiency, productivity, and competitiveness when they start their digitalization journeys. Cyber resilience is essential to ensure a seamless transition and continued functionality of digital activities in the face of potential disruptions. In digitalization, organizations should adopt a multifaceted strategy that includes a range of preventative actions and adaptive tactics to achieve cyber resilience. Identifying possible vulnerabilities in digital infrastructure, applications, and processes is fundamentally aided by continuous risk assessments. Organizations can effectively set priorities and spend resources to strengthen their cyber defenses by becoming aware of these hazards.

Data backup and recovery systems are essential for cyber resilience in the digital world. An insurance policy against data loss or compromise in the case of a cyber-crisis is provided by routine backups of critical digital assets paired with secure and redundant storage options. Carayannis et al. (2021) offered a study on cyber resilience, which is also improved by establishing a culture of cooperation and in-formation-sharing with external stakeholders. A cohesive strategy for cyber-security is created through regular communication and collaboration between IT teams, management, and other departments, which enables quick decision-making in an emergency. Annarelli et al. (2020) analyzed that cyber resilience is an all-encompassing and dynamic digitalization strategy that combines proactive measures, strong cybersecurity practices, employee awareness, incident response planning, data backup, and cooperation. By minimizing cyber risk, protecting digital assets, and guaranteeing the continuity and success of their digitization initiatives, organizations that embrace cyber resilience are better equipped to traverse the digital world with confidence. Zhu and Liyanage (2021) proposed an extended threat model to assess hazards and potential targets. They highlighted that all stakeholders should cooperate in developing a risk-based framework under the resilience umbrella to address security risks and strengthen aviation systems' defenses against future attacks. Eling et al. (2021) analyzed these challenges be-cause many well-known physical dangers (such as traditional electronic warfare tactics) can negatively impact cyberspace and vice versa. The idea of cyberspace underpins all the crucial operations of contemporary civilization and is significantly dependent on essential infrastructure for economic development, public safety, and national security. The recommendations for becoming cyber-resilient for SDG are illustrated in Fig. 4.

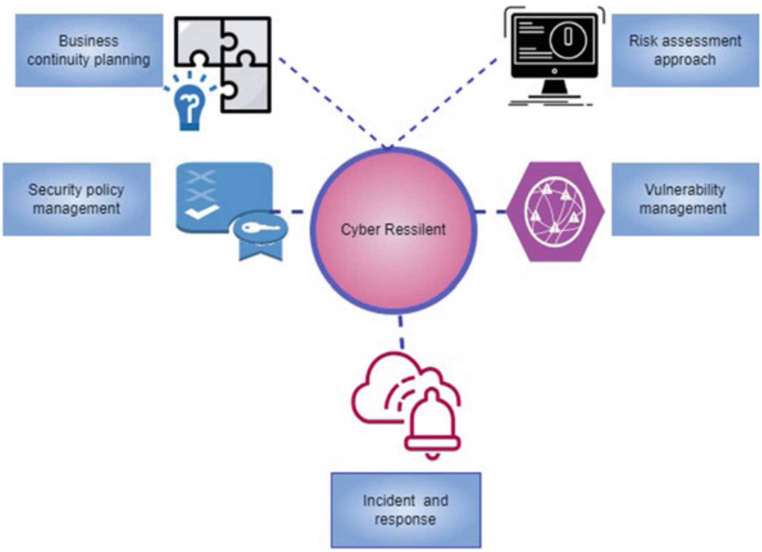


Fig. 4 Recommendations to become cyber resilient for SDG

4 Strategies in Cyber Resilience Toward Sustainable Growth in Digitalization

Diverse strategy-spanning strategies, methodologies, and technologies continuously digitize society's search for cyber resilience to strengthen and safeguard digital ecosystems. Goel et al. (2020) presented a study on organizations implementing proactive cybersecurity plans, focusing on risk assessment and mitigation to detect possible weaknesses and border security solutions. Plans for incident responses are created, including precise steps for quickly identifying, containing, and responding to cyber problems. Sharif and Ameen (2020) emphasized that Teams should enhance their response skills by participating in regular cybersecurity drills and simulations. Additionally, keeping up with new threats and attack trends is possible by engaging with cybersecurity groups and threat intelligence features. Kaur and Ramkumar (2022) proposed advanced encryption techniques to protect sensitive data, guaranteeing secrecy and integrity during storage and transmission. Barik et al. (2022a, b, c) presented a study on analyzing attack practices and safe-guards employing penetration testing. They conferred the elements and features while organizing a penetration test and included credential harvester, web jacking, and smartphone appliance penetration testing in their analysis. Potula et al. (2023) offered a study on endpoint protection products to protect individual de-vices from malware and unauthorized access, including sophisticated antiviral and endpoint detection and response (EDR) systems. Najafi et al. (2021) presented a study on network security solutions that collaborate to monitor and secure nework traffic, including firewalls, intrusion detection/prevention sytems (IDS/IPS), and security information and event management

(SIEM) systems. Barik et al. (2021) emphasized the necessity of forensic tools to investigate security attacks. They analyzed a few open-source network forensic tools and conducted a comparative study of six key parameters. Scalable and adaptable cloud security solutions can protect cloud-based services and data storage. Halbouni et al. (2022) presented a study on machine learning (ML), and Barik et al. (2022a, b, c) offered a study on deep learning (DL) methods that considerably improve cyber resilience. Analyzing enormous volumes of data to find patterns and anomalies suggestive of cyberattacks enables real-time threat detection and responses. Societies can strengthen their cyber resilience with the help of unified strategies, techniques, and cutting-edge tools, thereby reducing risks, protecting data, and ensuring a safe and sustainable digital future.

Javaid et al. (2023) presented a model based on cyber security aids in ensuring that all crucial assets are shielded from cyber-attacks and that private data is not lost or stolen. Cybersecurity solutions that use AI and ML approaches can dramatically enhance an organization's overall security posture and aid in defending against the increasing danger of cyberattacks. Macas et al. (2022) proposed a study on cybersecurity using machine learning. They highlight phishing detection, network intrusion detection, authentication, cryptography, human interaction evidence, and spam detection in social networks. Cavalcante et al. (2019) showed a study on how and when simulation and machine learning can be coupled to construct digital supply chain twins, enhancing resilience. The proposed data-driven decision-making methodology for resilient supplier selection may also be used to redesign the supplier base, invest in the most crucial and risky suppliers, or develop risk-mitigation methods in supply chain management models.

Khan et al. (2023) have analyzed a Blockchain, the IoT, with ML approaches that provide a secure framework for dispersed SMEs with a standardized process hierarchy and lifespan. The B-SMEs blockchain, which offers explanations to cross-chain platforms, is created with an IoT-enabled permissionless network topology. Kelli et al. (2021) proposed a study on digitizing health data with the necessary protection to ensure that only authorized staff may access patient information. In addition, establishing interoperable systems linked by several organizations, such as hospitals and insurance firms, while upholding a General Data Protection Regulation (GDPR) position is essential for ensuring the finest patient care. The strategies for cyber resilience strategies for SDG are exhibited in Fig. 5.

Fig. 5 Cyber resilience strategies for SDG

5 Different Technologies in Cyber Resilience Toward Sustainable Development in Digitalization

Society is evolving toward digitalization; multiple technologies are paramount for securing and protecting digital infrastructure in the quest for cyber resilience. AI and ML algorithms enable real-time threat detection and response, which analyzes enormous volumes of data to find patterns and abnormalities. Decentralized, tamper-resistant data storage, made possible by blockchain technology, promotes data integrity and confidence in online transactions. Popkova and Sergi (2020) presented a study on cloud-based security solutions that make scalable and adaptable cybersecurity measures possible, effectively protecting networks and data across numerous devices and locations. Biometric and multifactor authentication adds a layer of protection to pro-vide safe access control and lower the possibility of unwanted entrance. Maslak et al. (2021) presented a study on automated incident response systems that also use AI-driven procedures to quickly stop the spread of cyberattacks, boost cyber resilience, and lessen the effect of possible disruptions. These technologies work as brigades to defend against cyber-attacks comprehensively and dynamically, protecting society's digitalization and ensuring a safe and secure digital future.

5.1 Review of Digital Economy Transformation

An effective strategy could be to design a process for technological advancement based on models, collecting, storing, and using information or knowledge for understanding processes underlying human cognition. The IoT paradigm is open to new ideas and structures in various science and technology fields. Ganichev and Koshovets (2021) presented a study on electronic information that must replace different types of tangible commodities and services for the physical economy to transition to a digital economy. All physical assets must be converted into digital data, which can be used as a private company's main asset. Wang et al. (2018) analyzed that big data can lead to significant productivity and efficiency bene-fits. Llopis-Albert et al. (2021) studied many definitions in the literature to identify digital transformation. This study performed a fuzzy-set qualitative comparative analysis (fsQCA). This study aimed to determine how these changes could impact stakeholders. Digital transformation in the automobile sector has a wide variety of effects on many players. This study covers big data, connected and driverless automobiles, sources of digital information, mobility as a service for car sales, and other subjects. The market disruption caused by the sluggish adoption of electric vehicles was also considered.

Ziyadin et al. (2020) presented a framework with the phases, activities, and results of digital transformation that offers a cogent definition of digital transformation. Although the organized digital transformation of business models is a well-known idea, there is yet to be a method. Ghobakhloo and Iranmanesh (2021) analyzed this industry 4.0 to better assist small and medium-sized firms (SMEs) in the manufacturing sector; an interpretive model and interpretive logic knowledge base matrix were used to create an effective strategic directive. Albukhitan (2020) proposed a study to adjudicate the interaction between digital transformational leadership and digital transformation organizational agility. These findings provide insight into the relationship between these elements.

5.2 Review of Blockchain Technology

Cheng et al. (2021) presented a study that there is immense potential for applying blockchain technology to contemporary accounting and cybersecurity issues. Three blockchain development types are Blockchain 1.0, 2. Blockchain 1.0, with its popular cryptocurrencies such as Bitcoin, Litecoin, and Ethereum, has received considerable attention in the capital markets. However, Blockchain 2.0 also includes underlying technologies such as smart contracts, which extend its capabilities beyond ledger agreements. Casino et al. (2019) proposed a study on the blockchain 3.0 can be deployed for several applications, from domain names and digital identities to e-government services, smart cities, and online electronic voting, showcasing how broadly it will affect our lives in the coming year. Barik et al. (2023) presented an analysis using a blockchain-based framework for accessing customer satisfaction employing proof of concept and natural language processing to confirm the authenticity of the data.

Wang and Su (2020) offered a study of an energy blockchain research project focused on renewable energy to address the development process's obstacles and provide better options for replacing fossil fuels. Golosova and Romanovs (2018) analyzed the applications of Blockchain technology, and their effects on implementation success or failure were examined. This study examines the benefits and challenges of integrating blockchain technology across many industrial sectors. Mettler (2016) presented a study on the IBM Blockchain model used to codify and create a healthcare application for the healthcare sector. This study explored various entry points for blockchain technology in the healthcare sector. To identify the critical roles blockchain technology plays in tackling some of the most significant and challenging issues facing the healthcare sector, Attaran (2022) presented a study that summarizes essential companies and health-related blockchain technologies that provide solutions across various applications to the potential benefits and drawbacks of using blockchain technology in healthcare.

5.3 Review of Artificial Intelligence

The rise of cyberattacks, which prey on the weaknesses of networked devices, affects how well industrial organizations operate. Investments in innovation and automation have increased because of the growing digitalization and technology prevalent in the framework of Industry 4.0. Cyberattacks based on artificial intelligence (AI) may cause exponential harm to firms in Industry 4.0 when combined with traditional technology.

Guembe et al. (2022) presented a study on cyber threats with AI techniques. Zhang et al. (2022a, b) suggested an analysis outline of AI applications in cyber security. AI-based cyber security tools and the potential for upgrading defensive mechanisms to increase cyber security capabilities are also covered. Wei et al. (2023) studied a classifier that constructs a precise decision on every single significance of the data set domain with specified gradients that may use specific characteristics of the provided approach without modification. Hang et al. (2022) proposed a conceptual human-in-the-loop intelligence cyber-security model based on the identified limits and difficulties. Turransky and Amini (2022) analyzed a void in attempts to maintain some status quo. Ethics and morals significantly affect AI in healthcare. Several issues continue to arise when AI, cyber-security, and the healthcare business are considered together.

5.4 Review of Cloud Computing

Cloud computing (CC) has become a critical part of this technological ecosystem, revolutionizing business models and technologies. Lee and Shin (2018) presented a study on businesses now having access to various options for controlling their infrastructure, cutting costs, and outsourcing responsibilities that they previously may not have considered. When considering moving services and data for cloud computing, it is essential to note that both advantages and disadvantages exist. Motta et al. (2012) analyzed that cost-effectiveness, immense storage space, automated software application integration, quick access to information, rapid setup time, agility in using services, scalability of provisioned service levels, and swift offering of new services are the primary advantages of this advanced computational deployment model. Utility, grid, and autonomous computing are all components of this state-of-the-art cloud computing system. CC allows rapid provisioning of configurable network resources (e.g., networks, servers, storage, applications, and services) with minimal management effort or service provider engagement. Zhou et al. (2013) presented a study that cloud computing offers us-er convenience and on-demand access to shared resources.

5.5 Review of Internet of Things

IoT applications have become increasingly critical in terms of digitalization. The considerable advantages of digitalization include enhanced energy availability, dependability, and cost-effectiveness. These advantages can be further enhanced by integrating IoT devices into the public sector, which enables real-time energy system monitoring, analysis, and optimization.

Verma et al. (2022) presented a study on the analysis of assisting a patient in receiving the appropriate care. Traditional communication networks designed for human-based applications have several drawbacks, including high latency, limited computer power, and short battery life. On the other hand, the advent of 5G has led to the development of a new set of technologies that provide the necessary backbone for connecting to the impending IoT's billions of gadgets, which will fundamentally alter personal and professional lives. Gaining insight into the continuously growing body of work that focuses on the course, from being aware of the IoT to its continued application, begins with an understanding of the literature.

Koohang et al. (2022) proposed a model with five constructs: With the rapid proliferation of IoT technology, several key factors should be considered for its successful adoption. Alaa et al. (2017) presented a study on the IoT-based smart home automation that enables remote monitoring of different house devices from distant locations. In recent years, the number of smart city initiatives has increased worldwide. Smart cities are alluring because they can integrate cutting-edge technology, a sustainable

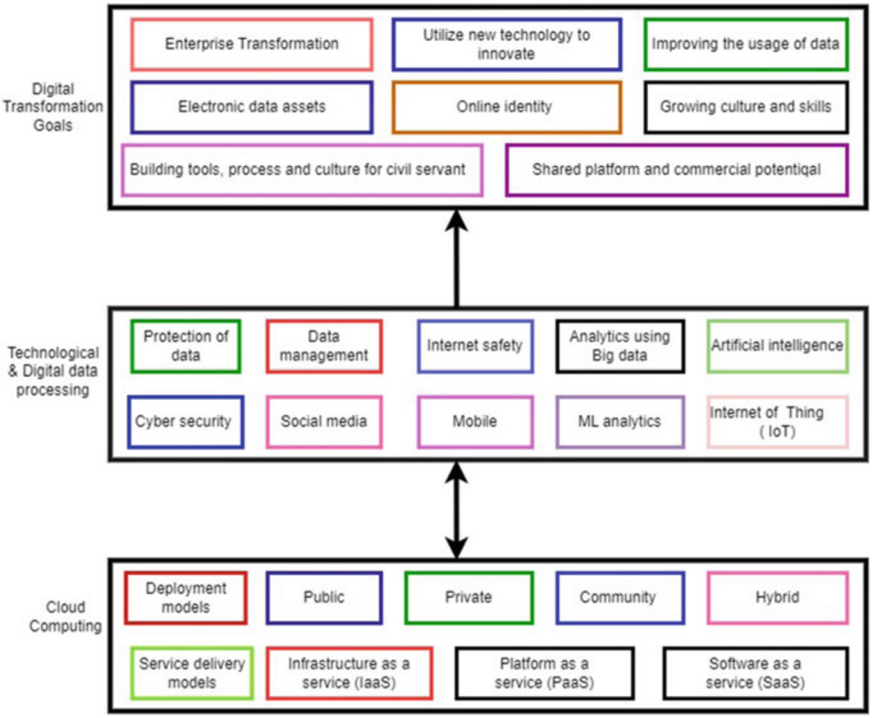


Fig. 6 Taxonomy for different technologies drives goals of SDG

environment, and the comfort of their residents, regardless of their culture or location. Mahmoud et al. (2015) pro-posed IoT architecture aims to connect everyone and everything on the planet. The network and application layers often constitute IoT architecture. Lee and Lee (2015) presented three IoT categories for corporate applications that increase customer value. These technologies are essential for the successful implementation of IoT-based goods and services. The taxonomy for different technologies and methods that drives goals for SDG for cyber resilience is proposed in Fig. 6.

6 Usage of Artificial Intelligence of Things (AIoT) Towards Sustainable Growth in Digitization

IoT refers to a broad concept that envisions a wide variety of sensors, data stores, and computational resources all interconnected and accessible over the web. Instruments with IoT capabilities can detect their environment, communicate with one another, process the data they collect, and act accordingly. The actual intelligence and usefulness of an IoT are limited by the amount of processing or action it is capable of. Assuming the goal is sustainable development and digitization, any intelligent IoT design will include AI. This section discusses how AI-enabled IoT systems can contribute to sustainable development growth and digitization.

Ghosh et al. (2018) offered a study on voice-based cloud services as virtual desktop assistants. The use of external applications and other nearby intelligent devices carries out a variety of functions. Using only the user's voice, they can perform diverse tasks, including answering questions, making dinner reservations, playing music, and turning smart lights on and off. Popular voice-activated assistants include Alexa from Amazon, Google's Assistant, etc. Liu et al. (2022) presented a study on how voice associates can achieve substantial tasks, especially those that involve the application of various branches of AI. Voice assistants can function in real-time because of the continuous execution of tasks such as wake word detection, speech-to-text conversion, natural language processing and understanding, contextual reasoning, and conversational.

Technological advancements in recent years have enabled developers to design robots that look and act more like humans and can interact with people while displaying a range of emotions. Liu and Cong (2022) presented a study on the Robots are IoT devices because they have multiple detectors, motors, and AI, enabling them to understand and acclimate over time. Maroto-Gómez et al. (2023) offered an analysis of robots that make comprehensive use of a wide variety of technologies, including but not limited to natural language processing, computer image detection and search, blockchain technology to explore inputs and responses, facial recognition, voice recognition; speech-to-text technology; obstruction recognition; etc. Dong et al. (2021) analyzed how Intelligent machines learn from human interaction and response. AIoT gadgets can also collect and analyze user data, allowing for identifying patterns and providing individualized support. Intelligent buildings use both AI and the IoT. Majdi et al. (2022) offered an analysis of the organizations installing smart environmental sensors throughout their workplaces to determine when an employee is present and adjust the building's climate and lighting accordingly to minimize power conservation. Alam et al. (2022) presented a study to build an AI decision-as-a-service function for HR professionals by integrating AIoT instruments with social networking sites and HR-related systems. Rajavel et al. (2022) proposed an analysis of AI and IoT employed together; they produce video surveillance that is both highly effective and highly intelligent for use in security applications. Najafi et al. (2022) presented a study on the stock levels across manufacturing industries that can be maintained using an AI and IoT-powered centralized platform. It has analytical elements that work for various applications. The summaries and challenges of AIoT are depicted in Figs. 7 and 8, respectively.

This chapter highlighted the significance of cyber resilience in enhancing cybersecurity amid society's rapid digitization. This chapter provides an in-depth analysis of the taxonomy of cyber resilience, classifying various approaches and strategies employed to strengthen cyber defenses and respond effectively. Application metrics are analyzed to assess the performance of cyber resilience techniques in real-world scenarios. Among the prominent technologies, AI, ML, and DL play a crucial role in bolstering cyber resilience during the digitalization of society. Nevertheless, this

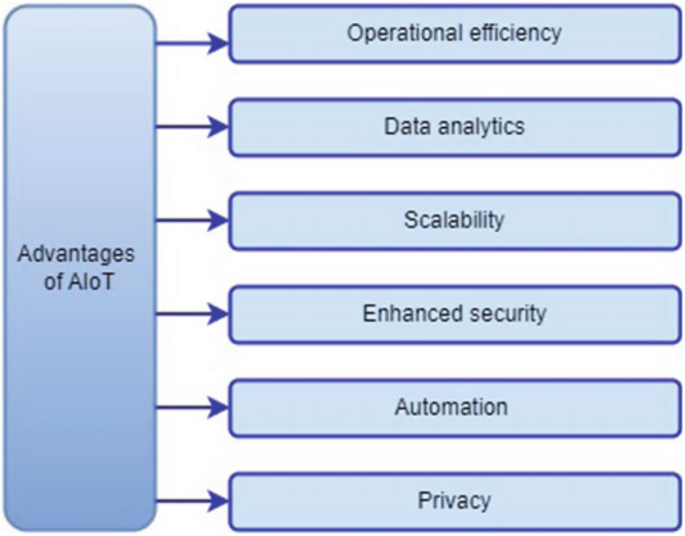
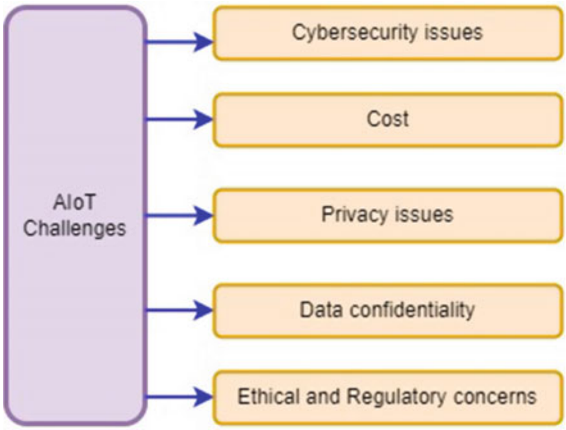


Fig. 7 Advantages of AIoT in SDG

Fig. 8 Challenges of AIoT in SDG



review realizes the need for further advancements, particularly in the speed and efficiency of deep learning and machine learning algorithms, to make them more viable in real-time cyber defense operations.

The evaluation of research publications, which covered a broad range of issues, such as cloud computing, blockchain technology, IoT, cyber resilience, and cyber security, is shown in detail in Figs. 9 and 10. This chapter looks at published works from different publishers, discussing the varied approaches used in these papers. The latest trends, developments, and difficulties experienced by researchers and practitioners in the area are revealed in this thorough overview, which offers insightful information on the current status of research in various fields.

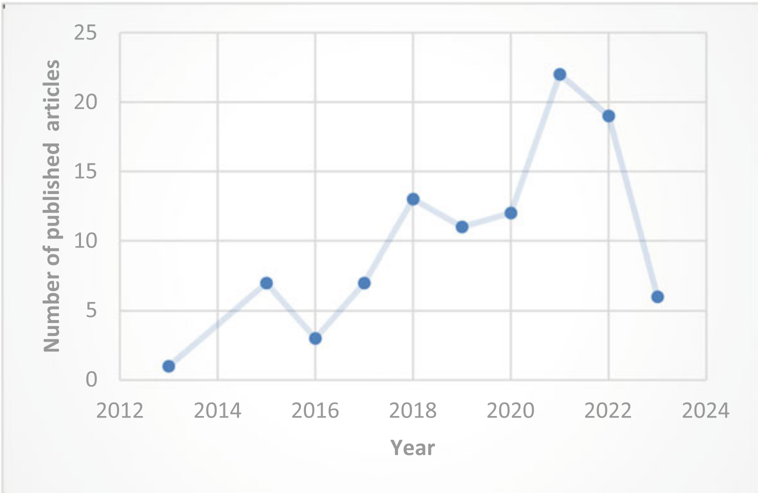


Fig. 9 Review of published papers

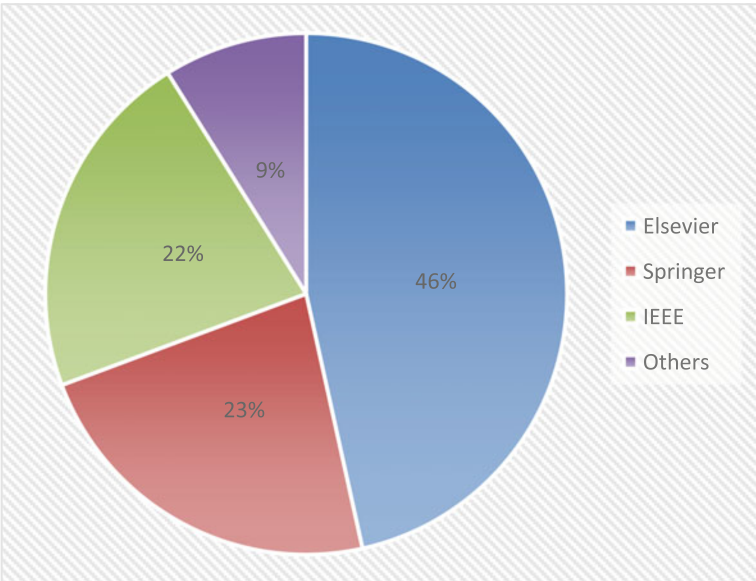


Fig. 10 Review of the publisher

7 Discussion and Open Challenges

The imperative for organizations to strengthen their cyber resilience capabilities in the face of cyberattacks has evolved prominently as the world has adopted the digital revolution. The investigation focused on cyber security, underscoring the significance of safeguarding digital assets, information, and systems against un-authorized access, disruption, and damage. Ligo et al. (2021) presented a study on cyber resilience has emerged as a critical aspect of cyber security, representing an organization's ability to withstand and recover from cyber intrusion effectively. Dwivedi et al. (2020) analyzed society's digitization, recognized as a trans-formative force that necessitates robust cyber resilience measures to ensure the secure functioning of public systems and enterprises.

This chapter explored the critical interplay between cyber resilience and the digitization of society, considering the escalating prevalence of cybercrime in the rap-idly developing digital landscape. A holistic view of cyber security and cyber resilience is illustrated in Fig. 3. The recommendation to become cyber resilience for SDG is pictured in Fig. 4. A taxonomy is presented to classify cyber resilience within the cybersecurity domain based on the formulated research questions, offering a review to understand and evaluate resilience strategies. The cyber resilience strategies for SDG are presented in Fig. 5. A taxonomy is presented for different technologies that drive the goals of SDG for digitalization in Fig. 6. The advantages and challenges of AIoT in SDG are highlighted in Figs. 7 and 8, respectively. The significance of cyber resilience in cybersecurity (RQ1) is demonstrated in Sect. 2. The recommendations to become cyber resilient (RQ2) are outlined in Sect. 3. The cyber resilience strategies for the SDG (RQ3) are presented in Sect. 4. The tools, techniques, and methods available for cyber resilience towards the SDG (RQ4) are depicted in Sect. 5. The role of AIoT towards SDG (RQ5) is presented in Sect. 6.

Further, the chapter explored various digitization contexts, providing insights in-to the industries covered and the types of content analyzed. This highlights the di-verse implications of digitization in society. In exploring strategies, methods, and tools employed in cyber resilience toward the digitalization of society, various ingenious techniques, such as deep learning, machine learning, and other cutting-edge technologies, are unearthed. This recreates a vital role in safeguarding the integrity and security of digital ecosystems. The chapter also presents a comprehensive overview of different technologies utilized in cyber resilience for digitization, including blockchain, cryptography, cloud computing, and the IoT. Despite the strides made in cyber resilience and digitization, this chapter al-so identified open challenges that require further exploration and resolution. These challenges include addressing cybersecurity and privacy concerns in organizations, promoting greater awareness and collaboration among stakeholders, and establishing best practices for cyber resilience (Kaur et al. 2023).

Addressing these challenges requires a multifaceted and collaborative approach involving governments, organizations, technology developers, and end users. Cyber resilience and secure digitization are ongoing processes that require constant vigilance and adaptation to avoid evolving threats (Erstad et al. 2023). Based on the articles selected in this chapter, the open challenges summaries are as follows.

1. *Cybersecurity Threats and Attacks:* The ever-evolving nature of cyber threats and attacks continues to challenge organizations and individuals. New attack vectors, sophisticated malware, and targeted attacks are constantly emerging, and implementing cybersecurity measures is challenging (Anandita Iyer and Umadevi 2023).
2. *IoT Security:* The rapid expansion of the IoT has connected many devices to networks, often requiring more security measures. Ensuring the protection of these devices and preventing them from becoming potential entry points for cyber-attacks continue to pose a significant challenge (Ahmid and Kazar 2023).
3. *Legacy Systems and Infrastructure:* Many organizations rely on outdated legacy systems and infrastructure that may need to be designed with robust security features. Updating or replacing these systems without disrupting operations poses a challenge (Hasan et al. 2023).
4. *Supply Chain Risks:* As organizations become increasingly interconnected, their supply chains can introduce potential vulnerabilities. Third-party vendors and suppliers may unknowingly expose businesses to cyber risk (Hammi et al. 2023).
5. *Human Error and Insider Threats:* Despite technological advancements, human error and insider threats remain significant concerns. Ensuring employees are adequately trained to recognize and respond to potential threats is an ongoing challenge (Pal et al. 2023).
6. *Data Privacy and Compliance:* With the increasing volume of data collected, stored, and processed, data privacy and compliance with regulations such as GDPR and CCPA have become critical challenges for businesses worldwide (Wylde et al. 2023).
7. *Digital Transformation Risks:* Digitization and digital transformation processes pose challenges. Integrating new technologies securely while managing organizational changes can be complex (Liyanage et al. 2023).
8. *Emerging Technologies:* The rapid adoption of emerging technologies, such as AI, ML, and quantum computing, introduces new security risks that can be addressed proactively (Bendiab et al. 2023).
9. *Capacity and Scalability:* As businesses grow and adapt to the digital landscape, ensuring that cybersecurity measures are scalable and can handle the increased capacity remains challenging (Sezgin and Boyacı 2023).
10. *Lack of Cybersecurity Resources:* The demand for skilled cybersecurity professionals often exceeds the available talent pool. Recruiting and retaining qualified individuals is challenging for organizations across various industries (Jahankhani et al. 2022).
11. *Rapid Proliferation of Data:* The massive amount of data generated daily adds complexity to cybersecurity. Managing and securing this data is an ongoing challenge (Duong et al. 2022).

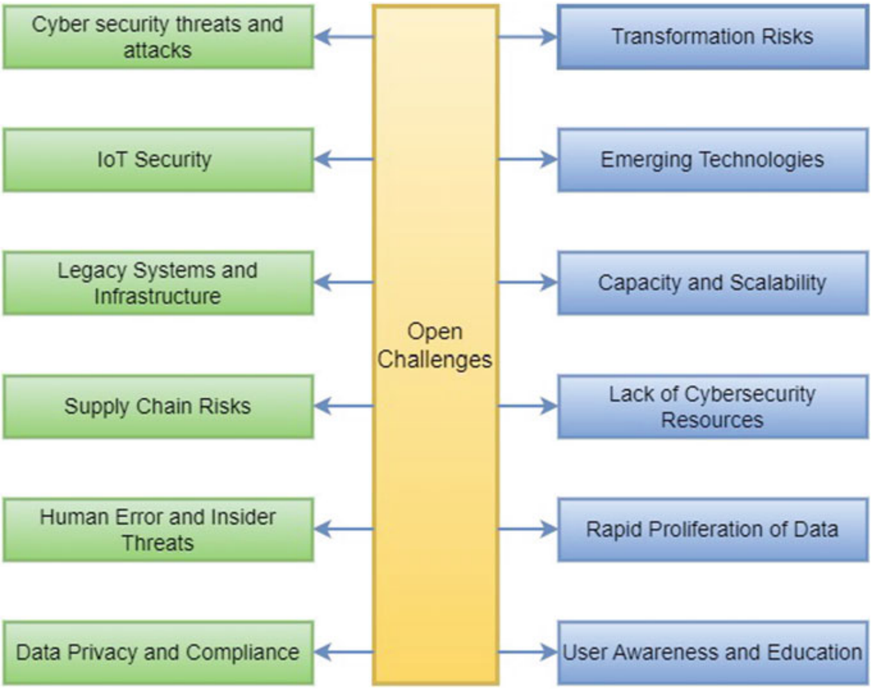


Fig. 11 Open challenges for SDG towards digitization

12. *User Awareness and Education:* Educating users about potential cyber threats and the importance of cybersecurity best practices is a continuous challenge, especially given the constantly changing threat landscape (Zwilling et al. 2022).

The challenges for digitization are outlined in Fig. 11.

8 Conclusion

This chapter emphasizes the importance of cyber resilience in successfully implementing and sustaining digitization for sustainable development and growth in society. The holistic view of cyber security and resilience is presented. The recommendations to become cyber resilience in cyber security are emphasized. The cyber resilience strategies for SDG are proposed. A taxonomy is offered for different technologies that drive the goals of SDG. The benefits and security concerns of AIoT in SDG are emphasized. The discussion and cyber resilience challenges toward sustainable development growth are illustrated. By providing a comprehensive understanding of cyber resilience, taxonomy, and the tools and technologies employed, this chapter offers valuable insights to the scientific community and relevant stakeholders. The digital landscape continues to evolve, and ad-dressing the identified open challenges will be instrumental in shaping a cyber-resilient future for society. This review directs researchers and organizations on cyber-resilient developments that can withstand the ever-changing cyber threat landscape for SDG in the digitized world. Further analyses of the industry-wise challenges, e.g., in the energy or education sector, for transportation and smart cities, and humanitarian aid and development of cyber resilience for SDG in digitalization are needed. Future work is to extend the factors that include investment decision-making in cyber resilience in digitization.

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