Environmental Footprints and Eco-design of Products and Processes

K. E. K. Vimal · Sonu Rajak · Vikas Kumar · Rahul S. Mor · Almoayied Assayed *Editors*

Industry 4.0 Technologies: Sustainable Manufacturing Supply Chains

Volume II—Methods for Transition and Trends

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Environmental Footprints and Eco-design of Products and Processes

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Preface

While moving through innovations, today's manufacturing industry realizes multiple transformations to achieve a competitive edge. Given the complexity of systems and transformations, manufacturing businesses worldwide face multiple sustainability challenges that necessitate adequate transition methods and measures analysis. Industry 4.0 technologies seem promising solutions to address such questions for manufacturing supply chains. In view of this, the current book presents an interaction between transitions and trends of Industry 4.0 technologies and sustainable manufacturing supply chains, offering reflections on various aspects.

Chapter "Big Data Analytics and IoT-Driven Supply Chain Performance Measures in Indian Coal Industry: A Framework for Implementation" offers an implementation framework for big data analytics and IoT-driven supply chain measures in the Indian Coal industry and identifies various enablers and barriers. Chapter "Recent Developments on Smart Manufacturing" highlights the importance of smart manufacturing and the challenges in adopting digital technologies. Chapter "Applications of Artificial Intelligence Tools in Advanced Manufacturing" covers multiple manufacturing themes through a hierarchical structure and explores the applications of artificial intelligence toward boosting efficiency. A comprehensive artificial intelligence-based implementation framework consisting of application, data, and computation layers has been developed in Chapter "Improving Supply Chain Sustainability Using Artificial Intelligence: Evidence from the Manufacturing Sector", and can help bridge the gaps between Industry 4.0 technologies and sustainability dimensions. Chapter "A Grey-DEMATEL Approach for Analyzing the Challenges for Lean 4.0 in SMEs" outlines a case of small and medium-sized enterprises (SMEs) for various challenges in incorporating the composite process of lean principles in Industry 4.0 scenario using the Grey-DEMATEL technique.

Similarly, Chapter "Challenges and Opportunities for Lean 4.0 in Indian SMEs: A Case Study of Jharkhand" focuses on Indian SME to identify obstacles and rank the factors affecting lean 4.0 implementation. Chapter "SME 4.0: Health Monitoring of Maintenance Management Approaches in Smart Manufacturing" investigates the optimal decision support with smart maintenance management systems for health monitoring SMEs. Chapter "Enablers and Benefits of Supply Chain Digitalization: An Empirical Study of Thai MSMEs" presents a case of medium small and medium-sized enterprises (MSME) in Thailand and reveals that most MSMEs employ basic digital tools. At the same time, the adoption level of intermediate and advanced technologies is moderate and low, respectively. A conceptual framework of a hybrid blockchain for the sustainable supply chain arena during COVID-19 is developed in Chapter "A Preliminary Analysis of Blockchain Impact on Sustainable Supply Chains: COVID-19 Perspective". On the other hand, Chapter "Effective Supply Chain Management Using SEIR Simulation Models for Efficient Decision-Making During COVID-19" presents a simulation model of the susceptible-exposed-infectious-recovered network for forecasting and efficient decision-making during COVID-19. Chapter "Digital Twins an Enabler of Digitalization in Supply Chain" discusses digital twins, their types, potential benefits to supply chain management, implementing digital twins, and the associated challenges. Finally, Chapter "Requirements for the Adoption of Industry 4.0 in the Sustainable Manufacturing Supply Chain" outlines various aspects of adopting Industry 4.0 technologies in the manufacturing supply chain environment.

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Big Data Analytics and IoT-Driven Supply Chain Performance Measures in Indian Coal Industry: A Framework for Implementation

Nilesh Vadkhiya and Sonu Rajak

Abstract Indian coal industry has very significance importance in Indian economy. In Indian economy core sectors like thermal power plant, cement industry, steel industry, and paper industry are still very much coal dependent. The use of big data analytics and internet of things (IoT) are still at very nascent stage for Indian coal industry. In this chapter, a framework for implementation of big data analytics and IoT in the Indian coal industry and across its supply chain is proposed. At present very limited research is undertaken in the field of application of Industry 4.0 in Indian coal industry and across its supply chain. Big data-driven supply chain and suggesting performance measures will give immense opportunity for coal industry and its consumer to improve the supply chain. The enablers, barriers of big data analytics, and IoT are identified across supply chain of Indian coal Industry.

Keywords Supply chain management · Big data analytics · Internet of things · Performance measure · Coal industry

1 Introduction

Indian coal industry is producing or generating lots of data on daily basis. Need of the hour is transforming this data into structural manner. These data can be utilized for performance improvement in coal supply chain. Industry 4.0 concept will help in categorization and classification of these data into structural manner. For monitoring of any supply chain, it is very essential to have closure look of factors affecting it. Further, it is not possible to measure these factors directly. These factors are manifested by the other predictor variables in the supply chain. Industry 4.0 techniques like big data analytics, machine learning algorithms, IoT, blockchain, etc., are useful ways to measure these factors and control them to gain desired output.

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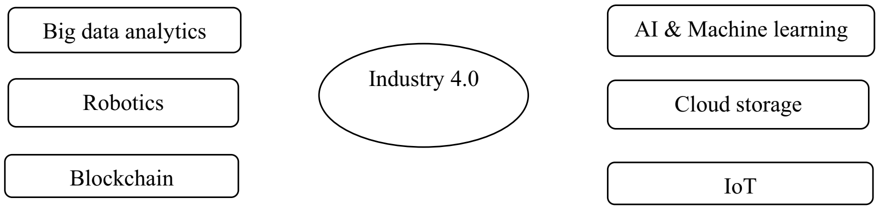

Fig. 1 Various Industry 4.0 techniques for advance learning

Supply chain in coal industry consists of exploration, project appraisal, land acquisition, land clearance, project approval, tendering, award of work and agreement (in case of contractual work), takeover of the site, drilling, charging, blasting (in case of overburden (OB) removal and in some cases of Coal), excavation/extraction of OB/Coal, loading, transporting of coal to railway siding, dispatch of coal to a plant as per requirement, etc. The application of industry 4.0 technology will give enormous opportunity performance and efficiency improvement. In case of underground mining technology real-time monitoring of ventilation status, real-time monitoring of harmful gases, optimum quantity of air circulation for ventilation to avoid any type of hazards, real-time roof strength monitoring, preventive maintenance of machineries, etc., can be done with the help of Industry 4.0. Industry 4.0 uses the concept of advanced data analytics, artificial intelligence, and machine learning (neural network, genetic algorithm, fuzzy algorithm, etc.) for decision-making. Internet of thing (IoT) uses the interconnected network and sensors for real-time monitoring of supply chain, machineries, healthcare equipment, robotics, etc. Cloud storage can be utilized for information and data storage leading to get rid of physical requirement of data storage and file maintenance. Various Industry 4.0 techniques for advance learning is given in Fig. 1.

Very limited research paper has been published till date using the above industry 4.0 technology. Examination of the barriers to green supply chain in Indian mining industry using the graph theory helps to rank the barriers [1]. Categorization of factors affecting mining operation was done [2]. To increase the digitalization of mining industry review of sensing technology applications in the mining industry was done [3]. For the purpose of process management key performance indicators in the mining industry were analyzed [4]. Evaluation of tools and data driven decision-making in the mining industry using industry 4.0 was done [5]. The relationship between the practices followed in the supply chain and measures using structural equation modeling to improve supply chain is investigated [6]. Case study on sustainability of industry 4.0 technologies has been done [7]. Identification of trends in the innovative development of mining industry as well as categorization of the basic elements of the Industry 4.0 projects on basic mining processes [8]. A framework for big data driven supply chain performance system for implementation and optimization of key performance parameters involved in the supply chain was done [9]. The supply chain performance measures proposed in this paper apply to both manufacturing and service industries and suggested for research in more industry specific performance measures. Therefore, it can be observed that implementation of the Industry 4.0 technologies in the mining industry is still at nascent stage. Industry 4.0 implementation project will demand high amount of cost involvement for the industry. For any industry, it is very important to go step by step for implementation of Industry 4.0 concept. In this paper, a framework to introduce the industry 4.0 concepts like big data-driven supply chain in coal industry and use of IoT concept of industry 4.0 for real-time monitoring of measures of supply chain processes and constructs of supply chain process is proposed. This will benefit the industry and stakeholders of industry.

1.1 Performance Measures in Coal Supply Chain

Supply chain of coal industry consists of process activities like survey, land acquisition, Environment clearance, project appraisal, deployment of fleet and site handover, OB removal, OB transportation, OB dumping, Coal extraction, Coal transportation, and various other associated activities to support all these activities. The main factors affecting the mining operation may be classified as operational factors, management, human resource factors, financial factors, resource utilization, Environment factors, marketing, and corporate affairs, etc. Further, Operational factors like drill and blast efficiency, energy management, geo mechanical conditions, working conditions and distance of transportation, production scheduling, operational excellence, Fleet deployment, dewatering, crusher plant, etc., affect the mining supply chain. Various domain of the supply chain operations reference (SCOR) framework can be used for categorization of supply chain processes/practices which has substantial effect on supply chain performance measures. SCOR domain structured around key supply chain (SC) process like Plan, source, make, deliver, and returns. SCOR framework is a tool for evaluation of performance measures of supply chain processes and strategic decision-making. This tool when used in conjunction with Supply Chain domain, the management have access for the measures where appropriate action will result in performance efficiency of the organization [10]. The Management plan all the actions for performance efficiency of the organization around the domains of SCOR framework [11]. SCOR framework and BDDSC provides precise, reliable, and accurate information to the managers for controlling the supply chain process domains and gain strategic performance objects Vis a Vis organizational performance. This will help the organization to plan their big data investment aligned with strategic targets [12]. In past, SCOR framework has been used for categorization and classification of the PMM. This was found to be helpful in identifying and rectifying the supply chain performance problems [13, 14]. Machine learning techniques using large data set available for pattern recognition in consumption in supply chain parameters and their sustainability [15]. Improvement in output level of the firm from the project of hiring contract exists in the supply chain [16]. In supply chain, the coordination with small business enterprises for successful implementation of project internal process as well as desired output level for the industry [17] is important.

It is important that the manager understands the necessities of sharing the required information in the supply chain and implement as practices to improve the performance of the projects [18, 19]. Further, to improve the performance parameters or constructs, understanding of the drivers of these parameters and how these drivers influence the parameters is very much important [20]. Big data and IoT-driven supply chain performance constructs is given in Table 1.

Further, the above proposed constructs may be manifested by different manifest variables. The SCOR framework of structural domain (i.e., plan, source, make,

Table 1 Big data and IoT-driven supply chain performance constructs

Performance constructs	Cost (C)/time (T)/ flexibility (F)/quality (Q)/innovativeness (I)	Qualitative (QL)/ quantitative (QN)	Remarks
Advanced big data analytics investment	C	QN	Investment made on advanced big data analytics adoption strategies
IoT investment	C	QN	Investment made on sensor technology and interconnected networks for real-time data
Domain knowledge	Q	QL	Understanding of industry process, regulations, norms, and practices
Gap analysis	C	QL	Analysis for training requirement of Human resource adoption of big data and IoT-driven SC
Willingness to learn	F	QL	Willingness to learn new technology and modern knowledge
Leaning ability	F	QL	Ability to understand the new technology and modern concept
Compatibility	F	QL	Compatibility of new concept with the existing systems
New initiatives	F	QL	Ability to take new initiatives to implement modern concept and technology
Integration	Q	QL	Ability to integrate the data from different files, texts, images, etc.

(continued)

Table 1 (continued)

Performance constructs	Cost (C)/time (T)/flexibility (F)/quality (Q)/innovativeness (I)	Qualitative (QL)/quantitative (QN)	Remarks
Co-ordination	Q	QL	Coordination between the analyst and line managers
DOP (autonomy)	F	QL	Amount of devolution of power to line manager and analyst
Degree of IoT embedded sensor technology used in machineries	T	QN	Machineries deployed for production have sensor for monitoring and tracking
On the job data collection	Q	QL	On the job or real-time data collection through the use of IoT-embedded sensor technology
Data accuracy	Q	QL	Ability of IoT-embedded sensor technology to collect accurate data
Data storage	C	QN	Storage of real-time data generated on the job/process
Data reliability	Q	QL	Goodness of fit of the data collected
Data completeness	Q	QL	All the relevant information are collected
Use of industry 4.0 skill set for categorization and classification	Q	QL	Ability of analyst to use appropriate skill set classification and categorization of variables
Use of industry 4.0 skills set for description, data visualization, and analysis	Q	QL	Ability of analyst to use appropriate skill set to identify happening in the past and causes
Use of industry 4.0 skills set for prediction and decision making	Q	QL	Ability of analyst to use appropriate skill set to predict future direction and causes
Use of industry 4.0 skills set for prescription and implementation	Q	QL	Ability of analyst to use appropriate skill set to control the process

(continued)

Table 1 (continued)

Performance constructs	Cost (C)/time (T)/ flexibility (F)/quality (Q)/innovativeness (I)	Qualitative (QL)/ quantitative (QN)	Remarks
Data security	Q	QL	Data security and privacy maintained in all stages of SC
Top management support	Q	QL	Top management commitment toward industry 4.0
Response time	T	QL	Time taken to respond the queries

deliver, and returns) for these manifest variables can be created and tested for implementation. These manifest variables will measure the performance of constructs variables. Therefore, the control and monitoring of supply chain will be increased. SCOR framework is shown in Table 2.

Table 2 SCOR framework

Domain	Predictor variables	Cost (C)/time (T)/flexibility (F)/quality(Q)/ Innovativeness (I)	Qualitative (QL)/ Quantitative (QN)	Remarks
Plan	Introduction of new technology	C	QL	As per requirements of business competitive advantage/environment
	Ability to learn new technology	F	QL	Human resource ability to adopt the new challenges before industry and built a culture of learning
	Scope of real-time monitoring using IoT-based sensor technology for new technology	C	QL	Understanding the IoT Scope, working environment, benefits, etc.
	Training need analysis	I	QL	Identify the skill gap for the required job using the past experience and future requirements
	Training as per needs	C	QL	Training using the skill gap analysis done and feedback evaluation

(continued)

Table 2 (continued)

Domain	Predictor variables	Cost (C)/time (T)/flexibility (F)/quality(Q)/ Innovativeness (I)	Qualitative (QL)/ Quantitative (QN)	Remarks
	Introduction of IoT-based sensor technology for each tipper for transport and movement tracking	C	QN	Use of IoT, sensors, and navigations system for monitoring of tippers throughout the designated transport route
	Introduction of IoT-based sensor technology for each HEMM for fuel consumption monitoring	C	QN	Use of IoT, sensor, and analytics for energy consumption (fuel) and inspections in case of variations from the norms
	Introduction of IoT-based sensor technology for each HEMM for preventive maintenance requirement	C	QL	Understanding the industry 4.0 technologies for maintenance of HEMM deployed in the mines
	Introduction of IoT-based sensor technology for each Shovel for load factor	C	QN	Use of IoT and sensor technology for bucket fill factor monitoring for shovel/excavator
	Introduction of IoT-based sensor technology for each tipper for load factor	C	QN	Use of IoT and sensor technology for overloading and underloading of tippers
	Introduction of IoT-based sensor technology for each tipper for kilometer tracking	C	QN	Monitoring of tipper kilometer running for the designated distance of destination from the mines
	Use of big data analytics for optimum fleet deployment using real-time data	C	QL	Identifying the optimum fleet using the past data, capacity of fleet, and target production for the mines
	Introduction of IoT-based sensor technology for wagon loading and weighing	C	QL	Monitoring of payloader load factor under loading and overloading of wagons, ideal time of loading, rake filling time for replacement

(continued)

Table 2 (continued)

Domain	Predictor variables	Cost (C)/time (T)/flexibility (F)/quality(Q)/ Innovativeness (I)	Qualitative (QL)/ Quantitative (QN)	Remarks
	Big data analytics for optimum quantity of coal dispatch to consumer using real-time data	C	QN	Optimization of coal dispatch matrix to customers using industry 4.0 technologies
	Text analysis of project report	Q	QL	Text analysis for the various report related to project report for faster appraisal
	Text analysis for document evaluation	Q	QL	Document evaluation using the text evaluation for acceptance and rejection of document submitted
	Performance evaluation of HEMM using appropriate big data analytics and machine learning	C	QL	Understanding the use of big data analytics and machine learning for optimum utilization and target achievement of HEMM
Source	Evaluate the performance of Supplier, contractor for work experience	Q	QN	Use of text mining and machine learning for the evaluation of supplier/ contractor using past data and visualization techniques
	Facilitate supplier and contractor needs at the work site	C	QL	Based on past experience and project needs agreement between contractor and owner
	Evaluate demand supply of coal to the consumer	F	QL	Identification of drivers of supply chain and optimization of supply chain for efficiency and performance
	Evaluate seasonal factors effect on production and supply chain	F	QL	Determination of seasonality for production and supply chain
Make	Identify the pattern of blasting	C	QL	Optimization of blasting pattern for optimum yield and sizing

(continued)

Table 2 (continued)

Domain	Predictor variables	Cost (C)/time (T)/flexibility (F)/quality(Q)/ Innovativeness (I)	Qualitative (QL)/ Quantitative (QN)	Remarks
	Identify fuel consumption and drawbacks	C	QN	Level of fuel consumption for the target production
	Determine the machine HEMM condition and health	Q	QL	Life of machine and noted working hours of the HEMM and maintenance schedule
	Predict HEMM failure	Q	QL	Regular inspection of the vehicle/HEMM against the set norms and noise monitoring, engine monitoring, preventive maintenance
	Predict blasting failure	C	QL	Explosive failure to get desired result, poor blasting pattern, hard strata, etc.
	Predict crusher failure	C	QN	Sprinkler failure, hopper mismatch, tooth mismatch, poor sizing of output
	Predict coal quality	Q	QL	Based on past experience
	Predict factors affecting quality	Q	QL	Exposure of coal face, use of technology, Coal handling plant, etc.
	Predict contractor failure	C	QN	Fleet size deployed by contractor, past experience, type of ownership, or business module
	Predict project failure	C	QN	Schedule of land acquisition, land clearance, environment clearance, schedule of operation, etc.
	Predict pump failure	C	QN	Slow rate of pumping, not matching with the inflow of water during rainy season, pumping network failure, etc.

(continued)

Table 2 (continued)

Domain	Predictor variables	Cost (C)/time (T)/flexibility (F)/quality(Q)/ Innovativeness (I)	Qualitative (QL)/ Quantitative (QN)	Remarks
	Predict ventilation of the mine	Q	QL	Low oxygen level in the mine, high humidity level in the mine, feeling of exhausted
	Predict water incursion into the mine	Q	QL	Prediction for sudden inrush of water from the nearby waterbody
	Prediction of poisonous gases level in the mine	Q	QL	Monitoring of harmful gases in the mine
	Production visibility	I	QL	Scheduling of mine operation for optimum level of production
	Predict ROM coal life span	T	QL	Prediction of fire in the coal
	Inventory status at siding	F	QN	Real-time status of inventory at coal stock/ railway siding
	Inventory status of consumer	F	QN	Real-time status of inventory at customer plant site
Deliver	Reduced distribution cost	C	QN	Linkage of customer plant site to railway siding vis a vis colliery
	Lead time	T	QN	Time required between order placement and order delivery
	Delivery performance	T	QN	Service level of the coal supplying units
	Responsiveness to consumer complaints	Q	QN	Giving importance to customer and their concern
	Responsiveness to urgent order of coal	F	QN	Flexibility for urgent fulfillment of coal at consumer plant site
Returns	Feedback from consumer	Q	QL	Company is dedicated for customer service and regular improvement
	Consumer supplier relationship	Q	QL	Trust among consumer and supplier

(continued)

Table 2 (continued)

Domain	Predictor variables	Cost (C)/time (T)/flexibility (F)/quality(Q)/ Innovativeness (I)	Qualitative (QL)/ Quantitative (QN)	Remarks
	Consumer satisfaction	Q	QL	Consumer satisfied with the product quality and service provided
	Flexibilities to change as per consumer needs	F	QL	Built in flexibility for consumer satisfaction
	Customer service level	Q	QL	Customer service index

1.2 Big Data and IoT-Driven Coal Supply Chain Process and Performance Evaluation System

Performance measurement matrix evaluates the big data and IoT-driven coal supply chain for decision makers enabling them to make appropriate decision based on the real-time data and past data and experience. IoT network will provide the opportunity to collect the real-time data and real-time monitoring of the supply chain. It is pertinent from this that successful implementation of IoT network from the origin of the supply chain to end customer and information flow from top to bottom and bottom to top is very much necessary and requires deep knowledge of decision science and domain knowledge. The first stage for big data and IoT-driven supply chain performance measurement system is planning for how to implement the big data and IoT-driven supply chain. The next stage is pilot real-time data collection for evaluation of measurement system and its capabilities. The next stage is data visualization and real-time monitoring of the performance measurement system. Next stage is measure of built in capabilities of big data and IoT-driven supply chain performance measurement platform—data visualization, predicting future outcoming, etc. Finally, predictive and prescriptive decision-making for the organization is done. Big data and IoT-driven coal supply chain performance measurement system is shown in Fig. 2.

1.2.1 Planning for How to Implement the Big Data and IoT-Driven Coal Supply Chain

Planning for implementation of big data and IoT-driven supply chain requires prior introspection of its human assets, technology assets, and relationship with market leaders. Human assets understanding of data, IT handling skills, visualization skills, dedicated business intelligence, etc., will significantly determine the process of planning. Knowledge is the backbone of the firm, and it is considered as the strategically

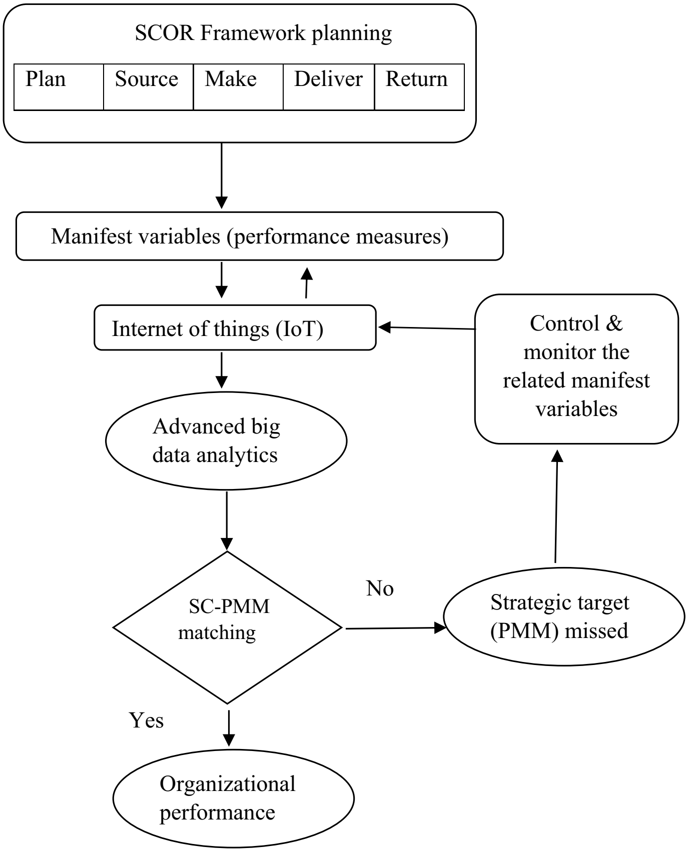

Fig. 2 Big data and IoT-driven supply chain (coal) performance measurement system

most important capital resource of the firm which is difficult to mimic. High-quality data acquired by the firm enable the strong big data analytics capabilities.

It is important for the firm to identify the need of the information or measures for strategic objectives. These required information or measures should be in conjunction with strategic targets of the firm. Once these measures are acknowledged, the firm should identify the weightage for these measures. Basically, the weightages for the measures are the values of contribution to which these measures contribute to the tactical targets. Firm should set performance target for these measures and select the different PMMs from the relevant supply chain process.

1.2.2 Evaluation of Measurement System and Its Capabilities

Coal supply chain is the base of many industries in India. India's power generation, steel sector, cement sector, paper industry are very much dependent on the coal supply chain efficiency. Built-in capabilities for big data and IoT-driven supply chain are the need of the hour. Big data and IoT-driven supply chain capabilities in coal supply chain improve the visualization in the supply chain measures and constructs which leads to optimization of organizational performance.

Pilot case: For the strategic constructs of adaptability of new technology, measures from big data and IoT-driven supply chain SCOR domain may be selected and target for these measures needs to fix by the management. Real-time data collection for these measures against the target can be done using IoT network. Based on the achieved outcome of strategic objectives using advanced big data analytics algorithm, the updating of measures and their target can be performed.

1.2.3 Data Visualization

Applying the advanced big data analytics algorithm for data visualization helps the firm to update the performance measures and their target for the achievement of the strategic objectives. Data visualization will help firm to control and monitor the supply chain process. If the strategic targets are not achieved, in that case controlling the measures and if required updating them with other measures and resetting a target for supply chain performance improvement can be done.

1.2.4 Built-in Capabilities of Big Data and IoT-Driven Supply Chain Using Training and Testing Data

The past data can be divided into two parts. One part can be used for training of the system and other part for testing of the system. Therefore, using the past data the big data and IoT-driven supply chain is trained for built-in capabilities for performance measures. The desired setting of performance measures is achieved using training of system. The other set of data will be used for testing of the constructs and their relationship with performance measures. If the result from the testing data confirms the strategic objectives and finally optimization of organizational performance, then the constructs formulated for supply chain performance and their performance measures are aligned to each other. Therefore, built-in capabilities for the supply chain can be incorporated in big data and IoT-driven supply chain. These constructs require updating on regular basis and real-time basis based on the change in business environment, policy changes of the government, entry of new competitors, change of law for taxation policy, change in environment clearance law, change in land acquisition policy, etc.

1.3 Decision-Making by Decision Makers

The big data and IoT-driven supply chain enable decision maker to make decision on the basis of real time, accuracy, transparent manner. This will give decision maker confidence in decision-making for the organization and supply chain.

1.4 Implications and Future Research Directions

The use of advanced big data analytics algorithms is suggested for analysis of the large real-time data collected and past data. In future various algorithms may consider for data filtration, categorization, and classification of the data. The mine managers should have thorough understanding of supply chain concept, big data, and IoT-driven supply chain concepts. The technological adaptable managers required for adoption of big data and IoT-driven supply chain.

The different combinations of performance measures need to be performed for the identifications of strategic performance constructs. For this data needs to be processed through training, testing, and validations.

Use of principle components and factors analysis for construction of performance constructs and according to them measures needs to be updated and revised.

1.5 Conclusions and Future Research Studies

Big data and IoT-driven supply chain is an advantage over the traditional supply chain as it aims to collect the real-time data collection, real-time data processing, accuracy of data collection, real-time control, and monitoring of supply chain performance measure, i.e., supply chain processes. The use of advanced concept of analytics, machine learning concept, and updating them with real-time measures helps the management to take accurate and precise decision for supply chain process improvement for strategic advantages of coal industry or any other industry.

The Coal industry practitioners and management need to validate the performance measures considered for big data and IoT capabilities and big data and IoT-driven supply chain. In future real time data collection with the help of IoT embedded sensor and network for the coal industry for monitoring of supply chain process like coal transportation from mines to railway siding, load confirmation for wagon loading by payloader, lead time monitoring for consumers, etc., can be done. Factor analysis and principle component analysis may be done for the framework proposed in the study.

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Recent Developments on Smart Manufacturing

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Abstract In the current setup, industries are doing many innovations and coming out with many new and innovative products. Industrial revolution is a driving force for innovations as it provides intelligent technologies that helps in new product development. In the current fourth industrial revolution, industries are becoming smart by adopting digital technologies. the prime focus on adopting digital technologies is to achieve sustainable benefits. Intelligent technologies namely machine learning, big data analytics, additive manufacturing and internet of things help in effective resource utilization and minimizing waste thereby achieving sustainability in manufacturing. In this regard, this chapter aims to highlight the importance of smart manufacturing by identifying various technologies adopted in industries to become smart. Various challenges faced by industries in adopting digital technologies were also highlighted in the study. The present chapter will help research practitioners, and industrial experts to achieve sustainability through adoption of digital technologies in industries and making them smart industries.

Keywords Digital technologies · Intelligent manufacturing · Smart manufacturing · Industry 4.0

1 Introduction

In recent years, a concept of smart manufacturing (SM) which was coined in United States, however increased its usage worldwide, has acquired substantial traction in business and academia. Several industrial systems are masquerading as SM systems.

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Smart manufacturing comprises several manufacturing practices that control manufacturing processes via the use of information and communication technologies (ICTs) and networked data. ICTs are concerned with production planning and control. Traditionally, manufacturing was restricted to a processor, a series of procedures that turn raw materials into completed commodities. However, the general concept of manufacturing encompasses many more. Manufacturing nowadays involves business operations driven by data at various levels, causing creation of many industrial paradigms such as smart manufacturing. Future intelligent systems will have distinctive self-assembly properties to manufacture sophisticated and customized items to leverage new and existing markets. The utilization of information by SM is ongoing to sustain and improve its performance. Numerous frameworks have been introduced in the realm of SM. Among these is a framework that prioritizes accuracy assurance for SMS, focusing on four key factors: planning of operations, awareness of physics principles, measurement of shape on the machine itself, intelligent monitoring and assessment of error causes.

From the middle of the eighteenth century through the late twentieth century, the manufacturing sector has been creating new developments that may be considered technical achievements [1]. One such advancement in production methods is SM [2]. SM is a continued development concept that intend for sustained development via planning and enhancement of the current main production variables, such as productive output, reliability, distribution, and versatility based on technological integration and several elements over communities, humans and the environment [3]. This type of manufacturing contrasts with lean manufacturing, which primarily focused on cost savings by eliminating waste during the 1980s and 1990s [4]. Lean manufacturing was primarily concerned with reducing waste to cut costs [5].

The phrase SM has been growing in popularity in recent years to describe products in the future and the number of scholarly works that focus on intelligent production is quickly expanding [6]. Automation in production has become increasingly in recent years because of developments in computing and machine-building technologies [7]. Most of today's machine equipment is controlled by computer programs rather than humans sitting at the controls. Material handling automation and automated retrieval and retention systems are responsible for moving and storing goods and components [8]. Since the 1980s, several different words have been employed to characterize the process of automated production such as computer integrated manufacturing, flexible manufacturing systems and intelligent manufacturing [9]. These terms were used to describe automated manufacturing in different ways based on the adopted degree of automation and its scope along with its integration with different functional units. At around the same period, Japan began undertaking intelligent manufacturing research, which led to the establishment of the "Intelligent Manufacturing System (IMS) Program" in 1995, which provided financial aid for research in industry [10]. It was discovered that the manufacturing industry of a single nation could not transform manufacturing on its own and that worldwide collaboration was required for this. Major firms from various countries, including the United States, Japan, Korea and European countries, have begun working together to discuss the manufacturing industry future, with Japan getting the greatest number of actively participating corporations [11]. A significant portion of the IMS operations that have been carried out in the United States has been conducted as part of the "Next Generation Manufacturing Systems (NGMS) Program," which was launched as a venture that was not intended to generate a profit [11]. However, the IMS Programme was extended after some time, and the European Union started researching intelligent manufacturing [12]. The manufacturing industry has become more interested in the idea of an internet connecting everyday objects in recent years [13]. The formation of cyber-physical systems is the primary emphasis, which is accomplished by integrating the tangible assets of manufacturing with cyberspace [14]. This novel idea has been accepted by various entities, including individual businesses, industrial consortia, regions and governments.

The term SM does not have a single, agreed-upon definition that is accepted everywhere. According to the description provided by the National Institute of Standards and Technology (NIST), SM is a method of production that is fully collaborative and integrated that reacts instantaneously to shifting prerequisites and specifications in the production plant in the customer needs and supply network [15]. Integrating today's and tomorrow's manufacturing assets with sensors, computing systems, communications technologies, computation modelling, regulation, analysis and predictive engineering is referred to as SM [16]. In SM, the concepts of technological systems, the internet of thing, cloud hosting, service-oriented software development, artificial intelligence and information science are all incorporated. When put into practice, the overlapping technologies and concepts will transform manufacturing into the defining characteristic of the subsequent industrial revolution.

2 Historical Aspects of SM

Historically, the development of SM is categorized under specifically four phrases [17]. These are Phase 1 (from Pre-2000), Phase 2 (2001 till 2010), Phase 3 (2011 till 2015) and Phase 4 (2016 onwards).

i. Phase 1: The technical focus during this phase was expert systems, system flexibilities and neural-based networks. The other work areas are concurrent engineering, fuzzy controls, flexible manufacturing and design concurrency.
ii. Phase 2: The technical focus during this phase was agent application, system integration, and knowledge engineering. The other focus areas were genetic algorithms, multi-agents and optimizations, holonic manufacturing, system simulation, artificial intelligence, fuzzy logic, RFIDs and SM.
iii. Phase 3: The technical focus during this phase was optimization, networking and system management. The other work areas were big data, Industry 4.0, RFIDs, sustainable manufacturing, etc.
iv. Phase 4: The technical focus during this phase is deep learning, data analytics, industrial IoT (IIoT) and industrial internet. The other areas of work during this present phase are IoT, big data, cloud computing and machine learning.

3 Primary Technologies of SM

While many technologies could be associated with SM, as time and technologies develop, the paradigm associated with SM also gets metamorphized. For instance, as discussed in the previous section, SM could be associated differently with different timelines. Considering the present timeline under phase 4, we have discussed the primary technologies of SM, such as digital manufacturing, smart sensors, IoT–IIoT, Data analytics, material informatics, and zero waste manufacturing.

The achievement of success in smart manufacturing is dependent on the availability of smart sensors and processors that are reliable, power efficient and cost-effective, as well as wireless networking interfaces [11]. For this reason, electronic skins, next-generation flexible, disposable sensors and self-powered are now being created. These sensors are enabled by nanotechnology and 3D printing. In addition, SM necessitates the utilization of variety of processors, including tiny low-end cores for actuators and sensors, high-performance cores for robots and intelligent devices, power-efficient and compact cores for intelligent devices and robots, etc. [18]. The need for a homogeneous software system, which must be met to facilitate intelligent interaction and reduce the possibility of failure, is even more demanding [19]. This demands a CPU design that can go from having very few cores at the low end to having highly powerful processors at the high end. For implementing such an architecture, conventional computer processor design must be rethought from the ground up [11]. These kinds of innovations are moving the complicated production system closer and closer to having a single processing architecture and a single open-source software platform.

As a result of the technological advancements in SM and connected systems, it is now possible to digitally connect many physical items and pieces of machinery in a system commonly referred to as the IoT and IIoT. The pervasive connectivity offers many benefits, including sharing and coordinating information, which can create new services and functions that were not possible in the past [20]. Additionally, the connectivity increases the reliability of the equipment because their condition can be examined on a more regular basis. These advantages have had far consequences for the manufacturing industry because they can make production more agile and responsive, reduce the amount of time that equipment is idle, and achieve greater efficiency gains in operations, ultimately leading to lower costs. They also make it possible for more accurate matching of supply and demand, potentially leading to a rise in income. The IoT and IIoT are becoming an increasingly important focus for engineering and aerospace industries. By the late 2020s, it is anticipated that far more than 50 billion devices will be connected to the internet [11].

The capacity to perform data analytics in real time on large dataset at various locations throughout the value chain is essential for SM [21]. Hadoop, which is employed for MapReduce operations, and Spark, used to perform in-memory large-scale data processing, are only two of the numerous approaches and technologies created by the open-source community for big data analytics [22]. These were all developed under the auspices of the Apache Software Foundation. These platforms have also developed machine learning frameworks such as Mahout and MLlib. These libraries are closely tied to data analytics.

Another area of increase in importance on SM is material informatics. With the increased focus on SM, materials informatics seeks to merge historically bio-led information systems with computational approaches. This will promote more factors and helps by discovering ways for historical and expenditure analysis. The thicket of data provided by new combinations and maximum throughput analytical techniques has surpassed the discovery and maturity of novel materials [23]. This has caused the discovery and maturity of new materials to fall behind. As a result of the development of this "quantitative avalanche" and the subsequent complicated, multi-factor studies that are necessary to comprehend it, attention, money and research are returning to informatics-based techniques as potential answers. This will greatly impact the manufacturing aspects and further specialize the SM methodologies in various verticals of implementation. This emerging area of data informatics in SM has a high scope of computing and analysing huge datasets and models, which would accelerate material and manufacturing innovations across various verticals of specialized materials.

Similarly, in zero-waste manufacturing (ZWM), SM has taken a new paradigm. The ZWM is a concept that was developed to assist countries in their transition to a circular economy. This was accomplished by developing manufacturing systems and technologies that minimize waste throughout entire value chains to the highest degree viable through reuse and recycling [24]. The entire life cycle strategy of ZWM can fulfil the dual aims of production breakthroughs and waste reduction. This could be achieved through a multipronged approach. For instance, one such approach can be by the design of the product for zero waste; another could be by performing waste audit and reduction planning, and the third approach could be by smart waste collection; or organizing a smart, collaborative platform for mutual benefit of the industries, etc.

Additive manufacturing is another upcoming area of SM that focuses on utilizing 3D printing technologies for building complex models into physical form. As a substitute to the traditional subtractive methods of production, which result in waste, this approach to additive manufacturing has been marketed as a manufacturing process that generates no waste [25]. It lends itself to the tailoring and production of limited volumes of tailormade items.

Virtual reality and augmented reality are other areas of focus on SM. The ability to experience computer-generated visuals and videos that simulate activities in the actual world is made possible by virtual reality (VR) technology. Wearable virtual reality (VR) technology consists of a video device, an audio device, navigation systems like GPS, external gateways to other devices and hardware that allows the user to feel as though they are physically present in a virtual environment that has been created through simulation [26]. Augmented reality is an artificial environment that has been produced using computer simulation all over the actual world and can be experienced via the use of mobile devices and wearable technologies. The new industries use the advanced technologies of incorporating the real physical ecosystem and the graphics generated through computers to visualize artificial added components to the existing, realistic situation for simulation, training, or validation before going for real manufacturing of some of the manufacturing designs. The adopters made this product realization in an already established setting possible thanks to the merging of simulated computer images with realistic conditions creating a way for SM.

The collecting and analysis of information from a wide range of sources namely manufacturing units, enterprises, customer feedback, new request systems, etc. may make it easier to make real-time decision selections for supply chain management in the context of big data analytics [27]. Manufacturers nowadays expect their consumers to submit feedback and personal thoughts on the items they use now or plan to use in the future. They want to use the feedback they collect from their existing clients as the basis for the direction of their future product development, which will focus on appealing to a diverse range of customers. The analysis of big data will be advantageous to the manufacturer in the identifying of the current state and causes of component failures in real time. Big data analysis will be of great assistance to the manufacturer in determining the present status of the product and the factors that are contributing to its failure in real time. Big data analysis will also be advantageous to the producer in the identification of the present state and induces equipment breakdown in real-time, pushing customers to buy their goods by recognizing their purchasing habits and prerequisites, and learning the prospect of data-based marketing for guidance and direction.

As a component of flexible and reconfigurable manufacturing systems (FRMS), the manufacturer is able to adapt to any changes that may have happened in the built-in priorities and functions as a result of shifts in the reconfiguration of the product or the market demand [28]. These shifts may have been caused by a combination of factors. Their preferences include efficiency in terms of money and time spent and rapid adaptation to ongoing structural shifts. It is the ability to produce in small batch sizes and can be effortlessly reconfigured to produce a wide range of products. These products can be separated into two groups, i.e. machine flexibility and routine flexibility. Machine flexibility enables the manufacturing industry to plan the manufacturing schedules of various machining locations, share the machining activity amongst them, and repeatedly switch the machining parts. Routine flexibility enables the manufacturing industry to create new products in the same production line. Modular design, ease of integration, adaptability, scaling and diagnosability are the deterministic qualities of FRMS in SM.

4 Barriers Associated with SM

Although there is a lot of development in various facets of SM, a few barriers or challenges are associated with SM [29]. Apart from the much-discussed cultural barriers such as availability of talent, financial resources and leadership support for the adoption of SM, the core challenges could be illustrated under security challenges, system integration, interoperability of systems, safety, multi-linguicism and return of investment (RoI) on the adopted technologies.

i. **Security challenges in SM**: The usage of an integrated network system inside a production system for the purpose of exchanging information between different production or machining units and with end consumers is what is meant by the term SM. Communication to a network is required for this purpose and must be accomplished using the internet. Sharing information on the internet necessitates protecting data or information at all points across the system, using data encryption techniques from beginning to end. And as a result, every node in the network had to be safeguarded against assaults from the outside and inappropriate use of data. When building networked systems like SMs, one of the essential things to keep in mind is how to maintain the safety of both the design and the process.
ii. **Integration of systems in SM**: Integration of newly developed technological equipment is another obstacle that must be overcome to deploy an SM system successfully. When deploying SM technologies, many issues are caused by the incompatibility of previously used devices with newly developed ones. The communication protocols being used to manage the older gear may be no longer up to date, and it's also possible that the newer gadgets use a different protocol. Additionally, the connection from machine to machine and the system's interconnectedness call for a more advanced communication system.
iii. **Interoperability in SM**: Interoperability refers to the capacity of separate computer systems to independently comprehend and use the functionalities provided by one another. This characteristic makes it possible for them to communicate data and information with one another regardless of the company that made either their hardware or their software. It is possible that the characteristic of interoperability will not be successfully realized if there is not a good match between the communication standards and protocols. The constraints on the system's interoperability are determined by the disparities in the communication bandwidth, operating frequency, method of communication and capabilities of the hardware.
iv. **Safety considerations in SM**: The issue of safety on SMs originates from the use of robots and their interactions with humans and human-operated non-autonomous machines. The primary safety considerations on SM with autonomous machine interactions such as robots are mainly related to health and occupational hazards. The occupational hazards could be originated owing to any of the factors such as mechanical and electrical depending on the particular application of the industry.
v. **Multilingualism associated with SM**: This aspect is quite general in connected systems, and its effect is amplified in the case of SM. The primary reason is the machines' interoperability with various languages and their meaningful conversions. Any plan to make SM more realistic would depend on the ability of the system and the device to be adept in multilingualism which should be meaningful and logical.
vi. **RoI in SM**: While adopting incremental advances in general manufacturing makes more financial sense, adoption of breakthrough technologies takes more gestation time with respect to technology readiness and maturity. For instance,

adopting new SM techniques in areas with shorter investment cycles will be more favoured than other sectors. This further would delay the adoption of SMs in areas such as steel making and infrastructure where the returns of the investment cycle are more, and there is considerable delay in reaping the benefits of the investments in adopting new technologies on SMs.

5 Smart Manufacturing Applications

The ultimate objective of smart manufacturing is to focus on diverse industry adoptions of various technologies, which may change industrial processes. Business 4.0 solutions possess a high level of adaptability, allowing them to be customized and developed to meet the unique and specific requirements of different industries. This is particularly valuable in sectors like the food industry, which deals with perishable items and demands a responsive approach. By leveraging these versatile solutions, dynamic manufacturing networks gain the capability to manage their supply chains and business models effectively. Through the use of configurable features from smart manufacturing layers, intelligent design, and smart decision-making, products can be evaluated comprehensively, taking into account practical considerations such as time constraints, logistics availability, production efficiency and various other criteria. The implementation of extensive sensor networks enables smart monitoring, which plays a crucial role in operating, maintaining and optimizing Industry 4.0 production systems. Real-time data from sensors, including temperature, vibrations, power consumption and speed, can be collected and analysed, allowing for proactive detection of abnormalities in machines or instruments. Key technologies in achieving smart monitoring within I4.0 are the Internet of Things (IoT) and Cyber-Physical Systems (CPS). Furthermore, advancements in technologies like augmented reality (AR) and virtual reality (VR) have revolutionized traditional design processes, resulting in the creation of smart designs. The integration of VR methods in additive manufacturing, for instance, has introduced hybrid prototyping. By combining 3D printing with AR and CPS, design software namely CAM (computer-aided manufacturing) and CAD (computer-aided design) can interact with smart physical prototype systems in real time, enabling the development of intelligent design paradigms. In the realm of smart manufacturing, IoT and CPS-based systems generate vast amounts of data, making big data analytics crucial for the effective design and operation of manufacturing processes. For instance, a comprehensive framework utilizing real-time big data analytics has been proposed for data-driven risk assessment in industrial production systems. This issue has received a lot of attention in order to help with production optimization and manufacturing CPS visualization.

6 Smart Manufacturing Adoption Framework

Figure 1 depicts smart manufacturing framework aiding in its smooth adoption in manufacturing sectors. The framework recommends adoption of smart manufacturing in four measures, namely, understanding the background, smart technologies, barriers hindering adoption and application sectors. With regard to understanding of smart manufacturing background, realizing its importance in expert systems, system flexibilities and neural-based networks is suggested. Further, agent application, system integration, and knowledge engineering, optimization, networking, system management, deep learning and data analytics are also recommended to explore. In second stage, several technologies facilitating smart manufacturing in industries, namely, cyber-physical system, Augmented Reality/Virtual Reality, Internet of Things, Big Data Analytics, etc. need to focus. Technology prioritization studies could be conducted for detailed understanding. In order to successfully implement smart manufacturing in industries barriers hindering its acceptance need to study. Several barriers are recognized in the study such as Security challenges in SM, Integration of systems in SM, Interoperability in SM, Safety considerations in SM and multilingualism associated with SM. Lastly, application sector where smart manufacturing need to implement could be focused for post-implementation analysis.

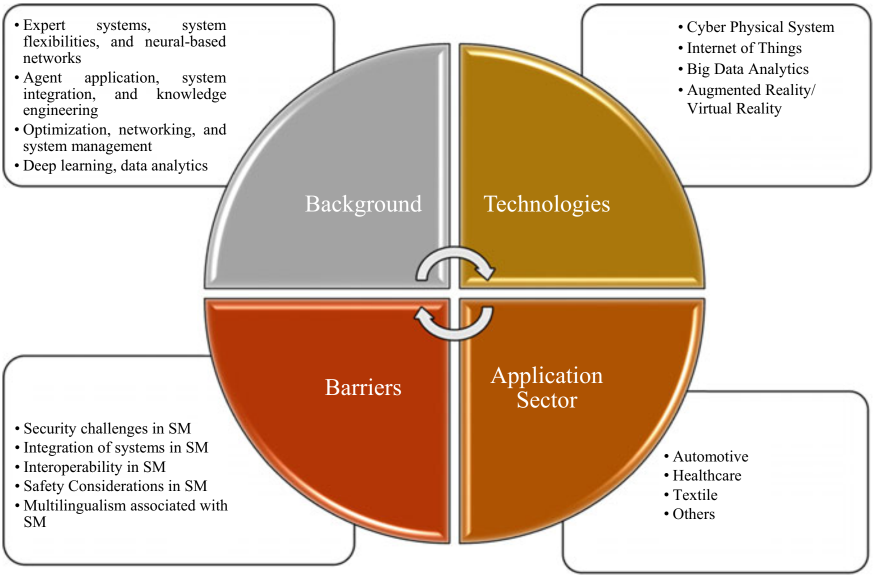

Fig. 1 SM adoption framework

7 Implications

The present study provided significant understanding on smart manufacturing concept. The paper presented smart manufacturing background, its technologies and barriers hindering its adoption. The resultant of the study is to be implied as the initial step in defining the smart manufacturing from historical perspective. The researchers and industry practitioners can utilize the study in smooth adoption of smart manufacturing in industries. The study facilitated in delivering glimpse of smart manufacturing which in turn provides strong foundation for its implementation. The industry practitioners may utilize this study in addressing key actionable areas for adoption of smart manufacturing such as inventory management, quality, marketing duration, supply and demand, service and maintenance, operations. The ultimate goal of smart manufacturing is to target various industry implementations of various technologies that have the potential to alter industrial processes. Business 4.0 solutions possess ample flexibility to facilitate tailored design and development in accordance with the distinct characteristics and specific demands of various sectors, including the food industry, which encompasses a significant volume of perishable goods. This empowers dynamic manufacturing networks to exert control over their supply chains and business models. By leveraging configurable capabilities from smart design and manufacturing layers, these solutions enable applications to adopt a comprehensive perspective, encompassing practical considerations like logistical availability, time limitations, production efficiency and multiple criteria.

8 Conclusions and Future Research Directions

Smart manufacturing is being recognized as a potential approach to achieve sustainability in manufacturing by leveraging the digital technologies. Digital technologies in manufacturing help in optimizing resource consumption, enhancing the machine life cycle through machine health prediction, real-time tracking of product and minimizing the waste generation. Some of the important digital technologies that help manufacturing firm to become smart are artificial intelligence, internet of things, cloud computing, big data analytics, additive manufacturing and intelligent robots. This chapter discusses the different aspects of SM starting with history of industrial revolution, different technologies of SM were also discussed. Then various barriers in adoption of digital technologies in manufacturing were also highlighted. Smart manufacturing may enable a manufacturing organization to produce higher-quality goods, boost productivity, improve energy efficiency and maintain safer plant floors. Furthermore, smarter manufacturing has the potential to increase employment. As more organizations embrace SM, new technology-based manufacturing jobs will emerge, producing both direct manufacturing and non-manufacturing occupations. SM skills allow a company to be more responsive to consumer requests and can be crucial in satisfying customer demands for more personalized goods. Employees will be able to operate a large amount of equipment thanks to SM. Manufacturers may gain a better understanding of predictive maintenance and minimize maintenance costs by combining AI/ML with IIoT. This chapter helps stakeholders in establishing smart manufacturing by embarrassing digital technologies. This chapter also establishes smart manufacturing adoption framework for smooth adoption in manufacturing industries.

This chapter further discussed the implications of the study in which industry practitioners and researchers were provided with the future directions of the study. Future researchers may explore the detailed analysis of barriers hindering smart manufacturing adoption in industries. Moreover, analysis of smart manufacturing enablers and motivating factors could be further investigated. The present chapter limits its scope in delivering background, technologies and barriers of smart manufacturing in general, however, future studies may be focused on application sector specific analysis for detailed understanding.

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Applications of Artificial Intelligence Tools in Advanced Manufacturing

N. Manikandan, P. Thejasree, K. E. K. Vimal, K. Sivakumar, and J. Kiruthika

Abstract Due to the complexity of current manufacturing systems, they are constantly facing challenges in terms of their dynamic and unpredictable nature. The development of artificial intelligence (AI) has shown that it can help solve these issues. With the help of these advanced prediction models, the analysing capability of those evolved models can be transformed into a powerful tool for analysing and improving the manufacturing processes. This chapter aspires to provide a wide-ranging overview of the various applications of AI in manufacturing, especially in contemporary machining namely wire electrical discharge machining and advanced joining processes such as laser welding. It also explores the potential of AI to enhance the competence of manufacturing. The chapter adopts a hierarchical structure to reveal the various interdependencies in a manufacturing plant's operations. The chapter covers a wide range of topics related to manufacturing, such as quality, throughput, and development of intelligent decision-making tools. It also explores the applications of AI in manufacturing engineering to improve the efficiency of factories.

Keywords Artificial intelligence tools · Grey analysis · Neural network · ANFIS · Advanced manufacturing · Wire EDM · Laser welding

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1 Introduction

1.1 Artificial Intelligence Tools

Due to the rapid emergence and evolution of new technology, the way manufacturing is conducted is changing. This has led to the need for companies to rethink their operations and strategies. The new era of Industry 4.0 is also expected to bring about significant changes in the way they work [1].

The increasing number of innovations that are being introduced in the manufacturing industry are driving the need for a more detailed analysis of how AI can help enhance the efficiency and effectiveness of the industry. Currently, the use of AI in the manufacturing industry has been carried out through the development of various techniques such as machine learning [2]. Due to the technological advancements that have been seen in the domain of AI, such as the development of computational hardware and sensing technology, the applications of these techniques have become more feasible. It also explores the potential of these techniques to enhance the competency of the manufacturing process. This knowledge and understanding can help manufacturers implement AI in their operations in current scenario intricate industrial environments. Each of these environments has its own unique requirements [3, 4].

AI is regarded as one of the most significant developments in human history. The impact of human activity on the global ecosystem has been the most dominant factor in the development of mankind. The pace of change has accelerated significantly since the invention of steam engines 250 years ago. The rapid emergence and evolution of new technologies such as AI and genetic engineering have created a new era of technological change. These innovations are expected to take a substantial impact on our lives in the future. Over the past hundred years, technological progress has greatly improved our lives. While it is still not possible to fully predict the future impact of innovations and technological development, it is clear that they will play a significant role in helping us move towards a sustainable future. During the 1940s, the concept of AI and machine learning was already widely discussed. The importance of AI and how AI could help the world's economy grows by automating tasks and providing jobs without leaving people behind [5–10].

1.2 Need for AI Tools in Manufacturing Processes

The evolution of tools has been regarded as the main factor that contributed to the survival of humans. The ability to make new weapons using the bones of animals gave humans an advantage over other animals in the food chain, and the need for harder weapons led to the development of metal tools. The increasing need for cutting tools resulted in the development of new manufacturing methods and technologies. Metal cutting processes are commonly used to remove material from a part by directly contacting it between the cutting edges of a tool and the surface of the part. A better cutting tool material has to be satisfied in order to reduce the force essential for moving it over the surface of a part. The various factors that affect the surface finish and accuracy of a part are the cutting force, the angle amongst the tool and the workpiece, and the existence of cooling and lubrication fluids. Despite the emergence of new techniques for shaping metals and the increasing number of metal-cutting processes, conventional methods still remain the most popular [11–13].

For traditional metal-cutting processes, the tool used must be harder than the one used to make the part. A relative movement amongst the two components is required for creating the ideal surface quality and shapes. This type of process involves all types of metal cutting techniques, such as mechanical abrasion and removal by cutting. The absence of contact between the part and the tool makes it a non-traditional technique. Traditional machining techniques are not suitable for every situation. The non-traditional method can be used to overcome these issues. The advantages of using non-traditional processes are far greater than those of traditional methods. This makes the use of such methods essential in modern times [14–16].

1.2.1 Need for AI Tools in Advanced Machining Processes

Superalloys are the most important materials adopted in numerous aerospace and industrial needs, such as nuclear reactors, rockets and submarines. Because of their hardness, they are not commonly machined using traditional methods. In order to overcome this issue, new methods were suggested.

Due to the intricacy of the machining process, it is often problematic to achieve the desired results with traditional methods. This has led to the evolution of new contemporary machining techniques such as WEDM [17, 18].

This WEDM material removal method is generally used in the manufacture of intricate parts, such as fuel injectors and turbine blades. It can also be beneficial for materials with high wear resistance. The WEDM process is like the Electrical Discharge Machining (EDM) in that it involves using electrical sparks to remove a material. This process can be beneficial for creating complex work pieces that are not feasible using traditional methods [19–22].

1.2.2 Need for AI Tools in Joining Metals

The role of welding and joining technologies in manufacturing is crucial. There are various types of welding and joining technologies that can be utilized successfully. The scope of their development and modification is constantly increasing due to the fast-paced commercial requirements. Various innovations and modifications in the conventional joining and welding techniques are being carried out to attain their desirable properties. These include better joint properties and the use of a combination of materials. The advantages of using welding and joining technologies include reducing the component cost, improving the quality of the finished product, and dealing with different materials. A new window has opened up for the use of innovative welding and joining techniques that allow the simultaneous processing of different materials [23–25].

A beam welding process is a type of fusion welding that involves using intense focused heat to melt a workpiece. Examples of this process are electron beam welding, plasma beam welding and laser beam welding. One amidst the most widely used and innovative welding processes in the field of manufacturing is laser beam welding. This process is commonly utilized for various uses such as aerospace, automobile and industries. It offers various advantages such as high degree of accuracy, fast cooling and low heat input. LBW is a kind of weld that is generally adopted for a wider range of materials. It has a fast and intense energy beam, which can produce high-quality joints. This type of weld can also reduce the effects of intermetallic and laves phase compounds on the fabricated joint's mechanical properties [26–29].

1.3 Applications of AI Tools in Advanced Machining Processes

1.3.1 Proposed Approach of Grey-ANN and Grey-ANFIS Models

The development of AI has greatly impacted the field of engineering. Through its development, scientists have been able to create efficient and effective procedures and models for controlling different processes. One crucial factor that they should consider when improving a process is its accurateness. One of the most important factors that scientists have been able to consider when it comes to creating effective and competent procedures and models for governing different methods is their accuracy. One amongst the common methods that researchers have been using to create network models is the usage of artificial neural networks (ANNs). A network model composed of the required number of input layers and an output layer has been designed with a single neuron in its architecture as illustrated in Fig. 1.

The goal of the network model is to perform various trials to improve its correlation coefficient. The results of these trials can be seen in Fig. 2. The multi-layer structure of the network model allows it to perform superior correlation analysis.

Similarly, an ANFIS model has been evolved using the information attained from the experimentation. The ANFIS model is created by means of the 'trimf' function, which creates around 243 rules per input. The model has been built by the GRA method, which considers various features and offers a framework for developing it.

Figures 3 and 4 show the editor and rule viewer of the ANFIS model, respectively. The latter provides a deeper understanding of the structure of model and multiple performance index (MPI) prediction.

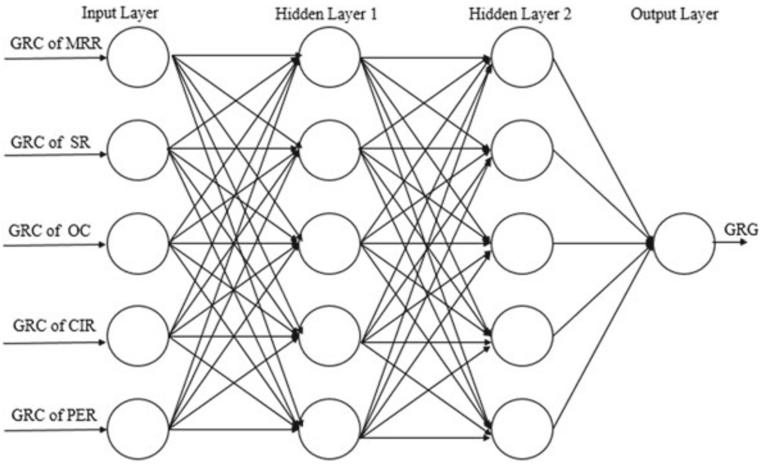

Fig. 1 Structure of evolved ANN model

1.3.2 Inferences Concerning ANFIS Model Outcomes

Figure 5 shows the influence of various performance measures on the selected multi-factor performance index using the GRC values. The illustrations show that the unification of the MRR and SR intermediate levels offers enhanced ANFIS-GRG.

The various combinations of the lower and higher levels of the GRC of MRR, as well as the circularity error and the perpendicularity error, offer enhanced multi-factor performance. In addition, the correlation between the three different combinations of these values is shown in Fig. 6.

1.3.3 Performance Investigation and Comparison Between Prophesied Values of ANN and ANFIS Models

The performance investigations on the aforementioned predictive models have been evaluated and presented graphically in Fig. 7. From the comparison, it is noticed that the ANFIS model offers better predictions comparatively than neural network models.

The aspiration of this investigational analysis was to develop an ANFIS model and neural network that can predict the predicted performance of the GRG. The correlation coefficient was used to analyse the different networks' performance. In addition to the number of neurons, the researchers also took into account other factors such as the hidden layers and the structure of the network.

The outcomes of the investigational study have been analysed by comparing with the results of the experimentation conducted by means of the ANFIS model as shown in Fig. 8. The researchers concluded that the correlation amongst the prophesied and actual outcomes is strong. The outcomes of the analysis exposed that the results were

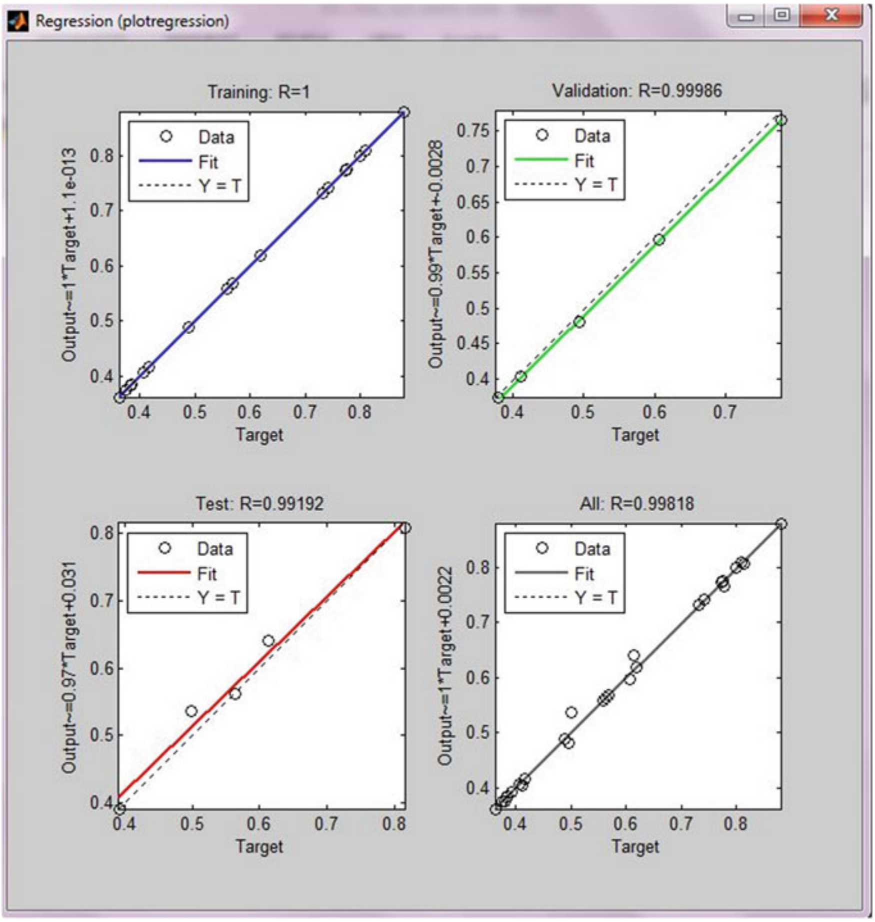

Fig. 2 Regression value for the ANN model

closely related to the prophesied outcomes of the ANFIS model and the real-time results of the experiment on Haste Alloy.

1.4 Applications of Artificial Intelligence Tools in Advanced Welding Processes

1.4.1 Ascendency of Process Parameters on Chosen Output Variables

The increasing laser power and the pulse period can cause a rise in the top width of the weld. This is because the higher levels of heat that are generated by the laser

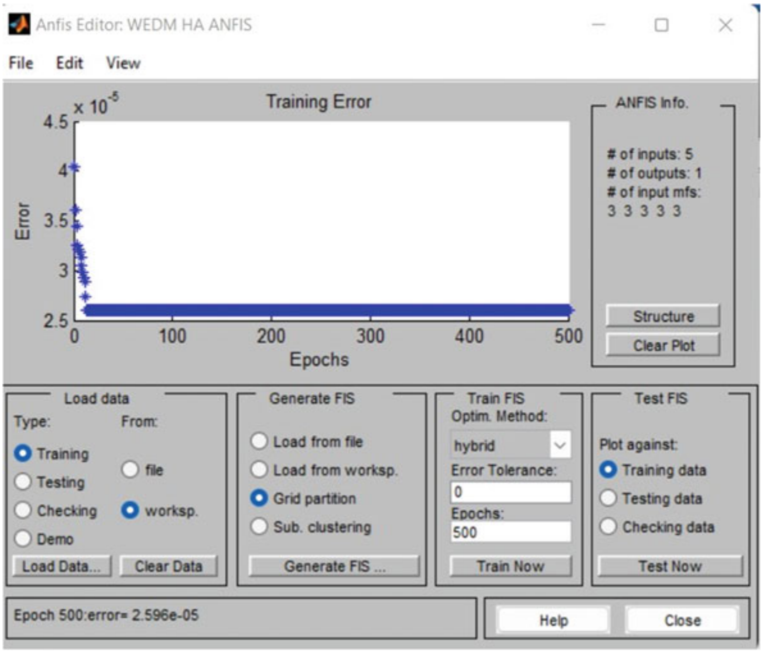

Fig. 3 ANFIS editor

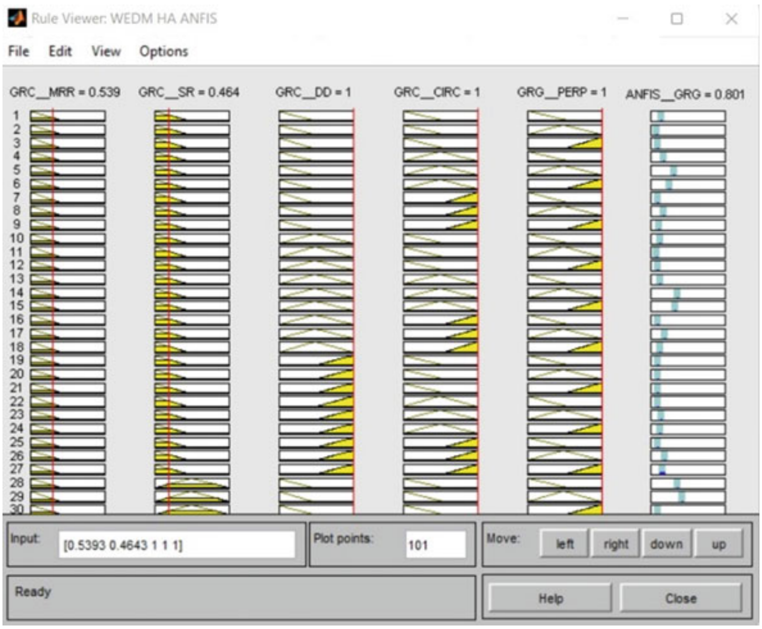

Fig. 4 ANFIS rule viewer

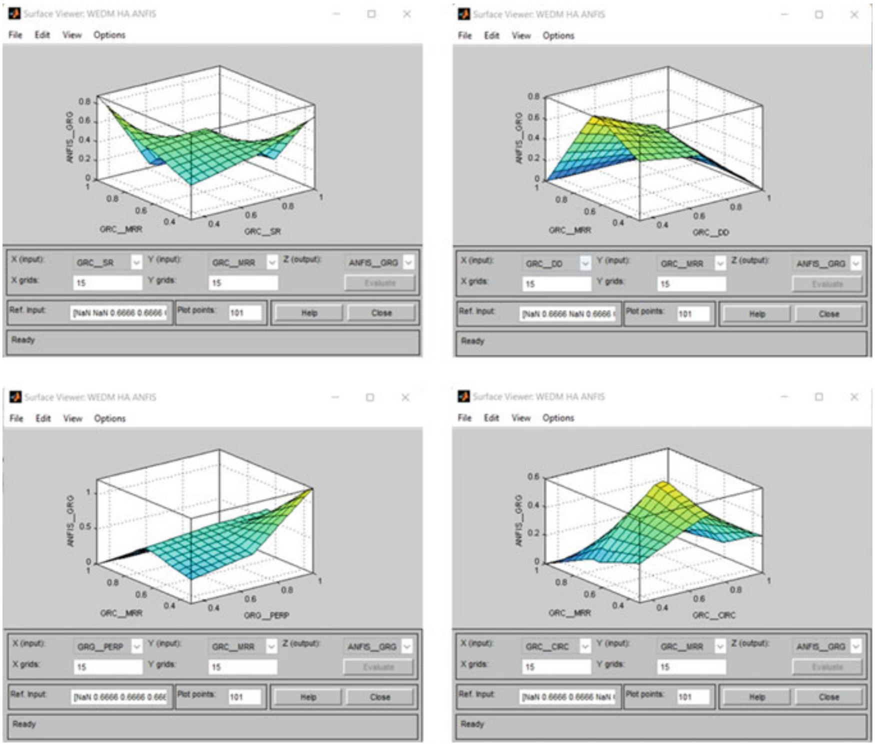

Fig. 5 Surface graphs on the effect of GRC of MRR, SR, DD and perpendicularity/circularity errors on ANFIS foretold GRG

can affect the wider weld beads. Increase in the weld speed also decreases the dwell duration of the supplied heat. The higher pulse duration and laser power can result in better penetration of the heat. Also, the upsurge in the weld speed can decrease the penetration due to the lack of time to reach the heat.

1.4.2 ANFIS Modelling on LBW of Nickel Alloys

The model has evolved by taking into account the input variables and the output of the single variable, which is known as the GRG. Once the training of the model is over, it is then adopted to foresee the GRG of the system. The construction of the evolved model and the rule viewer are also illustrated in Fig. 9.

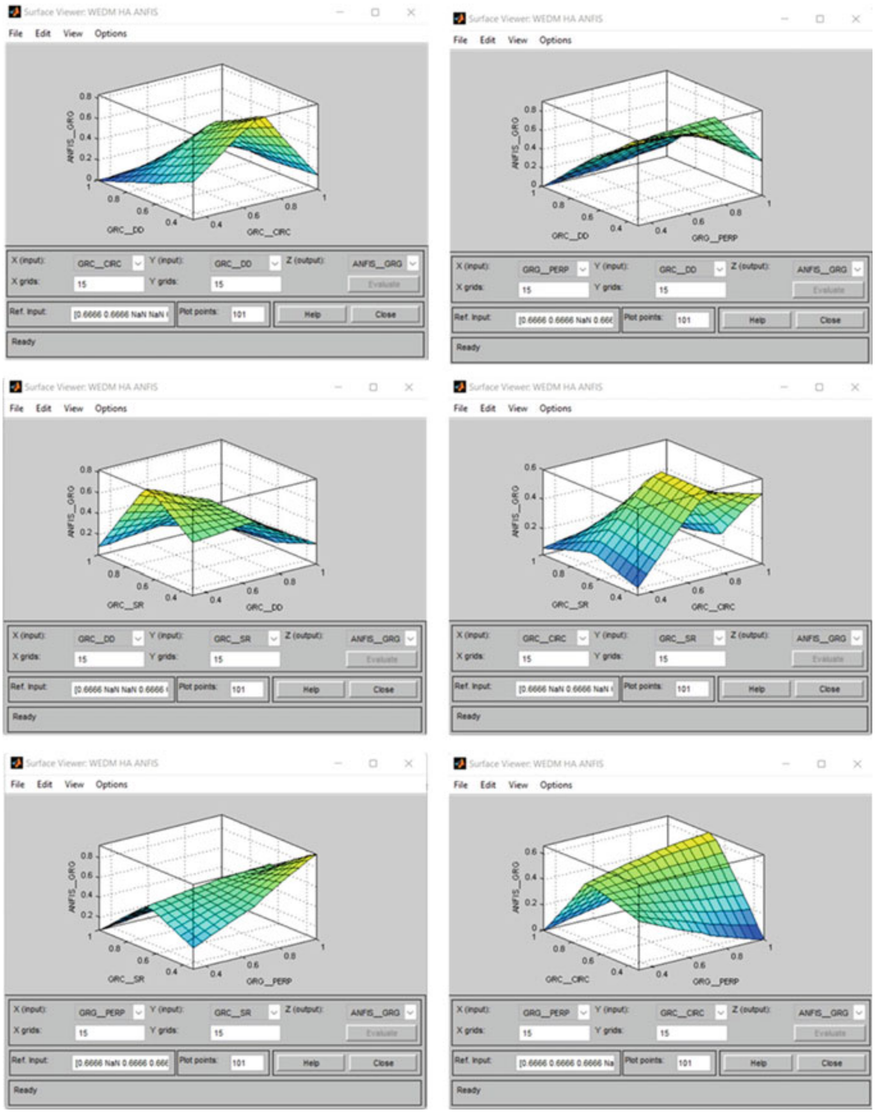

Fig. 6 Surface graphs on the effect of GRC of output variables Vs SR, DD and perpendicularity/circularity errors on ANFIS foretold GRG

1.4.3 Ascendency of Independent Parameters on ANFIS-GRG

The GRG and the peak power and weld speed data are depicted in Fig. 10. The reduction in the speed and the peak power of the weld can help improve the GRG.

The various plot models shown in Fig. 11 show the relationship between the peak power and the average pulse duration and their effects on the grey relationship grade.

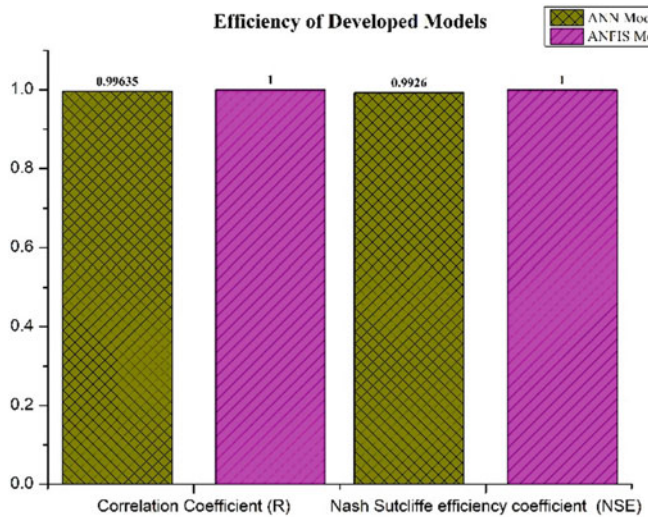

Fig. 7 Efficiency of developed models

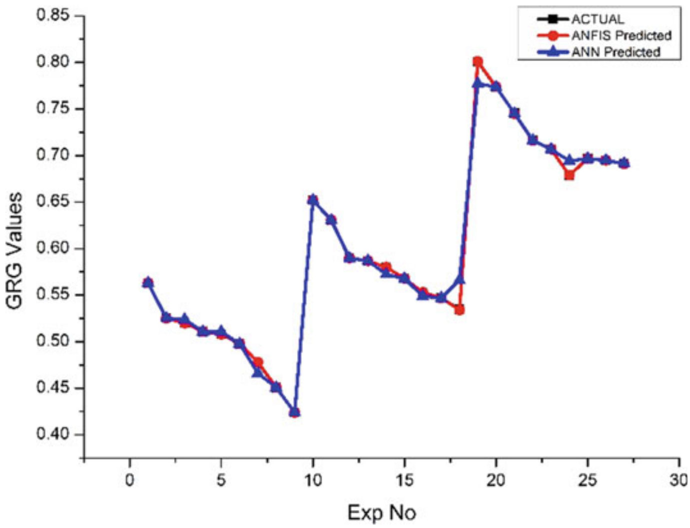

Fig. 8 Comparative analysis on experimental and ANN, ANFIS predicted GRG

The grey relationship grade and the pulse duration and weld speed data are shown in Fig. 12. The reduction in the speed and the shorter duration of the pulse can help improve the GRG.

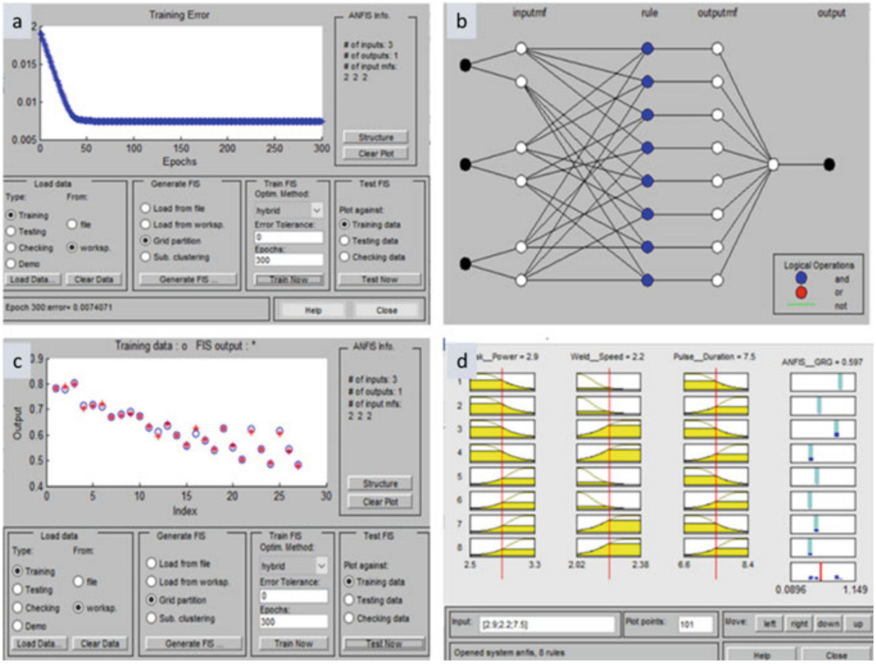

Fig. 9 **a** Error on training for model evolution **b** construction of ANFIS. **c** Comparative graph of actual and foretold GRG **d** rule viewer for model evolved

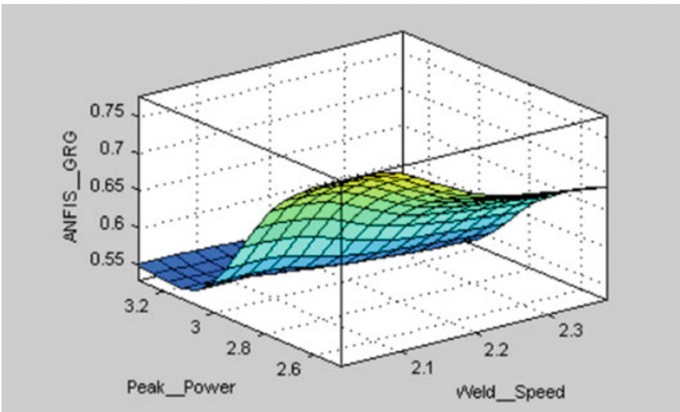

Fig. 10 Surface graph for the impact of peak power and weld speed on predicted GRG

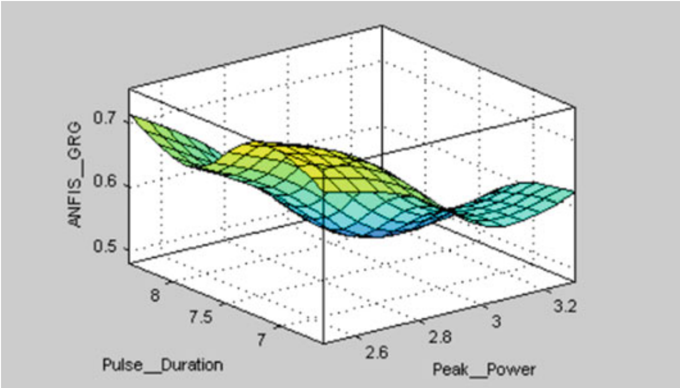

Fig. 11 Surface graph for the impact of pulse duration and peak power on predicted GRG

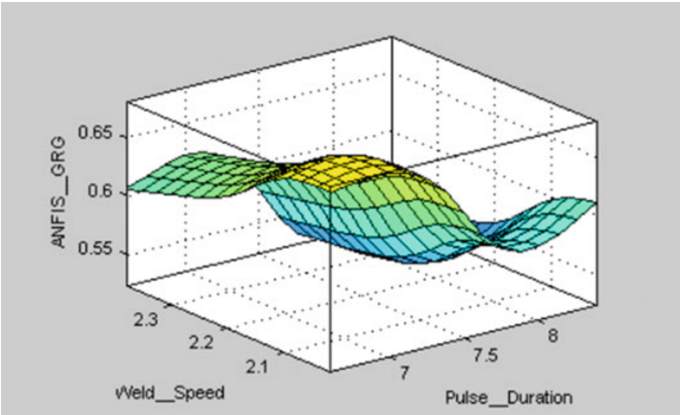

Fig. 12 Surface graph for the impact of weld speed and pulse duration on predicted GRG

2 Summary

The chapter covers the various applications of AI tools in the field of advanced manufacturing processes, such as laser welding and wire electrical discharge. The predictions developed using the ANFIS and ANN tools were then refined to achieve the chosen performance. The perception of the grey theory has been utilized to determine the MPI using the GRC. The model for the laser welding and WEDM processes is then inputted using the GRC values. The GRG values envisaged from ANFIS and ANN are then derived from the models that were evolved. The proposed model for the performance measurement was able to accurately predict the outcome. Also, it is perceived that the suggested model for the ambiguity reduction could improve its prediction capabilities. The investigational analysis exposed that the model, if implemented, can provide a more accurate prediction. The results of the performance investigations on the predictive model revealed that the evolved model was more effective than the previous one.

In a similar way, a study has also been done on the influences of distinct process variables on the performance indicators of laser welding, which is a contemporary method of joining metal. The explorative analysis revealed how the laser power affects the top and bottom width of the weld and the speed of the process. The outcomes of the exploration disclosed that the hybrid model used for the prediction was more accurate than the previous one. The study also stated that the ANFIS approach could be used for various kinds of machine tools. It is obvious from the analysis, that the implementation of AI tools will considerably improve the performance of various manufacturing processes.

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Improving Supply Chain Sustainability Using Artificial Intelligence: Evidence from the Manufacturing Sector

Sreejith Balasubramanian, Vinaya Shukla, and Linsy Kavanancheeri

Abstract Businesses and governments worldwide are implementing measures to tackle the significant sustainability challenges in the manufacturing sector, including environmental, health and safety and productivity related. As the sector moves toward Industry 4.0, Artificial Intelligence (AI) is viewed as a promising solution to address these challenges. However, current knowledge on these technologies and their interplay with the triple bottom line (TBL) sustainability dimensions is scattered and unclear. This study seeks to bridge this gap by creating a comprehensive AI implementation framework consisting of application, data and computation layers. The AI applications are categorized into virtualization, forecasting, automation and intelligent environment, while the computation layer comprises machine learning, deep learning, computer vision and natural language processing. These in turn use multimedia, time-series manufacturing, product parameter, sensor and location-based data inputs. Moreover, the framework assesses the impact of AI technologies on enhancing TBL sustainability, covering environmental, social and economic aspects. This novel and comprehensive framework, which is not seen in the previous literature, can support the development of policy interventions and support systems to promote AI adoption in the manufacturing sector, while also achieving TBL sustainability goals.

Keywords Industry 4.0 · Artificial intelligence · Triple bottom line (TBL) sustainability · Framework · Manufacturing sector · Supply chain

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1 Introduction

The manufacturing sector is a significant contributor to greenhouse gas emissions, accounting for one-fifth of such emissions worldwide [52], it also uses a considerable amount of energy (54% of the world's energy), water, and other resources, while generating a substantial amount of waste [18, 52]. Unsurprisingly, it has also been linked to an increase in pollution-related chronic diseases and a decline in the overall health of the population [45]. Furthermore, poor working conditions and work-related accidents are often associated with the sector, especially in emerging economies, due to the non-usage of cutting-edge production technologies [3]. As per the US Department of Labor estimates, the cost of such workplace injuries, which is in terms of wages, productivity, and administrative losses, is around \$161.5 billion per year [22]. Finally, the economic aspect has also come under sharp scrutiny, particularly since the beginning of the COVID-19 pandemic, with increased costs and lower sales/revenues [17]. Addressing the environmental and social implications while ensuring profitability, and doing so at a supply chain-wide level has become critical for manufacturing firms.

Given the emphasis on the triple bottom line (TBL) dimensions of sustainability, specifically economic, environment, and social, and in the emerging Industry 4.0 era, manufacturing firms have been forced to reexamine their conventional tools and approaches [6]. One approach that has emerged from this re-examination and is now at the forefront is Artificial intelligence (or AI). AI can be defined as the capacity of computer algorithms to execute cognitive tasks akin to human intellect, encompassing perception, reasoning, learning, and problem-solving [6]. It has the potential to support complex and critical supply chain decisions, such as forecasting demand under uncertainty, production planning and scheduling, and inventory management. The potential of AI applications for the manufacturing sector is huge: it is estimated to grow from USD 2.9 billion in 2021 to over USD 78 billion by 2030 as per Acumen Research and Consulting [2], these applications are also expected to generate USD 1.2–2 trillion in value for the manufacturing supply chain by 2025 through improvements in TBL sustainability [12].

Despite the significant potential of AI applications in the manufacturing sector, current knowledge and understanding about it is limited. Moreover, previous work in this area has been narrowly scoped and fragmented. For instance, Senoner et al. [43] focused on AI only from the perspective of improving process quality, while Sahu et al. [41] concentrated only on AI applications pertaining to Augmented Reality (AR). As a result, there is a scarcity of information about various AI applications, such as virtualization and automation, the diverse types of data that can be used for these applications, and the computation techniques that can be applied, such as Machine Learning and Deep Learning algorithms.

Even more limited is the examination of AI's impact on sustainability: we couldn't find any focused study that has related AI to TBL sustainability for the manufacturing sector. Knowledge of this relationship is therefore unclear. Understanding this relationship is important, as AI technologies' various sustainability impacts might conflict with one another. For example, AI algorithms can help reduce the requirement for raw materials, energy, and water; also help reduce wastages thereby supporting the environmental objectives. However, from a social perspective, AI application could lead to large-scale displacement of unskilled blue-collar workers and thereby an unstable social environment. From an economic perspective too, the large investments needed to exploit AI-related technologies may not be worthwhile for many small and medium scale enterprises. The critical question therefore is whether AI can realize all the three sustainability objectives simultaneously.

Another key gap is the absence of a comprehensive AI implementation framework that could guide various stakeholders within the manufacturing sector. All these knowledge gaps could hamper AI's large-scale acceptability/implementation, both technologically and from a sustainability perspective.

Addressing these gaps, including the development of a comprehensive enabling framework, is therefore important, and which forms the motivation for this work. Its specific objectives are

- To recognize and consolidate various individual AI applications in the manufacturing sector into coherent, management-relevant categories.
- To develop an inclusive, multi-faceted AI framework for the manufacturing sector that encompasses the data, computational, and application layers.
- To investigate the interrelations between diverse AI applications and the social, economic and environmental sustainability (TBL) aspects.

The proposed framework will serve as a valuable tool for evaluating the manufacturing sector's present and future readiness from an AI applications standpoint. It is novel as well as significant as no such framework exists at present. Moreover, it is the first comprehensive attempt to connect AI applications in the manufacturing sector with social, economic, and environmental sustainability dimensions. Practitioners and policymakers can benefit by comprehending the complex interplay between the various AI implementation layers (data, computation, and application) and their impact on the triple bottom line (TBL) sustainability dimensions. The improved understanding will enable them to create suitable policy interventions and support mechanisms to expedite AI adoption in the manufacturing sector.

The remaining paper is presented as follows. The next section explains the review methodology used. Section 3 covers the various AI framework components as well as the actual framework itself. The different implications of the study are discussed in Sect. 4 followed by the conclusions in Sect. 5, where we also cover the study's limitations and provide suggestions for further research.

2 Review Methodology

The literature review was conducted in three phases. Firstly, we undertook a review of previous academic work related to AI in the manufacturing sector. The aim was to develop an understanding of AI applications/solutions for the manufacturing supply chain and their impacts on TBL sustainability. Several gaps were revealed in the process. Firstly, compared to other Industry 4.0 technologies, such as Blockchain (e.g., [1, 36]), no study appears to have considered AI applications from an end-to-end supply chain perspective and from the perspective of realizing sustainability goals [37, 38]. The focus of these studies has predominantly been on manufacturing, with other areas, such as product development and distribution, including product returns, considered only to a limited extent. Even within manufacturing, except for some studies such as Arinez et al. [6], most have covered only one/few AI applications such as process quality [43] or AR-assisted manufacturing [41], or electricity consumption forecasting [7]. Secondly, most previous studies have provided a descriptive assessment/summary of AI applications in manufacturing based on systematic literature reviews and bibliometric analyses (e.g., [53, 28]) without considering the implications on the environment, economic, and social aspects. Finally, no comprehensive AI framework for manufacturing was found.

The above gaps led us to expand our review to secondary data. In the second phase, therefore, we reviewed websites, articles, reports, and case studies from leading consulting firms, manufacturing organizations, governments, and policy and industry bodies. The use of these sources is justified given the novelty of the investigated topic and the fact that practical solutions are needed.

Finally, to synthesize the results from the first and second phases and to organize them into a meaningful, managerially relevant framework, we reviewed several AI and Industry 4.0 frameworks in manufacturing and other sectors in the third phase. This included AI frameworks for public management (e.g., [49, 50]), AI frameworks for supply chain (e.g., [31]), Industry 4.0 frameworks (e.g., [9]), and blockchain frameworks (e.g., [8, 10]). Though not comprehensive, they provide a good theoretical basis for developing an overall framework structure and its components for our case.

3 Components of the Proposed AI Framework for the Manufacturing Sector

The components of the framework have been meticulously derived from the literature and which are discussed in detail below.

3.1 Data Layer

AI development depends on the quantity and quality of (input) data that is used to train the relevant algorithms/models [19], the greater the data available for training, the better is the AI algorithm's performance [42]. In manufacturing sector's case, vast amounts of complex and heterogeneous data (e.g., sensor-based and IoT data) are commonly available from today's factories. These include data collected by ambient sensors on process machines/stations such as temperature, pressure, humidity, current/voltage, vibration, flow rate, and velocity/acceleration [6, 28, 35]. Production/operations data recorded in controller systems such as machine downtimes, starvations/blockages, idle times, production outputs, and defects [6] could also be leveraged, also, image, video, radar, GPS, and haptic signals from autonomous vehicles and manufacturing robots [28]. Further, product design parameters such as length, breadth, weight, and thickness could be utilized for AI-enabled generative design. Finally, voice data could be used by speech-recognition AI solutions to facilitate human–robot collaboration [6]. The integrity of all of this data, though, is very important.

3.2 Computational Layer

The computational layer primarily consists of AI techniques or models (utilizing input data from the data layer) and includes three general approaches: machine learning (ML), deep learning (DL), and computer vision.

ML allows systems and machines to learn and improve automatically through experience without explicit programming. It is typically categorized into four main groups: Supervised, Unsupervised, Semi-Supervised, and Reinforcement Learning [28]. In manufacturing, common ML algorithms, such as Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Naive Bayes, and Random Forest (RF), are utilized to identify hidden patterns or extract information to solve classification, regression, and clustering-based problems [6, 28, 35].

Deep Learning (DL), a superior technique compared to Machine Learning (ML), mimics the human brain's functionality using a neural network that allows data to flow between layers for enhanced processing. A basic deep neural network comprises an input layer for accepting data samples, a hidden layer for training, and an output layer to produce the training results [34]. The number of hidden layers determines the depth of the deep learning architecture [25]. Common DL methods in manufacturing include convolutional neural networks (CNN), recurrent neural networks (RNN), and long short-term memory (LSTM). DL can capture complex patterns in training data and recognize various types of unstructured data, making it highly successful in object detection and realistic image synthesis [28].

Computer vision involves extracting meaning from visual elements [16]. In manufacturing, computer vision-based systems can perform inspection tasks more quickly, accurately, and efficiently than humans [15]. For example, such systems could be used to identify interior fabric textures in the automotive industry. Additionally, Natural Language Processing (NLP) is highlighted in the literature as being useful in manufacturing, particularly for speech-recognition AI technologies that facilitate human–robot interaction [6]. NLP algorithms are capable of handling human commands, detecting key terms and expressions within unstructured text or speech, and discerning human intentions [33].

3.3 Application Layer

The literature review revealed several AI applications in manufacturing, which are categorized into four groups: virtualization, forecasting, automation, and intelligent environments, depending on the nature of the application. These categories and their respective applications across different supply chain phases are discussed below.

3.3.1 Virtualization

Virtualization involves creating a virtual version of an object or process, such as AI-enabled virtual designs. These designs can be used to simulate and test their performance in real-world scenarios, allowing for automatic modifications and assessments until an optimal design is achieved [15]. Machine learning algorithms are employed to emulate an engineer's approach to design, using input data such as raw materials, size, weight, manufacturing techniques, cost, and other constraints to develop various design options [4]. These options can then be evaluated against numerous manufacturing scenarios and conditions to select the best one [12]. Companies like Airbus and Nissan have successfully utilized AI-enabled generative design techniques to create lightweight aircraft parts and unique car designs, respectively. Such designs can also be environmentally friendly that minimize raw material usage [12].

Another AI application in manufacturing is the digital twin, a virtual representation that precisely mirrors a physical object or process across its entire life cycle [23]. Digital twins can be used to manage devices and monitor production environments virtually [46]. Real-time updates to the virtual model allow for simulations, performance issue analysis, and the generation of improvements, which can then be applied to the original physical object [23]. Examples include virtualizing product packaging processes for error testing or optimizing warehouse layouts for maximum operational performance.

AI-driven product development also enables manufacturers to generate numerous simulations and assess them through augmented reality (AR) and virtual reality (VR) prior to production. This process minimizes trial and error, lowers prototyping expenses, and accelerates time to market [12].

AR-enabled wearable devices, like smart glass, can improve efficiency by providing real-time, hands-free information to workers as they perform tasks [15, 12]. For instance, a 34% productivity improvement was observed when using AR glasses for a wiring task [15].

3.3.2 Prediction/Forecasting

Demand forecasting is crucial for manufacturing firms to optimize production, reduce inventory costs, and maximize profits. ML and DL algorithms can be used to accurately predict consumer demand changes. According to McKinsey, AI can reduce forecasting errors and inventory by 20–50%, and lost sales on account of product unavailability by around 65% [29]. These algorithms can recognize patterns, identify complex relationships in large datasets, and capture demand fluctuation signals. For example, Walmart uses ML models to predict product demand instead of human forecasters, as ML models can detect subtle patterns and combine historical data with new data from various sources [15, 39].

IKEA has also developed an advanced AI-based Demand Sensing tool that improved their demand forecasting accuracy from 92 to 98% [24]. The tool considers more than 200 data sources, such as shopping behaviors during celebrations, the influence of seasonal shifts on buying trends, and weather predictions. It is capable of examining aspects like increased store visits during particular timeframes or consumer habits during festive seasons and holidays [24].

In addition to product demand forecasting, AI techniques can predict raw material prices by considering factors such as raw material characteristics, demand, seasonal trends, other commodities' prices, and offers from various suppliers [12]. AI-powered software can predict material prices with greater accuracy than human beings and also learn from past mistakes. Integrating demand forecasting and supplier/raw material price forecasting models can lead to efficient production planning [39].

Furthermore, AI-powered energy forecasting algorithms can optimize electricity production, distribution, and consumption in manufacturing plants or renewable energy sources like solar or wind [28]. ML enables optimal scheduling of energy-intensive activities to coincide with cheaper power availability [39]. Manufacturing firms utilizing renewable energy can use AI to accurately forecast energy output based on historical data and weather forecasts and schedule their manufacturing activities accordingly [47].

3.3.3 Automation

Automation involves the use of robots, computers, or other physical devices to execute tasks automatically without human intervention [6]. In manufacturing, AI-powered robots serve as cost-effective, faster, and more accurate alternatives to humans in processes like packaging, welding, painting, drilling, die casting, and grinding [12]. These robots can autonomously track, lift, move, and sort items in warehouses [12]. Automated Mobile Robots (AMRs) can independently navigate manufacturing and warehouse spaces, learn their environments, remember locations, and dynamically plan paths [28]. AI-enabled autonomous forklifts can also replace human-controlled ones [40]. Companies such as Amazon and Porsche use AI-driven robots to automate significant portions of their operations [12, 15]. In labor-intensive environments, cooperative and context-sensitive robots have the potential to increase productivity by as much as 20% [29].

Visual checks are crucial for quality management in industrial and manufacturing processes. Manual inspections can be repetitive, tedious, and error-prone due to human limitations [39]. AI-based automated inspection using computer vision technologies can enhance efficiency, reduce inspection times, and increase accuracy [15].

Around 60% of manufacturers employ AI for quality control [30]. AI algorithms can quickly categorize products based on parameters like curves, colors, and corners. Companies such as Google and BMW use AI-driven visual inspection systems to maintain high-quality standards [13, 21].

AI-enabled autonomous drones with computer vision are used in warehouses to manage inventory, identify different item types, and provide accurate inventory estimates [15]. Accurate automatic inventory assessment and demand forecasting can facilitate automatic purchase requisition creation [12].

Finally, autonomous trucks equipped with AI features for detecting roads, lanes, vehicles, pedestrians and drowsiness, avoiding collisions, and recognizing traffic signs can automate land-based logistics [28]. Companies such as Volkswagen and Rolls-Royce are developing AI-powered vehicles and ships for improved supply chain efficiency and safety [12, 14.

3.3.4 Intelligent Environment

AI can be used to examine numerous factors that influence the supply chain, including orders, purchases, materials, processing ingredients, production-specific elements like throughput quantity, defect rate, and machine downtime, as well as global factors like fuel costs and tariff rates. By analyzing these variables, AI can optimize operations and enhance supply chain management [15, 39]. One specific application is resource allocation, where limited manufacturing resources are allocated efficiently and effectively (through AI) to realize desired system performance [6]. Similarly, AI can optimize process quality. For example, in the case of laser metal cutting, it can optimize the cutting process to achieve the desired quality and predict the output based on inputs to the laser, such as power, cutting speed, and pulse frequency [6].

In supply chains, the complex network relationship between suppliers, distribution centers, and retail locations requires dynamic allocation and routing decisions to effectively manage the complexity. Traditional linear optimization algorithms are generally used but they rely on fixed parameters and cannot adapt to changing supply, logistic, or demand conditions, such as when a supplier is suddenly out of stock or there is a disruption on certain routes, or there is a sudden jump/drop in demand (Neal) [32]. This is where AI models come in handy, they can be trained to optimize the supply chain flows and inventory even when conditions are continuously evolving (Neal) [32]. They can suggest optimal product delivery routes and schedules and forecast delivery times more accurately by tracking driver performance in real-time, assessing weather and traffic reports, and using relevant historical data [12, 39]. Finally, AI-based predictive supplier assessment and monitoring can immediately notify when a supplier fails and assess the extent of related supply chain disruption [12].

AI has significantly advanced the transition from "preventive" to "predictive" maintenance, minimizing both machine downtime and unwarranted maintenance efforts [15]. This is because AI can monitor and analyze in real-time the different sensor-based manufacturing equipment data, maintenance logs, audio and video feeds, as well as data from external sources and decipher subtle patterns/changes in that data, such as in the vibrations or noise that indicate impending failure [12, 15]. Similarly, drones with AI-enabled cameras or 3D laser scanners can observe/monitor equipment damages that may not be noticeable to the human eye. Additionally, a trained deep learning model (e.g., convoluted neural network) can analyze photos of equipment and indicate their condition based on specific features recognized, enabling predictive maintenance [28].

AI can also improve the health, safety, and well-being of manufacturing workers. For example, the use of AMRs can improve health and safety standards by avoiding obstacles (intelligent collision detection) and unburdening workers from repetitive or back-breaking tasks, enabling them to focus on more valuable and fulfilling ones [28]. AI enables the detection of worker fatigue, for instance, an intelligent AI wristband can detect if a worker is fatigued, alerting the individual and other relevant people about potential dangers [9].

Finally, a manufacturing supply chain does not stop at the retail stage but extends beyond to the customer service stage, where again AI can contribute. The cognitive abilities of natural language processing (NLP) could be used to enhance customer service using intelligent Chatbots. Such Chatbots that have near human-like conversation capabilities can quickly understand customers' issues and provide suitable responses. Importantly, they are economical as well, as they can handle more customers and provide faster responses than call centers [48].

3.4 Impact of AI on Triple Bottom Line (TBL) Sustainability

While we did not find any research specifically investigating how the implementation of AI affects the triple bottom line (TBL) sustainability in manufacturing, the available information from the literature suggests that this is generally positive.

3.4.1 Environmental Performance

As can be seen from the various AI applications, AI-enabled manufacturing helps to reduce waste, emissions, and materials usage leading to a lower environmental impact [20]. For example, generative design through virtualization can lead to the creation and evaluation of a variety of environmentally friendly designs. Similarly, Digital twins can capture the environmental impact of a product or process throughout its life cycle, which can be used to improve its environmental performance. The use of AR-enabled smart glasses can minimize the need for paper-based manuals and drawings, thereby supporting a paperless manufacturing environment. Accurate demand forecasting can help reduce excess inventories and obsolete/out-of-fashion products (e.g., in the apparel industry) and expired products (e.g., in the food industry) which are often sent to landfills or burned. Furthermore, as highlighted earlier, AI forecasting models help in reducing energy wastage. Additionally, the high precision of AI-enabled manufacturing robots leads to fewer errors (with consequential lower defects, returns, and rework) and lower resource usage, which are both environmentally positive. Similarly, the improved accuracy in inspection and quality control that they provide reduces product returns, or safety recalls. Moreover, the autonomous vehicles and machinery (e.g., AMRs, automatic forklifts) used in the smart manufacturing ecosystem are often electric-powered resulting in significantly lower emissions than those based on fossil fuels and internal combustion engines. Finally, AI-enabled operations and supply chain optimization minimizes resource usage across the supply chain, including of raw materials, water, and energy. For example, AI-enabled route optimization software recommends the best delivery and product return routes considering distance, real-time traffic and weather conditions resulting in lower fuel consumption which is environmentally (and economically) positive.

3.4.2 Social Performance

One major advantage of incorporating AI in the manufacturing industry is the improvement in worker health and safety. In the United States, around 400,000 occupational injuries are reported each year, with numerous fatalities, caused mainly by falls from heights, collisions with moving objects, and incidents, where people are caught or crushed between two or more objects [9]. Intelligent context-aware manufacturing robots and equipment significantly reduce these accidents since their AI algorithms are trained to detect obstacles and prevent collisions. Moreover, AI-powered drones can conduct inspections and stocktaking, minimizing the risk of falling from a height.

Similarly, AI-powered machinery can automate repetitive tasks, especially those requiring employees to carry heavy weights. Further, the real-time sensing capabilities of AI enable the detection of noise levels and pollution levels such as harmful toxic gases in the factory. AI-enabled smart wearables such as intelligent electronic wristbands can detect in real-time if workers are tired or overworked or require immediate medical attention. Likewise, AI-powered surveillance cameras with facial and object recognition capabilities can automatically identify and report safety violations, such as workers not wearing appropriate protective gear or engaging in unsafe behaviors, like failing to maintain social distancing during the COVID-19 pandemic [39].

In addition to improving health and safety, AI also enhances employee productivity and morale. AR-enabled smart glasses improve employee productivity by receiving real-time information on various parameters faster. VR headsets facilitate the training of employees in a virtual setting that mimics the actual environment. Further, the automation of manual, repetitive tasks implies that employees can now focus on more value-added ones. In other words, AI will facilitate the upskilling of blue-collar workers into knowledge ones [9].

Another advantage of AI in manufacturing is that it can promote diversity and inclusion in the workplace. Traditionally, the industrial manufacturing setting is considered challenging and dangerous for women. With AI-enabled automation and a safe working environment, companies can attract and hire more female employees to reduce the gender divide.

3.4.3 Economic Performance

The purpose of adopting AI in manufacturing is to improve economic performance and this study demonstrates that AI can significantly improve a company's bottom line. For example, AI-enabled predictive maintenance can save up to 10–40% in maintenance costs and reduce manufacturing downtime by around 50% due to equipment failures (AI) [5]. Similarly, accurate demand forecasting using AI helps to reduce inventory costs and increase revenues by minimizing stockouts, while AI-based raw material cost forecasting reduces production costs [39]. In addition, automated procurement and order management driven by AI significantly reduces purchasing costs, and automated quality inspection facilitated by AI minimizes production risks and customer service issues before they have a wider impact.

Further, the AI-based generative design facilitates different design variants for a product, thereby enabling additional revenue from product customization. It also reduces trial and error in designing (which has cost implications) as well as time to market from design to retail (which has revenue implications), thereby providing a competitive advantage. Digital twins enable continuous improvement in production facilities thereby reducing costs and increasing productivity. As an example, according to Balasubramanian et al. [9], the digital twin of a building can identify parts of a building not being utilized and subsequently turn off the heating, ventilation, and air conditioning systems in those areas in real time, resulting in a significant reduction in energy expenses. instance, the digital twin can detect in real-time, parts of buildings that are currently unused and then automatically deactivate the heating, ventilation, and air conditioning in those parts, drastically reducing energy costs [9]. VR technology creates immersive training programs for employees, thereby reducing the cost of the more expensive face-to-face training [9]. AI-powered automation can lower labor costs both directly as well as indirectly (from fewer fatalities and accidents that have legal-related, medical-related, compensation-related, and insurance-related cost implications); the related (automated) equipment is also faster and less error-prone; it also ensures business continuity during labor shortage situations as was seen during the COVID-19 pandemic recently. AI also reduces over-reliance on a few experienced (more expensive) factory operators. Additionally, AI-driven resource optimization provides significant savings for manufacturing firms; for instance, AI adoption in the semiconductor industry resulted in a 30% reduction in scrap rates [12]. Finally, AI-enabled improvement in environmental performance enables manufacturing firms to generate additional revenue by selling carbon credits.

3.5 *The Proposed AI Sustainability Framework for Manufacturing*

Figure 1 depicts the proposed AI sustainability framework for the manufacturing sector which comprises three key layers: Data, Computational, and Application. The Data layer consists of heterogeneous data that ranges from material properties at the molecular level to imaging and GPS data. The Computational leverages various AI techniques such as machine learning (ML), deep learning (DL), natural language processing (NLP), and computer vision to process and analyze the data. The interconnection between the data layer and computation layer shows that the efficacy of these AI techniques depends on the quality and quantity of data available for training and running them [19]. The Application layer highlights the different AI application areas/domains in the manufacturing industry. They are grouped under four meaningful and managerially relevant categories: Virtualization, Forecasting, Automation, and Intelligent environment. Identifying these application areas itself was a significant undertaking, given that it is the central task of any technology framework [8, 9]. The interconnection between the Application and Computational layers indicates that different applications rely on the appropriate computational technique to achieve high performance, such as in accuracy, sensitivity, and specificity terms [48]. The framework's central component presents the distinct phases of the manufacturing supply chain, including product development, manufacturing, and distribution, all enhanced by AI applications. The bottom component illustrates the multi-faceted impact of AI applications on the environmental, social, and environmental sustainability (TBL) dimensions.

4 Implications

In recent years, the manufacturing sector has taken AI seriously to develop safer and more efficient ways of designing, producing, and distributing products. This study aimed to consolidate the fragmented knowledge of AI in manufacturing into a coherent and management-relevant framework. This framework, which encompasses AI data requirements and techniques used to implement various AI applications across end-to-end supply chains while considering the TBL sustainability impacts, is essential for the widespread adoption of AI in the sector.

The study has numerous implications. It presents the first comprehensive, evidence-based, and systematic approach to identifying diverse, standalone AI applications in the manufacturing sector, from product development to manufacturing and distribution. Given the industry's lack of AI frameworks, the proposed framework offers both novelty and significance. This study is also the first to thoroughly connect AI and TBL sustainability within the sector. By utilizing current evidence to show how AI can enhance supply chain sustainability in manufacturing, it bridges the gap between theory and practice. The framework is conceptually comprehensive

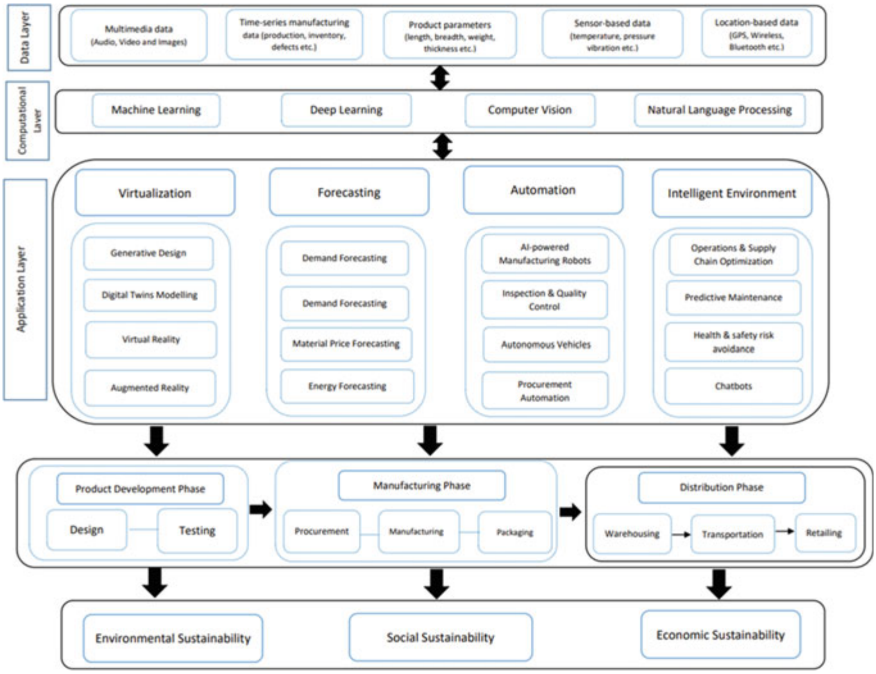

Fig. 1 Proposed AI sustainability framework for the manufacturing sector

and generic which makes it suitable for adaptation and adoption by researchers in different countries. The wide array of AI applications identified for various supply chain stages provides a solid foundation for future research.

In terms of practical implications, this study demonstrates that AI has immense potential to revolutionize the manufacturing sector and address its critical environmental and socio-economic challenges. The research findings and framework can help governments and professional associations develop roadmaps, craft supportive regulations, policies, and guidelines for industry-wide AI adoption. Given that the manufacturing sector has been slow in adopting technological changes, the study is especially relevant in the context of the industry's recovery from the COVID-19 pandemic. AI could help in addressing material and labor shortages, high shipping costs, lockdowns, social distancing measures, and fluctuating demand. Furthermore, AI can enable the development of safer and more intelligent manufacturing methods in the sector.

5 Conclusion

Manufacturing is a vital part of the global economy, making up 17% of the global GDP according to the World Bank [51]. However, it is also a significant source of environmental pollution [52]. Hence, the role of AI in achieving triple-bottom-line sustainability in manufacturing cannot be overemphasized. The findings of this study confirm that manufacturing is one of the most promising sectors for AI applications. They provide insights into the various implementation layers of AI, including the data, computation, and application layers. Regarding the data layer, the results highlight opportunities to utilize diverse and heterogeneous data for training, testing, and developing AI models within the manufacturing sector. Furthermore, the findings reveal the multi-faceted nature of AI computation techniques, particularly machine learning, deep learning, natural language processing, and computer vision, which are employed to develop various AI applications.

However, there are some limitations to this study. Although we present a comprehensive AI framework for manufacturing, it may not encompass every aspect of the three layers (Data, Computational, and Applications) and their impacts on TBL sustainability within the sector. For instance, the study only discusses the positive impacts of AI on TBL sustainability, not the negative ones. One such negative impact is the potential unaffordability of AI for small and medium-sized enterprises (SMEs), which could widen the technology gap between them and larger firms. Additionally, there are concerns about the energy-intensive nature of AI technologies. For example, machine learning and deep learning algorithms require substantial computational power, leading to the need for powerful data centers and servers with significant energy consumption and extensive cooling requirements [9]. Furthermore, there are social concerns related to blue-collar workers losing jobs and what their future role in the manufacturing sector would be. The growing implementation of AI tools for monitoring employees prompts concerns regarding individual liberty and privacy in the workplace. Likewise, it is important to examine the potential reduction in professional independence and innovation, especially for designers, as well as the subsequent effects on their sense of value and accomplishment within their jobs. Future studies should examine such negative impacts of AI on TBL sustainability. Finally, the applicability of the framework has not been empirically established in a real-life setting, which future studies should do through the use of a suitable case study.

Despite these limitations, the insights and the framework make a significant contribution to advancing theory and practice. We hope that they will inspire future research on this important topic. We anticipate that practitioners and policymakers will find this study to be a valuable starting point for implementing AI in the manufacturing sector.

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A Grey-DEMATEL Approach for Analyzing the Challenges for Lean 4.0 in SMEs

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Abstract Small and medium-sized enterprises (SMEs) are rapidly contributing to economic growth. With the ever-demanding growth in the market and changes occurring in the market, not a single company can be left behind in terms of the improvement of its processes. In this chapter, the focus is to understand how the case company evaluates the challenges that it faces in incorporating the amalgamated process of Lean principles in the Industry 4.0 scenario. Lean manufacturing broadly focuses on the fact that there are limited wasteful activities in the process. In addition to that if we were to consider the Industry 4.0 scenario, where emerging technologies such as artificial intelligence, cyber-physical spaces, big data, and other associated technologies could be studied. The complicated challenging situations that the SMEs need to consider while developing their products is what we are considering to evaluate for the company. The real-life condition of the cement industry is taken into account, and the criteria for a Lean 4.0 setup in manufacturing are evaluated using the Grey-DEMATEL technique.

Keywords Lean · Industry 4.0 · Lean 4.0 · Grey-DEMATEL

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1 Introduction

The organization's performance may be improved by focusing solely on value-added activities and reducing non-value-added activities. In addition to that the current trends in manufacturing are particularly on implementing Industry 4.0 (I4.0). It focuses on the industry utilizing the technology for better performance. Combining these with the lean principle highlights the concept of lean 4.0. In the fierce competition today, capability of manufacturing firms should be to produce the products which are key to the globalized digitally connected environment. The size of the organization does not matter, if they have to survive in the market today, they have to produce as per the demand of the market. Thus, even the SMEs need to focus on the concept of Lean 4.0.

One important solution for improving the manufacturing system, proposed in the previous century was the Toyota Production System. The aim was to minimize the time and resources, reduce waste and minimize lead time. The philosophy of lean was to continuously consider the activities which add value for the customer. The processes and steps were improved in order to have a process which can satisfy the customers.

Further, the current trends of I4.0 has been the focus. The aim of I4.0 is to improve the processes of the system by having a good digital linkage with the help of concepts of cyber-physical space and blockchain.

Both concepts, viz., I4.0 and Lean, and important concepts in the industry, seem promising to ensure better manufacturing output. The aim is to understand how this amalgamation is more powerful and support the process improvement for better output. The question that arises in front of them is that how can they support each other. Which I4.0 method is useful for lean practices? And which lean practice flows in tandem with the concept of I4.0? In the research either LM is assumed to be a prerequisite of the introduction of I4.0 [1] or I4.0 tools enhance Lean Management [2].

There are many authors who consider LM as a prerequisite of I4.0 owing to the following reasons: (i) the standardized, transparent, and reproducible characteristics of the process is the base of introducing I4.0 [1]. (ii) The decision-makers must be able to provide value to the customer and avoid waste. (iii) With the use of LM tools the efficiency and economic use of I4.0 is justified [3]. On the other hand, there are others who consider that lean principles can help refine the concept of I4.0. I4.0 helps in overcoming the limitations of LM. I4.0 also help to cope with the complexities which may not be addressed by LM alone.

In this study, our concentration is on the implementation of Lean 4.0 for SMEs in India. Every country's economy relies heavily on the micro- and small and medium-sized enterprise (commonly referred to as SMEs) sectors. The expansion of both the national and global economy is founded based on these organizations [4]. SMEs confront the difficulty of justifying I 4.0 technology and cannot risk being on the bleeding edge of technological innovation due to their limited financial resources [5]. To get the benefits of I 4.0's leading edge technology, large firms have access to enormous financial markets. SMEs, on the other hand, confront the issue of justifying the use of I 4.0 technology [5]. A large number of organizations, especially those that fall under the category of SMEs, continue to harbor the dream of being completely digitized while simultaneously becoming more efficient. SMEs include a vast number of factors that may be analyzed, which results in a long and complex model [6]. As a result of this, the objective of this article is to investigate and evaluate, on behalf of the company, the intricate and challenging situations that SMEs need to take into account while manufacturing their products. The scenario takes into consideration the actual situation that exists within the cement industry, and the evaluation of criteria is carried out based on the Grey Decision-Making Trial and Evaluation Laboratory (DEMATEL) technique, which is designed to evaluate the criteria for a Lean 4.0 setup within the manufacturing sector.

The research questions that are addressed by this research:

(i) What are the characteristics of Lean 4.0 Manufacturing in SMEs?
(ii) What are the challenges faced in implementing Lean 4.0 manufacturing?
(iii) What are the ways in which SMEs Lean 4.0 for the improvement of manufacturing?

The remaining of the paper is organized as follows: theoretical context is described in Sect. 2. Section 3 discusses the approach and a case study of its use. Section 5 discusses the paper's management implications, and Sect. 4 goes through the conclusion and future research directions.

2 Theoretical Background

The research has been undertaken to understand the challenges of amalgamating lean and I 4.0 for improving the process of manufacturing. In this section, we highlight in detail how lean 4.0 has come about and how the challenges which we have analyzed have been shortlisted. We divide this section into three main sections, (i) lean and its conceptual understanding, (ii) I 4.0 and its conceptual understanding, and (iii) lean 4.0. The last part of the section highlights the research objectives and research gap.

2.1 Lean

The concept of lean has been considered by many researchers and essentially details the idea of waste reduction [7, 8]. For instance, [9] evaluated the effect of lean principles on reducing waste in the construction industry. Zhang et al. [10] analyzed the effect of lean principles on reducing waste in the manufacturing industry. Singh and Ahuja [11] discussed the effect of lean principles on waste reduction in the healthcare industry. The study by Lee et al. [12] examined the effect of lean principles on waste reduction in the food industry. The study found that lean principles such as value stream mapping and pull production can significantly reduce waste in the food industry. Similarly, other researchers have investigated the effect of lean principles on waste reduction in different industries such as the automotive industry [13], the service industry [14], and the energy industry [15]. All of these studies have found that lean principles can significantly reduce waste in their respective industries. Muda (Waste) along with mura (unevenness) and muri(overburden) describes the complete concept of lean [16]. The study of these eight wastes along with the lean principles helps to develop an integrated management system [17]. The lean practices are applicable to complete organizations and not only to some departments. There are different authors who have given their own classification of lean principles and based on consensus we use them in the current study while exploring the challenges.

2.2 I4.0

With many changes in the industry that are happening, there are many new technologies that are part of the system. These technologies such as low-cost sensors, computing power, high-speed internet connectivity make the organizations able in their processes. Technology at various stages has had an impact on the improvement of the organizations' performance [18]. There are many technologies such as Radio Frequency Identification (RFID) which accentuate the working systems of retail outlets [19]. There is an increase in efficiency and increase in revenue by using technology. There are new technologies that keep developing every day. There are IoT solutions, virtual and augmented realities, advances analytics, autonomous vehicles, robotics, and digital manufacturing. These technologies enhance the current industry system and reach the aim of I4.0. Industry 4.0 is the fourth industrial revolution, which focuses on the integration of digital technologies into manufacturing and other industries. It is characterized by a high degree of automation, data exchange, and the use of emerging technologies such as the internet of things, artificial intelligence, and machine learning.

Research conducted by Zhu et al. [20] indicated that Industry 4.0 can bring significant benefits to manufacturing industries, such as improving production efficiency, reducing costs, and enhancing product quality. Similarly, Lu et al. [21] found that Industry 4.0 can help organizations achieve better supply chain management and logistics operations, resulting in improved customer satisfaction and increased profitability. Despite the potential benefits, implementing Industry 4.0 can also pose challenges. According to Zhang et al. [22], one of the significant challenges of Industry 4.0 is the lack of standardized communication protocols, which can lead to compatibility issues between different devices and systems. Another challenge highlighted by Kagermann et al. [23] is the need for a skilled workforce capable of operating and maintaining the new technologies.

As Industry 4.0 continues to evolve, researchers are exploring new applications and potential areas for improvement. For instance, Song et al. [24] suggested that Industry 4.0 could benefit from incorporating blockchain technology to enhance data security and transparency. Meanwhile, Jiang et al. [25] proposed using virtual reality and augmented reality technologies to provide more immersive and interactive training experiences for Industry 4.0 workers. As Industry 4.0 continues to evolve, researchers are exploring new applications and potential areas for improvement, such as incorporating blockchain and virtual reality technologies. Further research is needed to fully realize the potential of Industry 4.0.

2.3 Lean 4.0

Lean manufacturing has been an established concept for several years now and focuses on waste reduction in manufacturing processes. With the advent of Industry 4.0, the integration of lean principles with the latest digital technologies, such as artificial intelligence and the internet of things, has led to the emergence of the concept of Lean 4.0. The integration of these two concepts promises to optimize the manufacturing processes, make them more efficient, and reduce waste even further. A study conducted by Li et al. [26] investigated the application of Lean 4.0 in a manufacturing company in China. They found that the integration of lean principles with Industry 4.0 technologies resulted in a significant improvement in production efficiency and quality, as well as a reduction in waste. They also reported that Lean 4.0 facilitated real-time monitoring of production processes and enabled timely decision-making, which contributed to the optimization of production processes. Another study by Hussain et al. [27] explored the integration of Lean 4.0 with the digital twin concept. The digital twin is a digital replica of a physical object or process, and its integration with Lean 4.0 can facilitate the identification of inefficiencies and waste in manufacturing processes. The study reported that the combination of Lean 4.0 and the digital twin concept resulted in significant improvements in production processes, including a reduction in waste, lead time, and downtime. A recent study by Cen and Zhang [28] investigated the application of Lean 4.0 in a semiconductor manufacturing company in China. The study found that the integration of lean principles with Industry 4.0

technologies resulted in a significant reduction in production costs, a decrease in waste, and an increase in production efficiency. The study also reported that Lean 4.0 facilitated the implementation of just-in-time principles and improved supply chain management, which contributed to the optimization of production processes.

The amalgamation between Lean and Industry 4.0 brings forth the concept of Lean 4.0. has been discussed by a few researchers in the literature [29]. There are different points of view on the concept, even though there might be a broad consensus on the integration. Some describe lean forms as the basis of implementing I4.0. [30] and others claim that because there is I4.0 lean activities are successful. The integration of lean principles with Industry 4.0 technologies has led to the emergence of the concept of Lean 4.0. The application of Lean 4.0 promises to optimize manufacturing processes, improve production efficiency and quality, and reduce waste even further. The reviewed studies have shown that the integration of Lean 4.0 with digital technologies such as the digital twin, just-in-time, and real-time monitoring can result in significant improvements in production processes. The implementation of Lean 4.0 can thus be seen as a promising strategy for companies aiming to achieve higher levels of efficiency, reduce waste, and improve product quality.

2.4 Research Gap and Motivation

The aim of the study depends on the research gap that exists in the current literature. The research gap that exists is (i) lean and Industry 4.0 have been discussed but the challenges that are faced in the implementation have not been quantified, (ii) Lean 4.0 in SMEs has not been discussed, and (iii) lean 4.0 in developing countries is yet to be implemented in many industries. To address the research gap, we are carrying out this study and the following are the objectives as stated below:

Research Objectives

- To determine the concept of Lean 4.0 in the SME sector.
- To determine the challenges of implementing Lean 4.0.
- To prioritize the challenges for Lean 4.0 for successful implementation.

In the next section, the case study is described for the SME sector to address the research objectives.

3 Case Implementation

The case study discussed in this research concentrates on the cement industry. More specifically, the cement solid and hollow blocks industry has multiple firms (names not disclosed for reasons of confidentiality). For the current research, we have taken experts from four of these firms for advising on the challenges for the use of Lean 4.0 in SMEs. Based on the literature and the expert advice, the following are the challenges which have been shortlisted. Table 1 shows the challenges for the implementation of Lean 4.0.

Using the challenges that have been listed in Table 1, we try and prioritize the challenges using the G-DEMATEL approach. The G-DEMATEL is used for determining the significance of each challenge. In the traditional form of the approach, the challenges could be divided into the cause/effect groups. In the case of real-life decision-making, there is always some ambiguity [66]. To incorporate this ambiguity in judgments, we utilize the G-DEMATEL approach. Grey systems theory is utilized to handle the uncertainty in the problems, with imperfect information. We highlight step-wise how the G-DEMATEL approach has been utilized for the case.

Step 1: For the evaluation of the criteria (challenges for Lean 4.0) the greyscale given as "Very highly influence (VH)" given as "[0.75, 1]", "High influence (HI)" as "[0.5, 0.75]", "Low influence (LI)" as "[0.25, 0.5]", "Very low influence (VLI)" as "[0, 0.25]", and "No influence (NI)" as "[0, 0]".

Step 2: Direct relationship matrix is created for assessing the link between the criteria. This is done with the judgements of the experts. The experts perform a pair-wise comparison using the linguistic scale shown in Table 2. The initial grey matrix "M"

Table 1 Challenges for implementation of Lean 4.0

	Challenge	References
LC1	Insufficient workforce skills to implement lean	[31]
LC2	Inadequate implementation strategies	[32]
LC3	Top management resistance	[33–37]
LC4	Employees are not empowered	[38, 39, 40, 41, 36, 42]
LC5	Lean is incompatible with the company's rewards, bonus, or incentives programmes	[43, 44]
LC6	Lack of information sharing or communication with suppliers and customers	[45–51]
LC7	Inadequate supplier collaboration or a mutually advantageous strategic partnership between suppliers and customers (supply chain participants)	[52, 53, 43, 54, 55, 56, 57, 58]
LC8	Inadequate strategic action/logistical planning system	[34, 59, 60, 61, 62]
LC9	The lack of resources to invest	[63, 64, 60]
LC10	Cross-operational disagreements	[65]

Table 2 Average matrix

	LC1	LC2	LC3	LC4	LC5	LC6	LC7	LC8	LC9	LC10
LC1	[0.0]	[0.56, 0.81]	[0.5, 0.75]	[0.25, 0.5]	[0.25, 0.5]	[0.375, 0.625]	[0.25, 0.5]	[0.563, 0.813]	[0.625, 0.875]	[0.688, 0.938]
LC2	[0.5, 0.75]	[0.0]	[0.625, 0.875]	[0.438, 0.688]	[0.188, 0.438]	[0.375, 0.625]	[0.1875	[0.688, 0.938]	[0.563, 0.813]	[0.375, 0.625]
LC3	[0.25, 0.5]	[0.25,0 .5]	[0.0]	[0.438, 0.688]	[0.188, 0.438]	[0.313, 0.563]	[0.5, 0.75]	[0.5,0.75]	[0.375, 0.625]	[0.688, 0.938]
LC4	[0.5, 0.75]	[0.5, 0.75]	[0.5, 0.75]	[0.0]	[0.063, 0.313]	[0.5,0.75]	[0.188, 0.438]	[0.188, 0.375]	[0.375, 0.625]	[0.563, 0.813]
LC5	[0.75, 1]	[0.5, 0.75]	[0.688, 0.938]	[0.5, 0.75]	[0.0]	[0.688, 0.938]	[0.438,0.688]	[0.438,0.688]	[0.375, 0.625]	[0.438, 0.688]
LC6	[0.75, 1]	[0.625, 0.875]	[0.375, 0.563]	[0.375, 0.625]	[0.313, 0.536]	[0.0]	[0.75, 1]	[0.438,0.688]	[0.5, 0.75]	[0.75, 1]
LC7	[0.5, 0.75]	[0.75, 1]	[0.5, 0.75]	[0.25, 0.438]	[0.5, 0.75]	[0.563, 0.813]	[0.0]	[0.5,0.75]	[0.563, 0.813]	[0.75, 1]
LC8	[0.75, 1]	[0.5, 0.75]	[0.75, 1]	[0.688, 0.938]	[0.375, 0.536]	[0.75, 1]	[0.536, 0.813]	[0.0]	[0.688, 0.938]	[0.5, 0.75]
LC9	[0.188, 0.438]	[0, 1]	[0.75, 1]	[0.125, 0.375]	[0.25, 0.5]	[0.563, 0.75]	[0.5, 0.75]	[0.188, 0.438]	[0.0]	[0.5, 0.75]
LC10	[0.75, 1]	[0.75, 1]	[0.5, 0.75]	[0.375, 0.625]	[0.563, 0.813]	[0.438, 0.688]	[0.5, 0.75]	[0.625, 0.875]	[0.563, 0.813]	[0.0]

is generated.

$$M^E = \begin{array}{c} F_1 \\ F_2 \\ \vdots \\ F_n \end{array} \begin{bmatrix} 0 & \otimes m_{12}^E & \cdots & \otimes m_{1n}^E \\ \otimes m_{21}^E & 0 & \cdots & \otimes m_{2n}^E \\ \vdots & \vdots & \cdots & \vdots \\ \otimes m_{n1}^E & \otimes m_{n2}^E & \cdots & 0 \end{bmatrix}$$

where E is the number of experts, $\otimes m_{ij}^E = [\underline{m}_{ij}, \overline{m}_{ij}]$ are grey numbers, while $\otimes m_{ii}^E = [0, 0]$, $i = 1,2,\ldots,n$.

Step 3*:* The aggregate matrix "Z" is formed by taking the average of grey direct relation matrices as given below. This gives the average values of all the decision-makers put together. This is given in Table 2.

Step 4: *Creation and Assessment of structural model:* Using the normalization formula the linear scale transformation is modified for translating the criterion scales to comparable scales. The direct-relation grey matrix is given in Table 3.

Step 5: Crisp numbers are obtained from the grey numbers using the procedure given by (Serafim Opricovic, 2003). Next, the grey total relation matrix R is computed as shown in Table 4.

Step 6: Evaluating the results: (d + r) reveals the influence of the qualities, whereas (d − r) reveals the influence others have on the attributes given in Table 5.

4 Conclusion and Implications

The present research is being conducted to determine the problems that organizations experience when implementing Lean 4.0. These difficulties are divided into cause/effect groups to decide which challenges must be addressed first in order to eradicate the system's faults. Once the issues can be eliminated, companies can implement Lean 4.0 effectively. This research will guide the way for SMEs to take up new dimensions in their production systems in order to be sustainable in the future. The other implications of this study are, that it forms a base for all such organizations to look into their processes so that they can work on achieving Lean 4.0 effectively. The research, though fills in a major research gap, has some limitations which form the future research scope. The research can further be extended by taking a more robust set of decision-makers for giving their inputs. Further, in future studies, Lean 4.0 can be considered to be analyzed for different product segments as different products have different processes and thus implementation of strategies be different.

Table 3 Consolidated GM

	LC1	LC2	LC3	LC4	LC5	LC6	LC7	LC8	LC9	LC10
LC1	[0, 0]	[0.075, 0.108]	[0.067, 1]	[0.033, 0.067]	[0.033, 0.067]	[0.05, 0.083]	[0.033, 0.067]	[0.075, 0.108]	[0.083, 0.117]	[0.092, 0.125]
LC2	[0.067, 0.1]	[0, 0]	[0.083, 0.117]	[0.058, 0.092]	[0.025, 0.058]	[0.05, 0.083]	[0.025, 0.058]	[0.092, 0.125]	[0.075, 0.108]	[0.05, 0.083]
LC3	[0.033, 0.067]	[0.033, 0.067]	[0, 0]	[0.058, 0.092]	[0.025, 0.058]	[0.042, 0.075]	[0.067, 0.1]	[0.067, 0.1]	[0.05, 0.083]	[0.092, 0.125]
LC4	[0.067, 0.1]	[0.067, 0.1]	[0.067, 0.1]	[0, 0]	[0.008, 0.042]	[0.067, 0.1]	[0.025, 0.058]	[0.025, 0.05]	[0.05, 0.083]	[0.075, 0.108]
LC5	[0.1, 0.133]	[0.067, 0.1]	[0.092, 0.125]	[0.067, 0.1]	[0, 0]	[0.092, 0.125]	[0.058, 0.092]	[0.058, 0.092]	[0.05,0.075]	[0.058, 0.092]
LC6	[0.1, 0.133]	[0.083, 0.117]	[0.05, 0.75]	[0.05, 0.083]	[0.042, 0.075]	[0, 0]	[0.1, 0.133]	[0.058, 0.092]	[0.067, 0.1]	[0.1, 0.133]
LC7	[0.067,0.1]	[0.1, 0.133]	[0.067, 0.1]	[0.033, 0.058]	[0.067, 0.1]	[0.075, 0.108]	[0, 0]	[0.067, 0.1]	[0.075, 0.108]	[0.1, 0.133]
LC8	[0.1, 0.133]	[0.067, 0.1]	[0.1, 0.133]	[0.092, 0.125]	[0.05, 0.075]	[0.1, 0.133]	[0.075, 0.108]	[0, 0]	[0.092, 0.125]	[0.067, 0.1]
LC9	[0.025, 0.058]	[0, 0.033]	[0.1, 0.133]	[0.017, 0.050]	[0.033, 0.067]	[0.075, 1]	[0.067, 0.1]	[0.025, 0.058]	[0, 0]	[0.067, 0.1]
LC10	[0.1, 0.133]	[0.1, 0.133]	[0.067, 0.1]	[0.05, 0.083]	[0.075, 0.108]	[0.058, 0.092]	[0.075, 1]	[0.083, 0.117]	[0.075, 0.108]	[0, 0]

Table 4 Total relation matrix

	LC1	LC2	LC3	LC4	LC5	LC6	LC7	LC8	LC9	LC10
LC1	21.089	20.062	24.381	14.889	12.316	20.040	17.395	18.441	21.145	25.812
LC2	21.571	17.567	22.780	14.103	11.767	18.904	16.509	17.392	19.945	24.310
LC3	19.016	16.837	18.454	12.669	10.650	16.758	14.629	15.523	17.662	20.993
LC4	16.956	15.126	17.840	10.914	9.828	15.075	13.372	13.914	15.897	18.749
LC5	29.739	25.633	31.884	18.208	13.905	25.365	21.667	23.294	26.689	34.581
LC6	31.000	26.508	32.755	18.819	15.300	24.161	22.259	24.127	28.342	35.864
LC7	31.240	26.467	33.578	18.548	15.268	26.446	20.667	24.159	28.334	35.970
LC8	39.266	32.897	42.700	22.159	17.484	32.416	27.011	26.683	35.214	47.231
LC9	15.650	14.063	16.267	10.823	9.136	13.654	12.291	13.078	13.650	17.129
LC10	33.730	28.512	36.665	20.046	16.100	28.580	23.464	25.816	30.613	35.231
R	259.258	223.673	277.303	161.179	131.754	221.399	189.264	202.428	237.491	295.870

Table 5 Identification of cause and effect

	d	r	d + r	d − r	Cause/effect
LC1	195.571	259.258	454.830	−63.687	Cause
LC2	184.848	223.673	408.521	−38.825	Cause
LC3	163.190	277.303	440.493	−114.113	Cause
LC4	147.670	161.179	308.849	−13.508	Cause
LC5	250.965	131.754	382.719	119.211	Effect
LC6	259.136	221.399	480.535	37.737	Effect
LC7	260.677	189.264	449.941	71.413	Effect
LC8	323.062	202.428	525.490	120.634	Effect
LC9	135.741	237.491	373.232	−101.749	Cause
LC10	278.756	295.870	574.627	−17.114	Cause

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Challenges and Opportunities for Lean 4.0 in Indian SMEs: A Case Study of Jharkhand

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Abstract The SME sector is India's economic backbone and plays a critical role in insulating the nation from shocks and difficulties in the global economy. The development of India's economy depends heavily on the country's small and medium-sized businesses. Because of this, SMEs must embrace lean to survive in today's global business environment. Companies need new standards to address the requirements of increased customization and product variety; diversified markets; shorter product life span and development time; responsiveness toward customers; and waste minimization, which are increasingly becoming key features. These requirements are needed to survive in the present global scenario. By concentrating on their plans for continuous improvement in all areas of business and simultaneously improving their manufacturing processes by reducing waste prevalent at all levels, companies can improve their performance in the aforementioned areas. It is necessary to pinpoint the problems that, in the context of the Indian SME sector, would result in the approval of lean. Concentrating on Indian small and medium-sized business organizations, this chapter tries to identify the obstacles to lean 4.0 implementation and rank the factors that affect the system deployment in a business organization. The study emphasizes the difficulties Jharkhand's SMEs had implemented the lean method.

Keywords Internet of things (IoT) · Lean manufacturing · Lean yools · Waste minimization · Value stream mapping

1 Introduction

Lean manufacturing is an organized method of locating and reducing waste in processes through ongoing systemic upgrading in order to carry out every task more effectively, lower the cost of running the business, and satisfy the needs of customers who want the highest level of value at the lowest possible cost. Many businesses have

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discovered that they can produce high-quality goods more cheaply, even in smaller quantities, by only employing a small portion of the inventory used in everyday business operations. Lean manufacturing has proven to be a very trustworthy "good management practice" for businesses eager to gain and keep consumer confidence, realize efficiency and effectiveness in all business processes, and raise the likelihood of making profit continuously.

1.1 What is Lean Manufacturing?

The antidote to waste, lean thinking, gave rise to lean manufacturing (Muda). Lean thinking offers an approach to stipulate value, arrange value-creating activities in the finest order, and manner these events with less and less anthropological effort, fewer gear, a shorter interval, and less space while getting nearer and quicker to giving clients precisely what they need. Waste is specifically defined as any action that consumes assets but generates no worth.

The application of lean thinking has greatly helped numerous enterprises in Japan, the USA, Germany, India, the UK, and other nations. These businesses reduced costs while achieving superior quality, higher productivity, flawless delivery performance, overall high customer happiness, and corporate excellence. The exact situation might be different, but the general strategy was built on value stream analysis, value definition, putting in place an appropriate flow system, striving for perfection, and people empowerment through effective change management. The newest buzzword in manufacturing circles is "lean manufacturing." It is not particularly novel. It has precursors like Henry Ford, the Toyota Manufacturing System, and others [1]. The objective of the lean system is to eliminate wastes through improvement activities of various kinds which is lying within the company [2]. The ideal of the lean system is one-piece flow because it is a continuously improving manufacturing system with less waste [3].

The origins of lean manufacturing may be traced to the idea of interchangeable parts and reducing waste. The highlights of the history are covered in this chapter.

1.2 Origin and Concept of Lean Manufacturing

Lean manufacturing is a technique whose goal is toward optimizing the movement of manufacturing while continuously attempting to cut the means (e.g., straight and unintended labor, resources, etc.) requisite to create a specified set of articles; or, "Waste" refers to everything that is unwanted in the system [1]. Lean manufacturing focuses on a continual improvement process rather than aiming for a certain level of leanness [1–4].

Lean manufacturing seeks to eliminate waste in labor, inventory, time to market, and manufacturing space in order to produce products of the highest caliber possible while using the least number of resources possible [4]. Shigeo [5], an outspoken opponent of waste, advised not to think of it as inevitable. Eliminating waste is the cornerstone of lean manufacturing. "Anything other than the minimum quantity of equipment, materials, parts, space, and time that are necessary to add value to the product," according to Russell and Taylor [6], is considered waste. Waste can be found anywhere at any time in a variety of forms. Complexity, labor (the superfluous movement of people), excess output, energy, space, flaws, materials, time, and transportation are all wasted resources [7]. Waste depletes while adding no value to the finished product. Lean manufacturing combines the advantages of both mass and handcraft manufacturing: the ability to offer an ever-expanding range of products and increasingly difficult work while simultaneously lowering prices per unit and dramatically improving quality [8].

1.3 Waste and Its Effects

The existence of waste in various forms is largely to blame for the day-to-day issues that are experienced in carrying out the processes in the majority of industrial firms. Equipment downtime (caused by lengthy setup and changeover procedures or by frequent breakdowns), high inventories of raw materials, goods still in production, and finished goods are common examples of standard operating inefficiencies that businesses feel compelled to pass along to their customers as a necessary evil.

Any extra equipment, material, parts, space, or time above and above what is necessary to add value to the product is referred to as waste [6].

1.4 Wastes in Lean Manufacturing

Nicholas [9] identified that in all the manufacturing systems, waste is present in the form of complexity, labor, overproduction, space, energy, defects, material, time, and transport. Originally seven types of wastes are identified as part of Toyota production system [5, 10]. However, this list is extended and modified by many researchers to encompass many other wastes [1]. In this research, waste is classified into ten categories.

The following are some examples of waste offered by different lean manufacturing experts:

i. **Over-manufacturing**: Over-manufacturing occurs when anything is unnecessarily produced in excess of what is needed or too early. This raises the likelihood that the products will become obsolete, that they will be produced incorrectly, and that they will need to be discounted or thrown away as scrap. Even lean manufacturers, however, occasionally keep an extra supply of finished goods or semi-finished goods on hand.

ii. **Defects**: In addition to physical flaws that directly increase the cost of the goods supplied, this can also include paperwork problems, giving incorrect information about the product, late delivery, manufacturing to the incorrect standards, using excessive amounts of raw materials, or producing extra scrap.
iii. **Inventory**: Inventory waste is when there are abnormally high levels of new materials, works-in-progress, and finished commodities. Having more stock results in higher storage costs, higher fault rates, higher depreciation cost, and higher inventory costs.
iv. **Transportation**: Any movement that does not add value to the final product, such as moving materials from one workstation to another, is classified as transportation. The concept is that materials should be moved idle across manufacturing phases. The time it takes to move between processing stages adds to the length of the manufacturing cycle, consumes manpower and space, and occasionally results in brief manufacturing halts.
v. **Waiting**: Due to manufacturing flow bottlenecks or inefficiencies, waiting is considered idle time for both humans and machinery on the factory floor. Small delays in unit processing are also a part of waiting. Insofar as it raises labour expenses and depreciation costs per unit of manufacturing, waiting has a major financial penalty.
vi. **Motion**: Motion is defined as any unnecessary employee movement or walking that prevents them from completing their processing activity. For instance, because of poor layouts that slow them down, workers may have to scour the shop floor for a tool or even perform unnecessary or strenuous physical movements.
vii. **Correction**: When something needs to be redone because it was done incorrectly the first time, it needs to be corrected or reprocessed. Reprocessing frequently disrupts the efficient flow of manufacturing, which results in bottlenecks and stoppages in addition to the inefficient use of people and equipment. Reworking problems also frequently require a lot of management effort, which raises the cost of running the factory.
viii. **Over-processing:** Inadvertently adding finishing or cleaning to some product areas that the buyer won't see, which is more processing than the consumer needs in terms of product eminence or type.
ix. **Knowledge Disconnection**: This occurs when knowledge or information is not offered when or where it is required. This could include details on proper practices, requirements, approaches to problem-solving, etc. Inaccurate information frequently causes flaws and bottlenecks.
x. **Inappropriate Design**: Inappropriate design of product or manufacturing process.

1.5 Lean Thinking

The phrase "lean thinking," coined by [11], is used to describe Taiichi Ohno's way of thinking as well as the collection of techniques that describe the Toyota Manufacturing System, which highlights the stark action disparity between the Japanese and western car sectors and popularized concepts connected to lean thinking [1]. Within the lean manufacturing method, James-Moore and Gibbons [12] outline the following core areas of concentration: flexibility, waste reduction, optimization, process management, and personnel usage. Each area of focus has a related set of principles.

1.6 Lean Manufacturing

- Lean manufacturing is widely acknowledged as a tool to ensure that manufacturing processes are improved [13].
- Lean manufacturing seeks to eliminate waste such as labor, inventory, time to market, and manufacturing space while delivering products of the highest caliber possible in the most effective and economical way possible [3].
- Shigeo [5] advocated for the removal of non-value-adding items, arguing that "don't accept waste as unavoidable." The main objective of lean manufacturing is to eliminate waste.
- Samurdhie [14] found that Non-Value Adding Activities are the activities which do not add to the market form or function of the product. This is the main feature of lean manufacturing.

The types of waste that lean manufacturing includes are as follows:

(i) Overproduction in manufacturing (ii) Flaws in materials or processes (iii) Inventory-related issues (iv) Shipping problem (v) Waiting time (vi) Additional motion involved (vii) Over-corrections (viii) and over-processing (ix) Process information disruption

The process of lean manufacturing is shown in Fig. 1.

2 Value Stream Mapping (VSM)

The value stream mapping approach employs the principle of continuous improvement to increase process productivity and product value. It offers a range of tools for gathering and analyzing data in order to pinpoint waste that occurs at several points in the manufacturing process and its effects on the entire business. The core objective of the lean theory is to reduce waste. Value stream mapping plays a critical role in

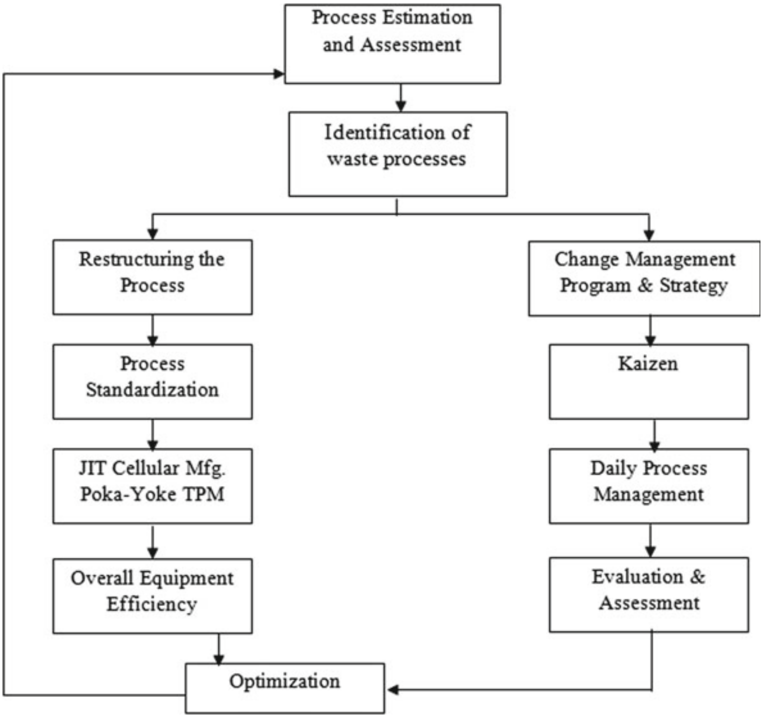


Fig. 1 Lean manufacturing process

their detection and subsequent decrease. Value stream mapping is a recommended item in the lean manufacturing toolkit that has been used in many different sectors. By documenting evidence and material flow, categorizing waste and its basis, and showing how the evidence and material should move, VSM offers a plan for the operation of lean manufacturing concepts [8].

A "value stream" is described as every value-added and non-value-added act, both internal and external to the supply chain, necessary to deliver a given good, amenity, or mixture of goods and services to a client [1, 8]. A manufacturing process can be improved by detecting waste and its sources by using the enterprise improvement technique known as VSM to visually display information and material flow throughout the whole manufacturing process [8]. An already-created set of signs is used to create the value stream map. VSM establishes a consistent vocabulary for a manufacturing process, allowing for more deliberate choices to enhance the value stream. A systematic method for enhancing a value stream is described by Rother and Shook (1999). Finding the pertinent product families and choosing one to focus on improving is the first step. Using data acquired from the actual manufacturing process, the upcoming stage is to develop a current state map for the product value stream. Mapping of the future state is the third phase in the VSM process. A future state map can only be created by providing answers to eight questions. Value stream mapping (VSM) is a set of instruments that assists practitioners and scholars in locating waste in specific value streams [2].

Toyota invented VSM, originally known as "Material and Information Flow Mapping." According to Rother and Shook [8], the method used by TPS experts to represent the present situation and the desired future state while creating implementation strategies for lean manufacturing paradigms.

This method looks at how information and materials move to concentrate on the entire value chain of a product, rather than just a single discrete manufacturing phase. The method entails reviewing the manufacturing procedures with responses from the workforce and manufacturing people. It recommends developing a "present state" map and a "future state" map using a set of precise fact-finding inquiries and preexisting data. The large picture map or current state map shows the operation in visual form. In VSM, a predefined set of signs is used to construct both the current state map and the future state map.

2.1 Application of VSM

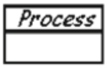
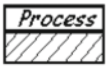
- It is easier to see the foundations of waste in the value stream rather than only at the single-process level, such as assembly and welding.
- It offers a common tongue for discussing industrial procedures.
- It makes judgements regarding the flow obvious.
- It connects several lean principles and methods.
- It serves as the framework for an implementation plan.
- It demonstrates the link between the flow of data and the flow of materials.
- It offers a great deal more advantages than quantitative tools and plan figures that calculate the number of inventory items, lead times, trip distances, and other metrics, as well as non-value-added steps.

The four essential steps of VSM are as follows:

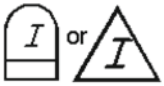
1. Choose a product family, and for that product family.
2. Create a map of the present.
3. Create a map of the future states.
4. Create a work schedule of tasks to go from the present to the future state.

Two maps must be created to use the VSM process: the current state map and the future state map. Normally, one would begin the current state map by mapping a family of products with strong sales and volume. The material flow will then be mapped using the VSM template's relevant icons.

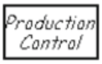
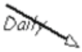
2.2 VSM Process Symbols

 **Customer/Dealer**	When positioned in the upper left, where the material flow often begins, this icon denotes the dealer. When positioned in the top right, the typical feature at which the flow of materials ends, the client, is shown
 **Dedicated process**	This represents a material-flowing procedure, activity, device, or organization. Typically, it depicts one category with non-intermittent flow that is internally fixed to ignore the unmanageable mapping of each individual operational step Although WIP inventory builds up within equipment or postings for the case of assembly with various connected workstations, the complete route appears as one box. Use many boxes for distinct operations that are isolated from others, inventory within them, and batch transports
 **Shared process**	This process department, work center, or activity is shared by other value stream families. Guess the number of workers required for the value stream that is being mapped rather than estimating the number of operators required to process all commodities
 **Data box**	This symbol is placed beneath other icons that contain important facts and information needed for system analysis and observation. The rate of shipment for the period of any swing, material management details, transfer lot size, mandate amount per period, and other distinguishing factors are displayed in a Data Box beneath the FACTORY signs Typical information in a data box next to the manufacturing process symbols Cycle time (C/T) is the amount of time (measured in seconds) that elapses between one component leaving a process and the subsequent component starting one. The term "uptime" refers to the percentage of time that a computer is processing data. C/O (changeover time) is the amount of time that one product in a process is switched out for another. "Every Part Every" number of operators is what EPE stands for. It is used to calculate manufacturing rates. Product differences, capacity, scrap rate, and transfer lot size are all represented by the OPERATOR icon inside the process boxes
 **Work cell**	It denotes the integration of numerous operations within a manufacturing work cell. These cells often only handle one product or a small family of related products. Small batches or single pieces of product are moved from one processing stage to the next

2.3 VSM Material Symbols

 **Inventory**	It represents the inventory lying in between the two processes. A rapid count can be used to estimate the quantity of inventory, and that number is written under the triangle while mapping the current state. Use a different icon for each inventory buildup if there are several This symbol also denotes raw material and finished goods storage
 **Shipments**	This symbol denotes the delivery of completed goods from the factory's delivery docks to consumers or the transfer of underdone materials from dealers to the factory's receiving docks
 **Push arrow**	Pushing materials from one process to the next is shown by this emblem. Push describes a procedure that generates output independent of the instantaneous requirements of a downstream operation
 **Supermarket**	The inventory supermarket is this (the kanban stock point). A modest inventory is already in place, similar to that of a supermarket, and one or more downstream clients visit the supermarket to choose what they want. Then, as needed, the upstream work center replenishes stockpiles Upstream processes must run in set mode when continuous flow is not feasible; therefore, supermarkets reduce over manufacturing and keep the overall inventory under control
 **Material pull**	This "Pull" indicator, which denotes physical removal, is used by supermarkets to connect to downstream procedures
 **FIFO lane**	Inventory that is first-in, first-out. This sign is used when the process is linked with a FIFO mechanism, which limits input and takes the most extensive inventory possible
 **Safety stock**	It characterizes inventory border and safety stock, aside from difficulties such as idle time, in order to defend the system against unexpected variations in client briefings. The sign is closed on all edges, as you can see. Because such inventory is intended to be temporary and not permanent stock storage, there must be a clearly defined rule for when it can be used
 **External shipment**	Externally transported deliveries from sellers or to customers

2.4 VSM Information Symbols

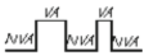
 **Manufacturing control**	It indicates a dominant manufacturing development and control section, person, and operation
 **Manual info**	The basic stream of evidence from memoranda, reports, or conversations is depicted by a straight, thin arrow. Other notes and frequencies may be important
 **Electronic info**	This wiggly arrow represents an example of electronic flow and is used to represent the Internet, LANs, and WANs. This could reveal the mode of communication (fax, phone, etc.), the frequency of data exchange, and the type of data replaced
 **Manufacturing Kanban**	The fabrication of certain numbers of parts is started when this icon appears. It instructs a process that supplies parts to the downstream process to do so
 **Withdrawal kanban**	It tells the material handler how to move components from the store to the unloading stage. A material handler (or operator) visits a grocery store and purchases what is needed
 **Signal kanban**	When a supermarket's on-hand inventory level between two procedures reaches the activated or least point, it is utilized. When a part highlighted on the kanban arrives at a supplying process, a triangle kanban indicates a changeover and the construction of a predetermined batch size for the part
 **Kanban post**	Place where pickup-ready kanban signals are stored. Frequently used to interchange drawing and manufacturing kanban with two-card systems
 **Sequenced pull**	This indicates a pull system, which directs subassembly operations to create a specific kind and number of products—normally one unit—without the use of a store
 **Load levelling**	It serves as a batch kanban tool to balance manufacturing size and mix over time

(continued)

(continued)

 **MRP/ERP**	MRP/ERP systems are used for scheduling
 **Go see**	Information assembly using visual methods
 **Verbal information**	It denotes the flow of spoken or private information

2.4.1 VSM General Symbols

 **Kaizen burst**	It identifies areas that need improvement and schedules Kaizen workshops for certain processes that are essential to realizing the value stream's future state map
 **Operator**	An operator is represented by this icon. It shows how many operators are required to complete a VSM family procedure in a specific workspace
 **Timeline**	It displays wait times and cycle times, which are times that add value. Using this, you can estimate lead time and total cycle time of the process

Using VSM with the Industry Forum, you may get a general understanding of how businesses operate. It then assists in creating strategic and tactical action plans that will result in financial savings. Through value stream mapping, one will have the chance to

- Align business with consumer demands.
- Shorten lead times.
- Extend the time spent adding value.
- Cut costs.

3 Case Study of Hydraulic Pump Manufacturing Plant

This study was carried out in a job shop industry in the state of Jharkhand. There were numerous issues related to the waste. The two main factors for this study were the manufacturing time and inventory levels. The lean idea was taken into consideration when conducting the investigation. The company manufactures hydraulic pumps with horsepower ratings ranging from 1/2 HP to 800 HP. There are literally thousands of different pump configurations available, including single phase, three phase, multi-speed, inverter duty, hazardous duty, severe duty, marine duty, spin master AC micro drive, and pumps with premium efficiency ratings.

4 Current State Map

The Company produces numerous products, such as pumps, generators, pump guidelines for belted applications, belting and chain drives, etc. One product family, specifically pump assemblies, is the primary focus of value stream mapping. Customizations made to a conventional product family don't significantly affect how long things take to process or set up with reference to average cycle time, change over time, or downtime. Further, how it is connected with the basic industry 4.0 tools. Cycle times for various process steps of various pump families are given in Table 1 and current state map is shown in Fig. 2.

Improvement plan for the AB manufacturing line:

- Manufacturing 80 pumps every day, based on the apparent market requirements (current manufacturing throughout is 67 pumps everyday), means increasing the manufacturing of the AB product line without experiencing the extra capital outflow.

Table 1 Cycle time of different process steps for different Pump family

Cycle time (min.)				
Processing stage	Pump family			
	Pump family A	Pump family B	Pump family C	Pump family D
Pump assembly	61	60	60	58
Stator assembly	50	50	52	48
Rotor assembly	20	18	20	19
Housing machine	15	14	15	15
Shaft machine	14	14	14	14
Saw	1	1	1	1
Testing machine	15	14	15	14

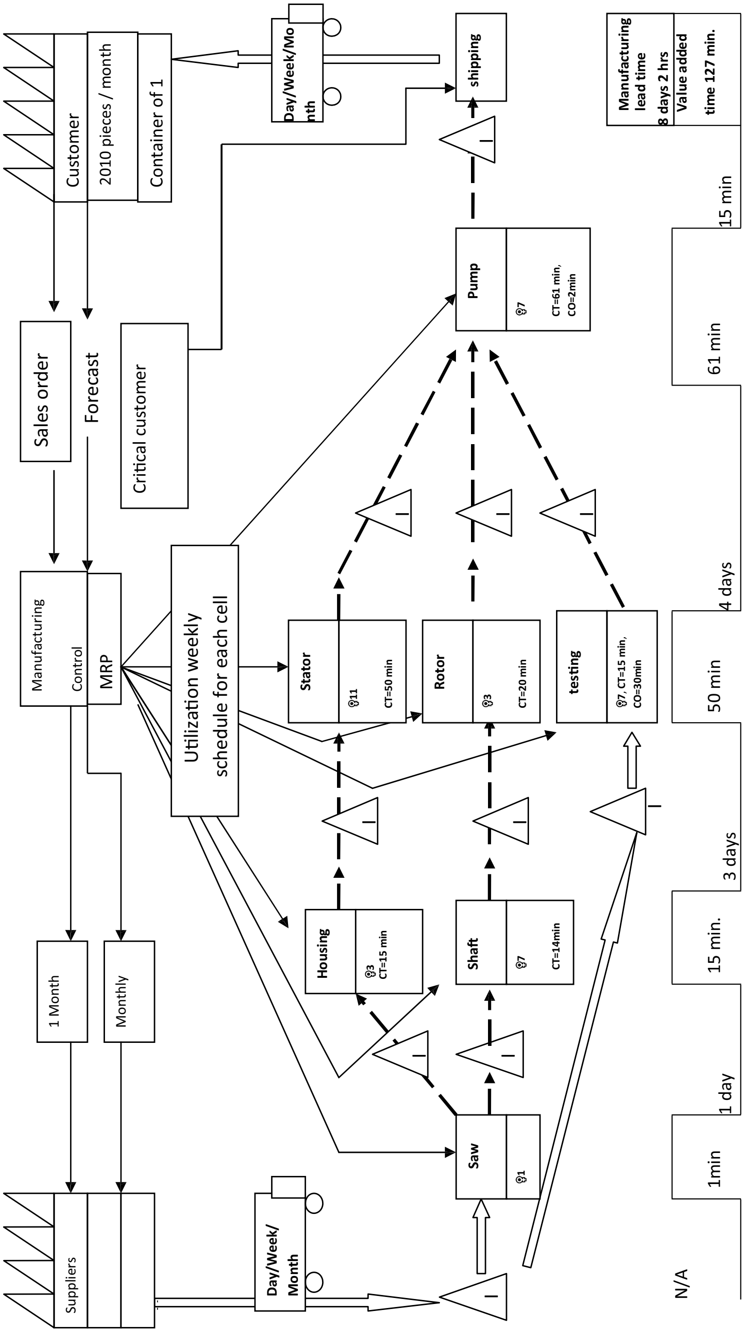


Fig. 2 Current state map

- The Manufacturing lead-time of less than 24 h (current lead-time is 8 days).
- Shrink in-process inventory and the non-value-added time.
- 99% of deliveries will be made on time (now, it is just 70%). The VSM was pinched with the help of conventional icons used for mapping. Figure 4 shows the current state map.

5 Future State Map

According to the results of the present state map, the three main wastes that have an impact on how industry operates are identified as faults, waiting, and inventories. This section examines the waste brought on by waiting, excessive manufacturing, and inventory. Analytical treatment is also implemented by taking into account elements like takt time, pitch, heijunka box, etc. Future state maps have been produced in reaction to developments in the present operation.

By explicitly answering eight questions using the approach described by Rother and Shook (1999) [8], future state maps are produced.

Eight questions have to be answered to develop a future state map. All these questions need new approaches as well as tenders.

The **first five questions** relate to basic concerns **related to the construction** of future state maps.

The following two questions deal with specific technical implementation information, such as "heijunka" control system details. aid in specifying non-mapping specifics like product mix, order release timing, etc.

The final query concerns the specification of the actions ("Kaizen") required in order to transition from the present condition to the future.

Question 1: What is takt time?

Takt Time = The amount of time available to work per day or per consumer call per day.

Takt Time = (15 h $\times$ 60 min per hour) / 80 pumps = 11.25 min per pumping.

Question 2: Will manufacturing send goods directly to shipping or to a supermarket for final goods?

A supermarket, which is situated at the end of the manufacturing line, is nothing but a buffer zone for the storage of goods that are prepared to be sent.

Question 3: Where along the value stream will the company need to use a pull system supermarket?

Depending on the uptime, the changeover time, and the proportion of faults at various processing stages, eight additional pull systems are needed to create a continuous flow at the entire pump assembly.

Average cycle times for various processing stages for various pump families (taking into account the quantity of resources available), and by knowing the average cycle time, we can estimate the average monthly and daily demand. i.e., 30, 20, 20, and 10 for Pump Part Families A, B, C, and D, respectively.

Calculating the lot size, start point, and quantity of kanbans for various supermarkets comes next.

Steps for setting up triangle kanban after analyzing the current state map:

Calculation of available time for changeover (work) at each workstation: 450 min per shift, or 900 min per day; also, we have to find the required run time per day and also the time available for setup and changeover. i.e., 311.35 min.

The number of changeovers per day after calculation is 8.28, or 8 changeovers per day.

Computation of batch factors: Batch factor = 0.4831 (Amount of product families/families/number of daily modifications).

Preparing a lot size for manufacturing: by multiplying the daily demand by the batch factor.

(Lot size = Kanban numbers) = 39 pieces (14 + 10 + 10 + 5).

Set the reordering's beginning point in motion: complete replenishment as a starting point Lead time/Takt time for parts.

We can define the time available for changeover or cycle time per day, the average lot size for manufacturing, and the starting point for reordering in 8-pull supermarkets in the whole value stream by performing all four steps. Calculation of the starting point for reordering is only necessary for SM-B, D, E, and G, as changeover time is longer and the company requires a triangle kanban. In the other four SM, the changeover time is less, so the calculation of the starting point for reordering is not necessary, and easy withdrawal kanbans are used.

Stock levels at various supermarkets: We can calculate the required run time per day, the time required per day to meet the typical demand, the net time available for set-ups and changeovers, the typical downtime, the desired number of changeovers per day, batch factors, lot sizes, and the number of kanbans, or inventory levels, at various supermarkets by using the same procedure everywhere.

Table 2 computes the lot size, number of kanbans, total lead time, takt time, and the starting point for reordering to the supermarkets prior to each processing stage based on the aforementioned calculations. For lot size, kanban count, total lead time, takt time, and the starting point for reordering between supermarkets, analogous calculations can be made.

Question 4: Where is the use of continuous flow processing possible?

When the supermarkets are completely full, the corresponding processing stage may be changed to produce different product categories.

Table 2 Lot sizes, number of kanban, and starting point of supermarket B (SM-B) that is between Pump assembly and stator assembly

Part	Average demand per day (pieces)	Average cycle time per piece (min)	Average changeover time (min)	Average scrap rate	Down time	Required run time per day
A	30	7.14	30	2.5%	7%	219.64
B	20	7.14	30	2.5%	7%	146.43
C	20	7.43	30	2.5%	7%	152.29
D	10	6.86	30	2.5%	7%	70.29
						588.64
Net time for installation and changeover (min)						311.3571429
Average downtime, excluding setup, and replacement in (min)						63
Available time to change over (min)						248.3571429
Number of desired changeovers per day						8.28
Batch factor = number of parts/no. of desired changeovers per day						0.483175151

Products	Lot size	No. of kanban	Total lead time (min)
A	14	14	156
B	10	10	119
C	10	10	122
D	5	5	79
First container time	=	10 min	

Part	Lot size	Longest lead time (min)	Takt time	Starting point	Starting point (no. of containers)
A	14	122	30	4	4
B	10	156	45	3	3
C	10	156	45	3	3
D	5	156	90	2	2

Question 5: What particular procedure (pacemaker process) should be scheduled in the manufacturing line?

There will be one treating stage for supplier-to-customer value stream that requires to be designed to break over manufacturing at the workstations in value stream. The processing stage is called the pacemaker process because it coordinates the manufacturing tempo for all upstream operations.

Question 6: How should a pacemaker company process manufacturing?

The manufacture of the four motor part families will be distributed equitably along the assembly line at the pacemaker process as the foundation for answering this question. Level the product mix in a specified pitch interval and manufacture the four different products at a steady rate to establish the manufacturing order. The formula is qir = (r - 0.5) (Q/Ddi). Table 3 shows the generation of manufacturing order for smooth manufacturing.

Question 7: What type of work growth ("pitch") is regularly released to the pacemaker process?

How frequently should one release and withdraw (the "pitch") the increment of production from the pacemaker process according to the order established by the previous question? The pitch serves as the fundamental time unit of a product family's production schedule. Number of pitches for every product is shown in Table 4.

Question 8: What Process Upgrades Will Be Required?

To understand the future state map (Fig. 3), the organization must take into consideration the predicted improvements in material and information flow that will result from a careful examination of several processes. No matter how valuable the concepts of takt time, pitch, kanban control, production leveling, etc. addressed in earlier questions are, they may not result in production improvements unless special efforts are made to enhance the processes by utilizing a particular set of lean tools for the specific type of production.

Table 3 Generation of manufacturing order for smooth manufacturing

Product(i)	Unit(r)	q_{ir}	q_{ir} (sorted)	Product(i) (sorted)
A	1	1.33	1.33	A
A	2	6.00	2.00	B
A	3	10.00	2.00	C
A	4	9.33	4.00	A
A	5	36.00	4.00	D
A	6	22.00	6.00	B
A	7	26.00	6.00	C
A	8	20.00	6.67	A

Table 4 Number of pitches for every product

Product	Number of pitches per day
A	30/3 = 10
B	20/2 = 10
C	20/2 = 10
D	10/1 = 10

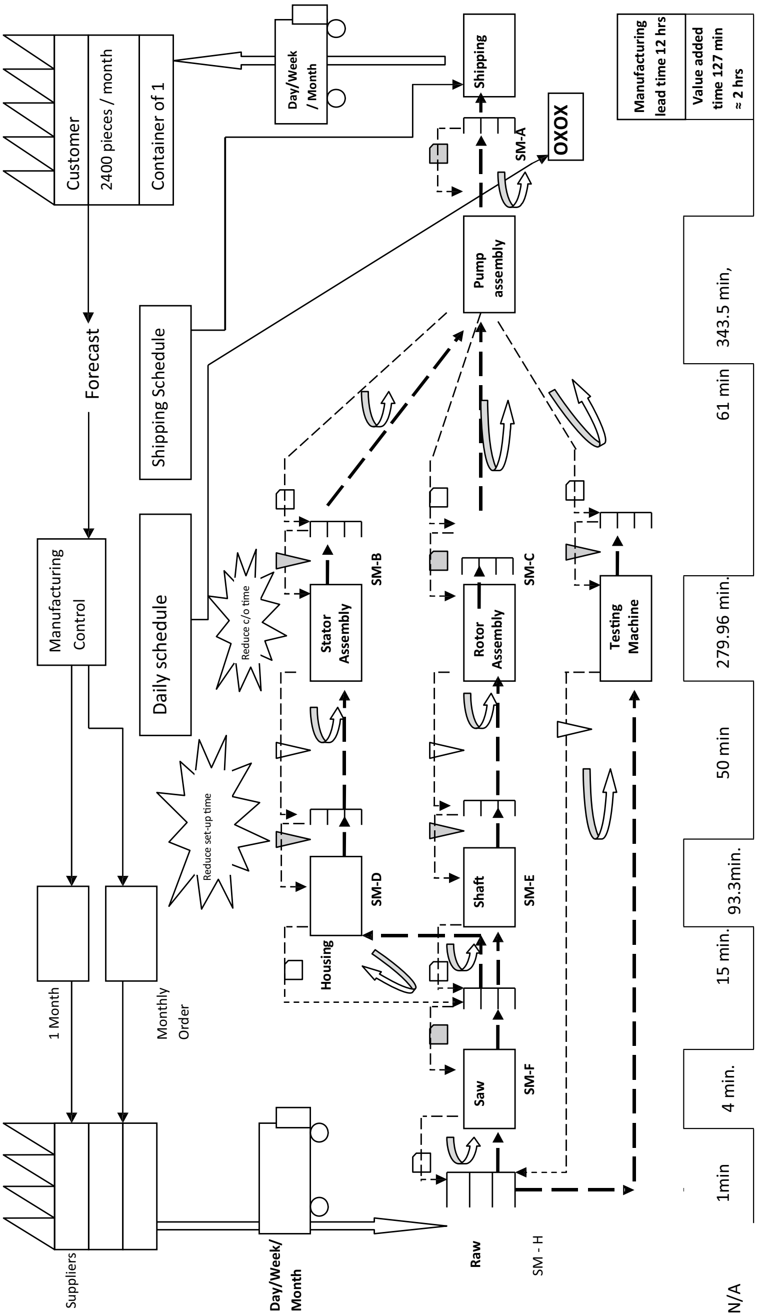


Fig. 3 Future state map

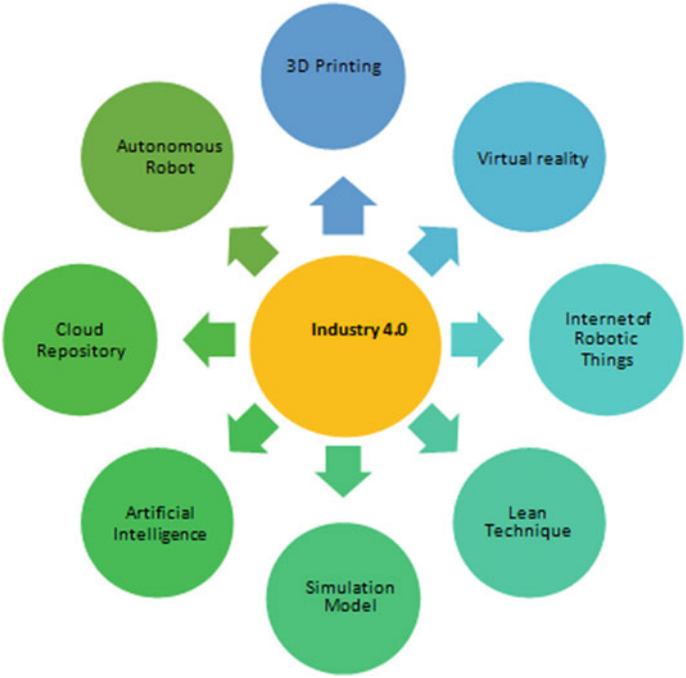


Fig. 4 Process improvement through lean techniques and industry 4.0

6 Lean and Industrial 4.0

The Industry 4.0 paradigm, in a nutshell, links various operational processes of manufacturing systems and supply chains into a seamless digital environment by integrating all current computerization and automation technologies that organizations use.

In other words, the Industry 4.0 paradigm is focused on utilizing cutting-edge technology to create supply chains and integrated manufacturing systems that are highly adaptive [15]. The fourth industrial revolution, often known as "Industry 4.0," is the integration of computerized advances with modified advanced manufacturing systems and creation frameworks, sometimes referred to as "futuristic factories" or "smart factories." There is a lot of room for request-driven store network administrators for process improvement using lean technologies in Industry 4.0 smart manufacturing innovation. As a cutting-edge industrial paradigm, Industry 4.0 is starting to gain popularity.

For manufacturing activities, industrial paradigms like Lean and Industry 4.0 provide a strong basis. Widespread adoption of information and communication technology, which might theoretically improve organizational performance, serves as its cornerstone. While Industry 4.0 relies on current technology to show the challenges that businesses face today, Lean is a technological rival whose guiding principles are grounded in people, processes, and the custom of continuous improvement. In light of this, it could appear at first that the cutting-edge digital and automated technologies of Industry 4.0 and the Lean principles of simplicity and people-centeredness are at odds. The non-technological, lean-centered elements of people and processes will still be essential in modern digital manufacturing systems and supply chains, notwithstanding Industry 4.0's concentration on technology. In the end, despite the high and widespread computerization, digitalization, and automation of manufacturing and supply chain processes, businesses still rely on people to design, program, operate, maintain, and improve the machines and robots that enable digitalization and automation. [16, 17].

In order to improve their entire operations, businesses have mostly adopted a lean manufacturing mindset over the past thirty years. The primary flaw with traditional lean methodologies was the requirement to modify the calculation for each small change in the data.

A progression of advanced innovations, including computerized reasoning, distributed computing, huge information investigation, profound learning, and simulation modeling, can tackle the significant process improvement issues. Subsequently, Industry 4.0 can be interlinked with the modern approaches of lean and utilize its high-level computation data, which is altered subsequently through the cloud [18]. Figure 4 shows some major digital innovations and devices that have gigantic possibilities for process improvement in pump manufacturing through lean.

This chapter presents a point-by-point analysis of the application of anticipated technological advancements for process optimization using lean methodologies and Industry 4.0. The continuous improvement program for a manufacturing line could purposefully alter a variable, test it in real time, and then evaluate the outcomes.

6.1 Conceptual Unification of Industry 4.0 Tools and Lean Methods

As an outcome of a general suggestion of available literature and practical executions, Table 5 illustrates a matrix to demonstrate which Industry 4.0 tools can be accepted to help investigate lean methods. Based on various research and many commercial applications of lean in SMEs, Industry 4.0 tools are used [19].

7 Results and Discussion

A lean manufacturing system has been used to address the three wastes—inventory, overproduction, and waiting time—that were recognized as critical wastes after discussion with company personnel (developed in the future state map). The eight supermarkets equipped with a pull manufacturing system have been categorized

Table 5 Combining industry 4.0 tools and lean methods [19]

Industry 4.0 tools	Lean methods			
	VSM	Kanban	JIT	Heijunka
Digital object memory			xxx	
3D printing			xxx	
Virtual representation			xxx	
Intelligent bins		xxx	xxx	
Utility computing	xxx		xxx	
Reactive computing	xxx	xxx	xxx	xxx
Big data analytics	xxx	xxx	xxx	xxx
Machine learning	xxx			
Digital twin/simulation	xxx	xxx	xxx	xxx

as one of several stages. Each supermarket's lot size and kanban count have been determined. Four supermarkets (housing, shaft, stator, and end bell), located after the processing stage and requiring greater setup times and inventory levels, are replenished using triangular kanbans. By employing a pull system, it is predicted that waste resulting from over manufacturing will be eliminated and the in-process inventory will be drastically reduced.

The inventory lead time decreases from 8 days, 2.8 h, to 12.0135 h. The future state map is used to calculate a 90% reduction in in-process inventory and the Pump manufacturing company's ability to adapt to change (from a semi-automated varnishing unit to an automated unit) in order to have a flexible manufacturing system.

Industry 4.0 innovations increase lean continuous improvement and utilize cloud storage to save data for further processing or smoothing of processes.

8 Conclusion

The major goal of this paper is to propose solutions to reduce wastes that are present in the manufacturing sector and lead to operational inefficiency, which raises manufacturing costs and lead times for manufacturing. The wastes were discovered to exist in layers within the industries. A new layer will appear after removing an earlier one. As a result, eliminating or minimizing waste present in the form of layers in industries necessitates continuous improvement of manufacturing processes; thus, this chapter looks at the lean manufacturing system's internal logistics and value stream mapping to see how digitalization might improve such processes. In this regard, the main challenges in internal logistics and value stream mapping are first acknowledged, and then prospective improvement possibilities are sought to increase the productivity of the production system by incorporating digitalization. Manufacturers can now test their theories first in the virtual environment before putting them into practice or putting them to the test in the actual world, thanks to technologies like robust simulation models, VSM software, and digital twins that virtually represent the manufacturing process with simulation tools. Because of the unknown complexity of the data, the lean and industry 4.0 approaches would be used not only for process improvement but also for analysis of the supply chain from vendors to manufacturers' ends. We also need to investigate several design options for modeling the VSM difficulties.

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SME 4.0: Health Monitoring of Maintenance Management Approaches in Smart Manufacturing

K. P. Paranitharan, K. Velmurugan, V. Balaji, P. Venkumar, and R. Kumarasamy

Abstract Now a days Small and Medium sized Enterprises (SMEs) are also interested in lean with smart manufacturing due to the increasing demand of the product and customer satisfaction in the developing country. In that situation, most of the SMEs addressed in the developing countries are facing lots of hurdles and challenges for converting their traditional manufacturing environment into a smart environment. The most important reason behind that digital transformation is the impact and the application of the recent technologies of the Industry 4.0 with the smart and autonomous systems in the SMEs. Maintenance is the most important activity of all the large and small-scale manufacturing industry in and around the world. The unexpected machine fault, causing machine down time and delay of maintenance actions leads to major losses in the industry. This study is to investigate the optimal decision support with smart maintenance management systems for SMEs. This study identified the most critical systems and their subsystems based on their performance. The most critical systems and their subsystems were monitored and implemented the IIoT based continuous real-time health monitoring approaches. Using artificial intelligence techniques and machine learning algorithms, the proposed methods have helped to predict the Remaining Useful Life (RUL) of those critical systems and their subsystems in the SMEs. The result of this study, maintenance personnel are scheduled and assigned to service actions at the right time automatically. Based on the optimal availability and RUL, it also identifies real-time health degradation and potential disturbances of critical subsystems.

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Keywords SME · Artificial intelligence · Smart preventive maintenance · Remaining useful life · Optimal decision-making system · Planning and scheduling

1 Introduction

The industrial revolution and the data mining method in maintenance will improve better decision-making activity of the Predictive system. In the manufacturing organization, several techniques such as 'Artificial Neural Networks (ANN), Genetic Algorithms (GA), Fuzzy Logic Systems (FLS)', and Case-Based Reasoning are applied to develop the most effective predictive maintenance system. Smart maintenance management systems are applying the IIoT and integrating two communication technologies, like Cloud Computing and Fog Computing, to produce a new framework for smart maintenance management systems to reduce the privacy and security challenges in the manufacturing industry [1]. The predictive maintenance management in Industry 4.0 application of the Cloud Computing techniques utilized for continuous monitoring of machines to identify the maintenance issues. Based on that, they developed autonomous decision-making to rectify the maintenance issues in Industry 4.0 [2]. Using unsupervised learning algorithms like Self-Organizing Mapping, Machine Learning, and Gaussian Mixture Model, autonomous maintenance management systems with various architecture levels of the Cyber-Physical Production System have been able to predict future failures of machine components. In this way, the autonomous maintenance system can make better decisions. The application of new technologies like Big Data Analysis, IoT, and CC in the maintenance management system. The Predictive Maintenance model with the application of the Cyber-Physical Production System in the manufacturing industry developed the new design of the Knowledge-Based Maintenance function. The application of CPPS, IIoT, and Big Data Analysis developed new architecture [3]. Rødseth et al. [4] discussed the Deep Digital Maintenance system in the manufacturing organization to predict the life cycle of products and losses by the Profit Loss Indicator of the Deep Digital Maintenance Management in Industry 4.0.

In general, health monitoring techniques are applied across all fields of research. But in this research, the study focus was mainly on monitoring the health of critical system (machine) and their subcomponents. This study identified the novel approach in most critical machines and their subcomponents through the availability of the machines. Next, we predicted the optimal maintenance parameters to ensure the maximum availability of the machines (St and their critical components. Then optimal maintenance parameters were fed into the sensors for the continuous monitoring of the machine's health and behavior changes. Finally, these activities were controlled and accessed through the internet and web-based devices. In order to provide SMEs with the best solution for preventive maintenance actions, we can develop smart health monitoring strategies with intelligent working environments. As part of this research study, the following research question will be addressed in order to fill the gap between current research studies, such as: RQ 1: How to classify the machine as most critical? RQ 2: How to predict optimal maintenance parameters? and RQ 3: How to develop a smart working environment?

This study aims to implement the recent technology of Industrial Revolution for Small and Medium-sized Enterprises in Tamil Nadu, India. It is presented along with the strategy for implementation of a smart manufacturing system with optimal decision-making methods. This real-time study has the following main objectives. They are (1) Analyze the real-time problems of the SMEs for design and develop the architecture for the smart maintenance management system with the addition of the smart Prognostic Health Monitoring system in the manufacturing industry. (2) Finally, Implement the smart or autonomous real-time prognostic machine health management system for the optimal decision-making process of the maintenance system in the industry. This section was a general introduction to the chapter. It consisted of the following subsections, second section explained the detailed overview of the present trends in the smart industry, third section illustrated the methodology of the smart factory system of the SMEs, fourth section dealt with the discussion of the implementation of the smart health monitoring and maintenance management system of the SMEs, Finally, the fifth section described the conclusion and future scope of the present research in the smart maintenance management system in the SMEs.

2 Literature Review

This section has described the systematic literature reviews of the closely related and recently published research articles in the field of smart maintenance system, lean management, predictive maintenance management, and smart manufacturing, etc. The application, challenges, and advantages of the smart technologies are also explained in the theoretical background of this research study. Birgelen et al. [5] examined ways of manufacturing industries used Self-Organizing Mapping, Cyber-Physical Production Systems, and other analysis tools to identify anomalous conditions and locations of machine components are continually monitored, and original data is analyzed to forecast anomalous conditions and component locations, resulting in an autonomous maintenance management.

Masoni et al. [6] explored how augmented reality technology can be used to remotely monitor maintenance management in Industry 4.0 to communicate easily with skilled trainers and unskilled labor through this technology in an industry environment. With this technology, unskilled workers can organize remote maintenance through 3D image representations, videos, and text chats, as well as create effective maintenance plans using Prognostic Health Monitoring System to determine the remaining useful life of the machining tool.

Similarly, [7] developed and compare the maintenance policy of the electric motor with vibration analysis of the components in the industry through the request of the various gateway systems of IIoT, Machine Learning, and LABVIEW software in the industry. Bousdekis and Mentzas [8] applied the Markov model to identify the optimal plan and logistic functions of the manufacturing industry and developed the architecture of Smart Maintenance and Logistic Functions with the help of the IIoT in Drilling Machine Operation. A study by Kuo et al. [9] conducted an analysis of the spring manufacturer to create smart manufacturing that is capable of predicting the next production status of the machines. Artificial neural networks, IoT, and ICT were utilized to accomplish this system. Kosicka et al. [10] analyzed the new intelligent techniques for predicting the future availability of the machine components and the failure of the systems with the application of the IIoT to produce the future forecasting and failure detection purposes of the machinery park in the production industry.

For the purpose of developing a new architecture of proactive maintenance management systems in the manufacturing industry. Bousdekis and Mentzas [11] examined the machine components in conjunction with the application of Prognostic Health Monitoring systems and the IIoT for Condition-Based Predictive Maintenance functions. The coal mining industry's safety and predictive maintenance activities have been enhanced through continuous health monitoring of ventilator equipment [12]. Schmidt et al. [13] discussed the data management with ICT of the manufacturing organization for the autonomous maintenance activity in manufacturing industries, which has resulted in predictive maintenance management systems. Myrzabekova et al. [14] analyzed and continuously monitored for the failure and repair rate of machine components in mining vehicles by the application of RFID and Bluetooth data-driven methods to increase machine availability in mining operations.

In another research, [15] analyzed the grinding machine operation with the application of Big Data analysis to obtain the predictive maintenance activity of the grinding machine operation using IoT with 5G Technologies. The application of the Root Cause Analysis and Decision Tree Algorithm in the manufacturing industry identifies the best decision-making activities of predictive maintenance systems. Rivera et al. [16] discussed the predictive maintenance system of injection molding machine to collect and analyze the data using Tele maintenance hydraulic pumping system of an injection molding machine by Big Data Analysis and Artificial Intelligence. Spendla et al. [17] examined the machine function that collects the necessary data for the predictive maintenance model using Hadoop cluster technology and Data Mining methodology to create Industry 4.0 maintenance system. Sakib and Wuest [18] illustrate the Preventive Maintenance techniques and the future scope in the manufacturing industry by reviewing the literature and understanding present problem-solving techniques of optimal maintenance action in the manufacturing organization. The benefits and challenges of the predictive manufacturing system using intelligent techniques, big data analytics, and cloud computing technologies in Industry 4.0 are detailed by Nikolic et al. [19] and Zhang et al. [20]. Their study also examines the challenges, factors, and applications of the model framework, architecture, and technology of the CPPS, by the Internet of Things.

The barriers of implementing smart manufacturing in Industry 4.0 are examined through the application of the Multi-Criteria Decision-Making approach such as DEMETAL analysis [21]. The barriers were analyzed and predicted, as the challenges and difficulties in the implementation of Industry 4.0 manufacturing working environment. The adoption of the new technology in the industry was illustrated by Abhilash et al. [22]. A review of Machine Learning applications in the smart industry can be found by Carvalho et al. [23]. For the prediction and continuous monitoring of the behavioral changes of machines or components, the maximum use of machine learning was made. The most significant application of machine learning in the manufacturing industries is predictive maintenance and smart working environments. Based on this critical overview of the utilization of ML techniques in the various fields of industrial applications helps the industrial and academic researchers to initiate better smart maintenance and manufacturing working environment through the application of machine learning techniques. This literature will explain the challenges, risks, applications, and the requirements of the implementation of these machine learning techniques based on smart manufacturing for better decision making of the future developments in the industries.

The use of newly created technologies by local and regional SMEs in Germany the fourth revolution of industry learning techniques was described by Faller and Feldmülleret al. [24]. To optimize their own energy utilization of the manufacturing process and maintenance costs by applying new technologies like Health Monitoring Systems, Key Performance Index, Cyber Physical System (CPS), and ERP systems. Additionally, they developed techniques related to Industry 4.0. They described how CPS and IoT will be used to create a virtual quality control system in the upcoming industrial revolution. Jasiulewicz-Kaczmarek et al. [25] described the further evolution of the plant in micro ergonomics.

In solar cell factories, the team has developed a new maintenance policy based on the analysis of health index hierarchies, CC, IoT, and CPS, in order to understand the current maintenance system and prepare for the next revolution. According to Zhang et al. [20], Industry 4.0 implementation presents a number of difficulties, including the use of the model framework, the CPS architecture, and the use of the Internet of Things. The authors evaluated the challenges, contributing factors, and applications for implementing Industry 4.0.

On the basis of the literature analysis above, we discuss the challenges, applications, and levels of various smart maintenance implementation strategies for the manufacturing industry. Through this review technique, the research gap in the application of the various industry 4.0 key terms and technologies employed for the smart maintenance management system in the different plants (Aero, Ship construction, mining, wind forming, etc.) of the manufacturing industry around the world. In addition, smart manufacturing and maintenance management systems are developed using the latest software and technologies. It was never attempted in previous research articles that the intelligent, autonomous, and optimal decision-making process in manufacturing and maintenance systems would be integrated into our integrated approach (incorporating mathematical analysis and optimization techniques with industry 4.0 technologies). In this research, the proposed novel integrated approach used for the smart optimal preventive decision-making process in the manufacturing industry is detailed in the following sections.

3 Methodology for Smart Factory System (SFS)

This research study gives you a clear overview on implementing IIoT based SFS in SMEs, particularly focusing on the smart maintenance management systems. To this end, we intend to select the two different SMEs in our area, namely automobile sheet metal forming industry, Secondly with Sensor and switch manufacturing industry. Finally, it will transform into IIoT based maintenance management system with SFS architecture. Figure 1 shows the smart maintenance management system implementation approach.

The above diagram specifically describes the smart maintenance and smart production system, and a detailed process description is also given in Smart Ecosystem. Every industrial enterprise has its own best or necessary manufacturing processes and applications of machinery. The following section explains how to implement an IIoT based smart production system (smart manufacturing, smart handling, smart quality analysis, and smart maintenance).

3.1 Smart Maintenance Management System

Through these proposed digital ecosystem frameworks, the traditional maintenance management activities are transformed into autonomous and smart with the help of the utilization of Industry 4.0 technologies. The optimal Remaining Useful Life (RUL) of the manufacturing machine has been measured exactly through this digital ecosystem of smart maintenance system in the SMEs [26]. The reduction of the RUL

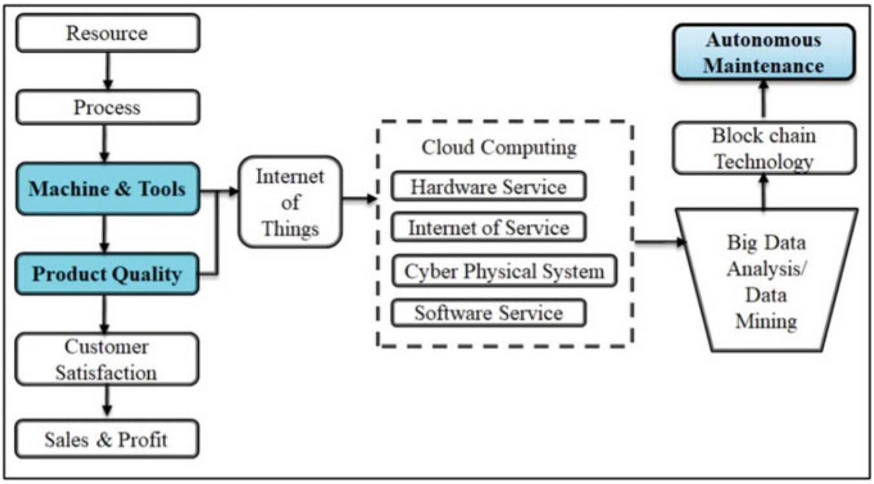

Fig. 1 Approach to the smart maintenance management system

of the manufacturing machines has been monitored continuously by the implementation of the IIoT based prognostic health monitoring system. The actual measured data were collected and stored in the device for further analysis. Further, these data have been analyzed with suitable mathematical modeling and recent analytical approach for finding the optimal results of better decision making in the SMEs. Through the application of the ML algorithm, better decision making has been achieved. The logistic regression analysis was applied for the classification of the machines based on their availability and performance of the maintenance characteristic like failure rate and repair rate. In order to identify whether a machine is in good or bad condition, the following equations are applied based on its performance and optimal availability predictions. In order to make optimal maintenance management decisions, this information is necessary. In these techniques, the machines are classified into two types, good or bad by the indication of the binary code 0 and 1. If the corresponding machine maintenance parameters are bounded within the acceptable range it will indicate as binary value 0, otherwise if maintenance parameters are violated the optimal constraints will indicate as 1.

$$P(V = 0) = 1 - P(V = 1) \tag{1}$$

$$\mathrm{V} = f(B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n) \tag{2}$$

$$\mathrm{Z} = B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n \tag{3}$$

$$e^z = e^{(B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n)} \tag{4}$$

$$\text{Prediction} = \frac{1}{1 + e^{(B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n)}} \tag{5}$$

If Y > Optimal failure rate categorize as 1
Else Y < Optimal failure rate categorize as 0

$$B_i = B + \alpha(Y - Prediction) \times Prediction\,(1 - Prediction \times X_i) \tag{6}$$

where,
i = 1, 2, 3,…… n
α = Constant (0.1 to 0.3)

$$f(z) = \frac{e^z}{1 + e^z} \Rightarrow \frac{e^{(B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n)}}{1 + e^{(B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n)}} \tag{7}$$

$$P = P(V = 1) \Rightarrow \frac{e^{(B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n)}}{1 + e^{(B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3 ......B_nX_n)}} \tag{8}$$

$$\text{Sigmoid} \Rightarrow \ln\left(\frac{P}{\text{1-P}}\right) = B_0X_0 + B_1X_1 + B_2X_2 + B_3X_3......B_nX_n \tag{9}$$

Based on these optimal results, the finding is to improve the RUL of machines in the Gemba. The optimal workforce allocation of the maintenance employee in the manufacturing plant has been achieved by prioritizing the critical machines concerning the availability analysis results.

3.2 4.0 Technologies and Its Application

In smart manufacturing systems, numerous recent analysis methods and Industry 4.0 technologies are widely used for developing smart and autonomous working in the manufacturing industry. In general, most of the recent smart development in the manufacturing industries is achieved by the application of Machine Learning Algorithm, Artificial Intelligence Techniques, Cyber Physical Production Systems, and the Nature inspired optimization techniques. ML algorithm is one of the branches of artificial intelligence techniques. Generally, this machine learning algorithm is used for two different purposes like prediction and classification based on this action it can be classified into more types. Real-time experiments were conducted using a classification type ML algorithm such as logistic regression. This logistic regression analysis technique is one of the supervised learning algorithms. It is the most widely used approach in the real-time problems in the classification type. The outcomes of this analysis reveal the decision by the binary code (0 or 1). That digital binary code will convert into the qualitative research of classification like Yes or No, Accepted or Not Accepted, etc.

In future, this technology will have the greatest impact on the predictive accuracy of the RUL of critical equipment and industrial machinery. This is especially smart maintenance management systems, logistics, and smart manufacturing on the shop floor with the significant application of Industry 4.0 shown in Fig. 2. The real-time industrial research was to investigate predictive maintenance management. Prognostic Health Monitoring is considered to be the most important part of predictive maintenance management systems. By continuously monitoring the critical systems and their subsystems in real-time, maintenance management activities in the manufacturing industry can be optimal and more efficient decision making in the industry [27]. Due to that implementation increased the productivity manufacturing plant and critical machine utilization time. The detailed description of the smart prognostic health management system has been illustrated in the below sections with the implementation architecture of the proposed outcome of this research.

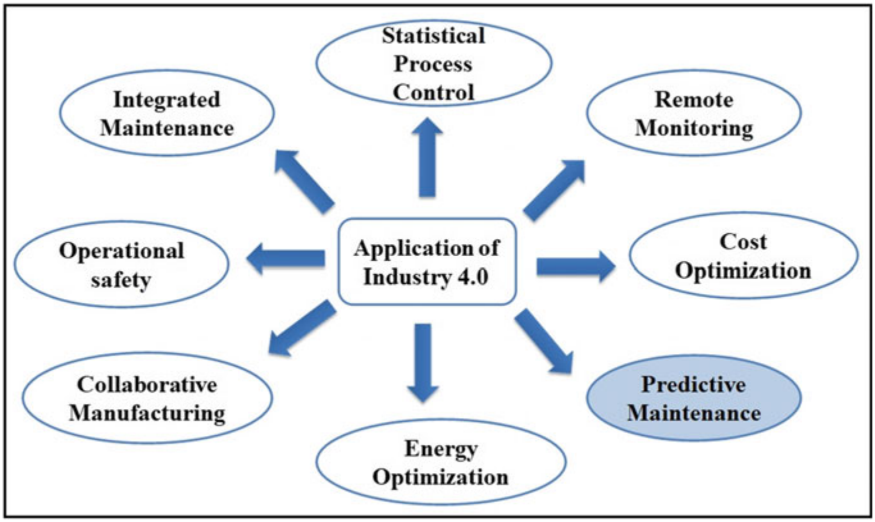

Fig. 2 Applications of industry 4.0 technologies

4 Discussion

Through the proposed outcome of this research study, the various factory systems have been digitalized through the application of Industry 4.0 technologies and lean practices in the industry as shown in Fig. 3. In the smart manufacturing environment these following most significant activities are majorly considered in the industry such as Material handling, Manufacturing, Quality Inspection, and Maintenance management system.

4.1 Smart Material Handling System

Material handling is one of the most important activities in the manufacturing organization. Increasing the productivity and profitability of the organization requires a significant amount of labor. Considering this we first implemented it with the intention of transferring this process smartly. Accordingly, IoT enabled micro-instruments can be fitted to the materials used in production to ensure continuous monitoring of its quantity and function. To deliver the right amount of material at the right time for the machines to the relevant workers about the right information (amount of product stored before it is emptied) to prevent any mechanical shutdown. With this smart process, SME is being upgraded to a smart material handling organization that takes care of machine usage, worker involvement, and unnecessary delays.

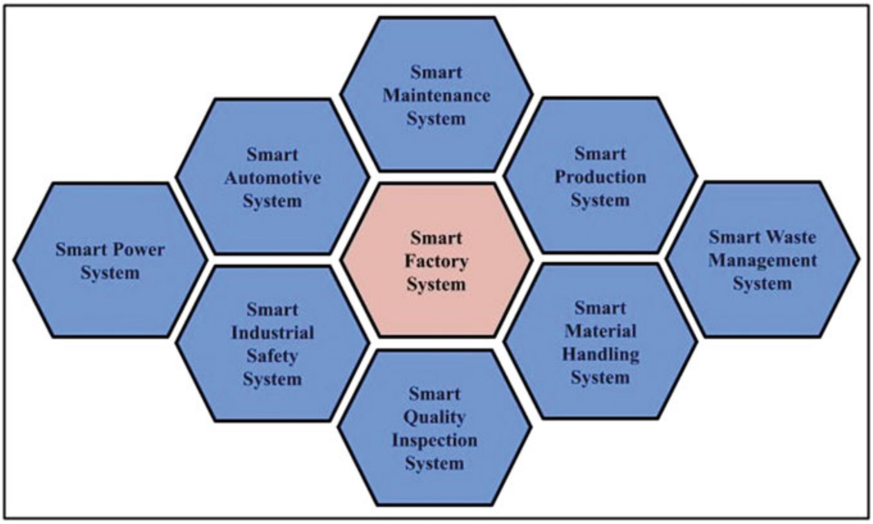

Fig. 3 List of activities in the smart factory system

4.2 Smart Manufacturing System

All manufacturing companies are based on their best practices and different manufacturing processes to produce products. Accordingly, the most widely used process in sheet metal forming and electro mechanical manufacturing industry is stamping process i.e., the monotonous process of converting a given sheet metal into the specific shapes they want so we decided to exchange this important manufacturing process smartly. Through the application of the mathematical analysis integrated with the Non-Traditional Optimization technique, the critical system has been identified to proceed with the smart predictive management system. In this technology, the microscopic device (IIoT) is tailored to the critical systems and their subsystems, such as the hydraulic pressing machine and the manufacturing equipment used in the process. The industry's profitability is determined by identifying the use of the machines, the number of products, and the employee performance, exploring the productivity in the industry, and suggesting optimal decision-making processes to increase it with the help of the proposed architecture of IIoT based prognostic health monitoring systems information shown in Fig. 4. This implementation leads to maximum productivity and minimum down time of the critical machines in the production system. The real-time behavioral changes of the critical systems and their subsystems are continuously monitored and automatically shared the deviations information to the concerned or responsible person for the quick and optimal decision-making process.

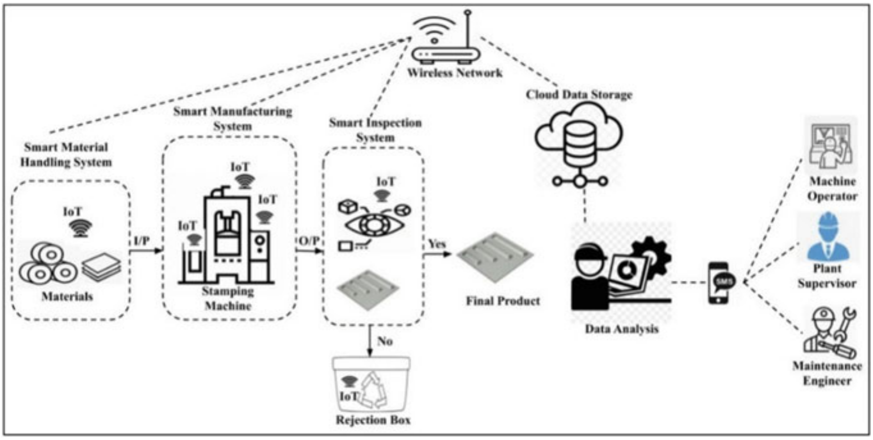

Fig. 4 IIoT based prognostic health management system of SMEs

4.3 *Smart Quality Inspection*

Quality inspection and maintenance are the most important processes in the industry and these two are directly related to each other i.e., the quality of the product can be improved by the maintenance process of the most critical machine for achieving high performance. The computer can use modern technologies (artificial intelligence, image processing, and convolution neural network) to monitor the quality of the product and analyze the current state of the machine with the information obtained from it. As well as recording information about the product if it is rejected during a quality inspection, placing the product in the rejection chute, and suspending the next production of the machine until appropriate action can be taken to control the recurrence of that particular rejection. The production and rejection rate of the day can be easily calculated with the help of a micro sensor fitted in the rejection box. Figure 4 shows the smart production and Prognostic health management system structure of SMEs.

Smart system is a smart technology company that integrates, the fore mentioned smart manufacturing systems with wireless internet connection, analyzes various types of information with it, stores with cloud data, analyzes with the help of a computer, and automatically transfers the best optimal results about it to the concerned persons.

5 Conclusion

This research article has proposed an implementation of the smart factory system with application of the industry 4.0 technologies and lean approach. Systematic literature reviews are conducted to predict the possible link between the lean approaches with industry 4.0 technologies for smart manufacturing and factory systems. Subsequently, an analysis of the optimal and smart predictive maintenance management system has been proposed. The most significant lean approaches are also linked with this proposed smart manufacturing and factory system. In this research study, the predicted Failure rate and Repair rate of critical machines were fed into the sensor monitoring. That will continuously monitor the behavioral changes of the machines. The total number of failures attained in the given time periods and the total utilization time of the machine have been monitored through the IR sensors implementations. That measured data was preprocessed and measured the actual failure rate of the machine as on time and date. The measured data were sent to the analysis section for the comparative analysis with the fixed or optimal range of the failure rates. Through this, comparative analysis of the standard and present measured data is used to predict the remaining useful life of the machine for smart preventive maintenance scheduling. The optimal maintenance parameters have been monitored through the application of Machine Learning algorithm and IIoT sensors based prognostic health monitoring system. Through the architecture, the smart and optimal maintenance management system has been motivated to implement in the smart industry. This primary implementation leads to the smart manufacturing operation in future investigations.

In future, these real-time industrial case studies explore industrial activities like material handling, manufacturing, quality, and inspection and are investigated and further implemented in the industry to achieve a smart working environment of the industry through the application of Industry 4.0 technologies.

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Enablers and Benefits of Supply Chain Digitalization: An Empirical Study of Thai MSMEs

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Abstract Supply chain digitalization is increasingly critical to the competitiveness of micro, small, and medium enterprises (MSMEs). However, knowledge about it, including the technologies, enablers, and benefits from the perspective of these enterprises is limited, particularly in developing economies. Addressing this knowledge gap is essential, as around 95% of enterprises in these economies are MSMEs. This study aims to bridge this gap using Thailand as a developing economy case study, gathering relevant information through a survey (with 574 responses) and semi-structured interviews. The findings reveal that most Thai MSMEs use basic digital tools, while the adoption of intermediate and advanced technologies is moderate and low respectively. Consumer and competitor pressures primarily drive digitalization efforts, with the government playing a somewhat limited role. These (digitalization) efforts were found to have accelerated during the COVID-19 pandemic, despite budgetary constraints. From a benefits perspective, digitalization was found to improve business processes and enhance sales and customer satisfaction. These findings offer insights for emerging economy practitioners and policymakers to develop suitable policy interventions and support mechanisms for MSME digitalization. This study makes a novel and significant contribution to the literature, as no previous studies have comprehensively investigated digitalization in emerging economies or in Thailand.

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Keywords Digitalization · Industry 4.0 · Micro · Small and medium enterprises (MSMEs) · COVID-19 · Supply chain · Thailand

1 Introduction

The integration of digital technologies into supply chains, known as supply chain digitalization, has become increasingly important in recent times due to the emphasis on Industry 4.0 [9]. This process involves leveraging digital technologies such as the Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IoT), and Blockchain to connect functional areas within a company or between companies, enabling more efficient and effective resource management [17]. For example, enhanced visibility and real-time information access (provided by digital technologies) can foster transparency, optimize logistics processes, and improve inventory and resource management [6, 11]. Moreover, new opportunities for revenue and value creation may emerge through digitally connecting and engaging customers [17]. The COVID-19 pandemic has further accelerated the drive for digital transformation.

While digitalization is important for all businesses, it is particularly critical for MSMEs, which form the economic backbone of most countries (accounting for 95% of firms and 60% of total employment) [33]. Without digitalization, MSMEs may find it challenging to compete with larger enterprises or other businesses that have implemented digital solutions. Digital tools such as e-commerce platforms, enterprise resource planning (ERP), and customer relationship management (CRM) software can enable MSMEs to utilize their networks and employees to overcome size-related constraints [30–32]. Recent studies suggest that these firms still lag in digitalization, raising concerns that this could further widen digital disparities compared to large firms. Consequently, promoting MSME digitalization has become a primary policy focus for many countries [12, 26], especially emerging ones like Thailand, where MSMEs represent 99% of all businesses (OSMEP 2020).

Knowledge on digitalization in MSMEs, however, remains limited and fragmented, particularly from the perspective of developing economies [25]. Prior research in this area has largely focused on developed Western countries [12, 22]. The few studies on MSME digitalization in emerging economies have either been conceptual [3] or, if empirical, have focused on one or a few digital technologies, such as e-commerce (e.g., [23]), digital marketing (e.g., [21]), and digital finance (e.g., Hermawan et al. [19]). Consequently, a comprehensive understanding of the adoption of various digital technologies and the antecedents and consequences of digitalization in these enterprises is lacking [12].

The aforementioned concerns and gaps form the foundation for this study which uses Thailand as the country case setting. Its specific objectives are:

- To map the relevant digital technologies for MSMEs and examine their current adoption status
- To comprehend the various factors enabling MSME digitalization

- To understand the benefits of digitalization for MSMEs
- To evaluate COVID-19's impact on MSME digitalization.

While achieving these objectives, the research questions sought to be answered are:

1. What is the extent of adoption of various digital technologies by MSMEs?
2. What are the enablers fostering the digitalization of MSMEs?
3. What are the benefits of digitalization for MSMEs?
4. What is the impact of COVID-19 on MSME digitalization?

Since there has been no prior empirical research on the various aspects of digitalization in Thai MSMEs, the study's findings are both novel and significant for Thailand as well as other similar emerging economies. Answers to these questions can help develop suitable policy prescriptions and support mechanisms that could accelerate the digitalization of MSMEs in these economies. The remaining paper is structured as follows: In the next section, contemporary literature on digitalization in MSMEs is reviewed, while Sect. 8.3 provides details on the methodology used. The findings related to each research question are discussed in Sect. 8.4, and the final section presents key conclusions, implications, and suggestions for further research.

2 Literature Review

As highlighted in the introduction, the literature on MSME digitalization is limited and fragmented. Additionally, its focus has predominantly been on Western contexts, such as Europe (e.g., [8]) or individual countries within it, such as Germany (e.g., [22], Austria [12], or Italy [11]). These studies are also narrowly focused from the perspectives of technologies, enablers, and benefits. For instance, Gavrila and Ancillo [18] concentrate solely on the enablers of e-receipt applications among Spanish retail SMEs. An extended literature search, inclusive of other emerging economies including Thailand, yielded similar results. MSME digitalization studies were found to have a narrow technological focus, such as e-commerce (e.g., [23]), digital marketing (e.g., [21]), or digital finance (e.g., Hermawan et al. [19]). Others, such as [1], have focused on the enablers of MSME digitalization in Oman, specifically technological, organizational, and environmental, while still others, such as [3], on conceptual ideas based on the literature review. We found few focused efforts to understand the digitalization of Thai MSMEs, and they too had a narrow focus on e-commerce and simplistic digital tools, such as Microsoft Excel [2, 29].

Although there are gaps in the literature as above, our initial goal is to examine and consolidate the dispersed research on MSME digitalization that currently exists. This allows us to build an understanding of the types of digital technologies being adopted, the enablers (motivating factors) that promote digitalization, the benefits gained from digitalization, and the impact of COVID-19 on digitalization in these enterprises.

2.1 Digital Technologies Adopted by MSMEs

While much of the conversation on digitalization focuses on Industry 4.0 technologies, it's important to acknowledge that many MSMEs still lack basic digital infrastructure, such as websites, email, and social media. This basic infrastructure is vital as it lays the foundation for implementing intermediate technologies (e.g., Enterprise Resource Planning, e-commerce, e-payments), followed by advanced Industry 4.0 technologies (e.g., Blockchain, Artificial Intelligence, Internet of Things). For example, having warehouse management software and understanding its application is necessary before setting up and operating an online store [7]. In this paper, we adopt a digitalization classification for MSMEs, comprising Basic, Intermediate, and Advanced levels, as suggested by the Economic Research Institute for ASEAN and East Asia (ERIA) [13]. The sub-technologies within each level, as identified from the literature, are presented in Fig. 1.

According to [16], the digital transformation journey begins with businesses adopting basic digital technologies such as email, office software, cloud storage, and social networks. The Intermediate digitalization technologies that follow include having an in-house e-commerce platform and offering online payments or having a third-party provider for such services [9, 27], additionally, businesses may implement Enterprise Resource Planning (ERP and Customer Relationship Management (CRM systems [1, 3]), as well as supply chain management systems [1], which encompass e-procurement, warehouse management, and transportation management systems [6, 7].

With regards to advanced digitalization technologies adopted by MSMEs, the literature suggests these technologies to be a part of Industry 4.0, including Artificial

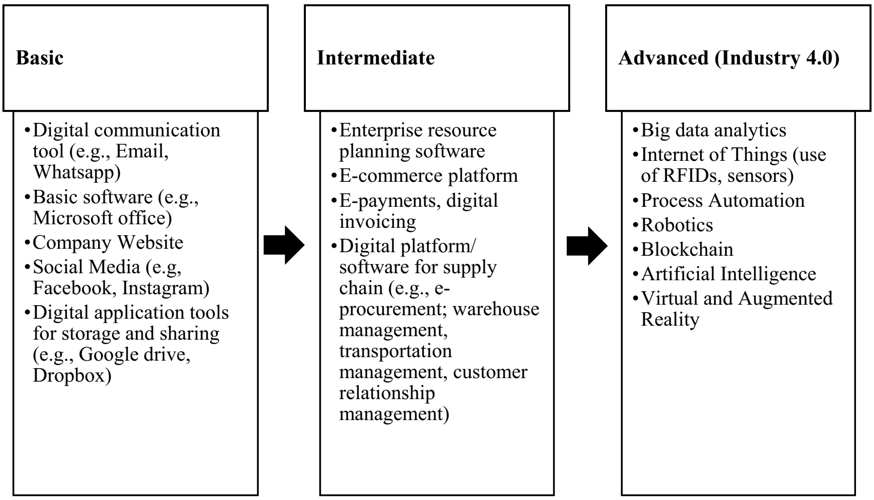

Fig. 1 Different levels of MSME digitalization

Intelligence (AI), Internet of Things (IoT), and Blockchain [6, 27]. Additionally, the automation of business processes and robotics [11, 18], virtual and augmented reality [27], and big data analytics [6, 11, 27] are also considered advanced digitalization technologies. How these technologies benefit supply chains is summarized in Table 1.

Table 1 Industry 4.0 technologies for supply chain digitalization

Industry 4.0 technologies	Description and significance for supply chain	References
Big data analytics	Descriptive, predictive, and prescriptive analytics to improve decision-making for all activities across the supply chain	[27]
Internet of things	An integrated network of physical devices utilizing digital connections to sense, monitor, and interact both internally within an organization and externally with its supply chain. This connectivity fosters adaptability, transparency, tracking, and data sharing, facilitating swift planning, management, and synchronization of supply chain activities	[6]
Process automation	Automation of processes across the supply chain, such as production automation, procurement, and order fulfillment. In the absence of automation, these processes would demand significant time and resources	[3, 11, 18]
Robotics	Incorporating robotics, such as drones, autonomous forklifts, and picking robots, enhances the supply chain by reducing error rates, decreasing the need for frequent inventory checks, streamlining picking, sorting, and storage durations, and enabling access to hard-to-reach or dangerous areas	[10]
Blockchain	Facilitates immutability, transparency, and security in supply chain transactions and ensures traceability along the entire supply chain. It also facilitates self-executing smart contracts across the supply chain and eliminates the need for a trusted third-party	[3, 27]
Artificial intelligence	Machine learning (ML) and deep learning (DL) algorithms can discern patterns from vast quantities of data, which can be utilized for predicting demand, setting prices, selecting suppliers, and forecasting consumption	[6]
Virtual reality (VR) and Augmented reality (AR)	VR and AR technologies, such as smart glasses, facilitate faster and more accurate order picking, allow customers to interact virtually with products, and support employee training	[15, 27]

2.2 Enablers of MSME Digitalization

Enablers drive MSMEs towards digitalization, and they are mostly the different pressures/expectations from external and internal stakeholders [11]. The external stakeholder pressure can be understood through the lens of institutional theory, which examines how these pressures, which can be coercive, normative, or mimetic in nature, affect organizational actions [28]. The significance of these enablers/drivers for MSME digitalization has been explored in previous studies (e.g., [3, 14]).

Coercive pressures are formal or informal forces on organizations to adopt specific practices. In the case of MSMEs, the push for digitalization could originate from various sources. One potential source is regulatory pressure from the government to adopt digital technologies [3]. Another could be customer pressure as customer orientation toward digital technologies has been found to encourage MSMEs to implement them [14]. Similarly, third-party logistics and e-commerce providers, who offer affordable and customized digital solutions without requiring upfront software and hardware investment, can motivate traditional MSMEs to digitalize [18]. Lastly, MSMEs possess lower bargaining power than their larger customer or supplier firms, so coercive pressure to digitalize may also come from these entities [7, 14].

Normative pressures are the forces that compel social actors to undertake certain actions to maintain their legitimacy within a specific community, even if those actions do not align with their interests [14, 28]. In the current context, MSMEs' participation in digitalization training provided by governments could represent one such pressure, leading to the subsequent adoption of related technologies. For instance, [3] highlighted the role of governments in increasing digital technology awareness levels and providing associated technical support/assistance for MSMEs. MSMEs have also been found to digitalize following related public awareness campaigns by non-government organizations.

Mimetic pressures are voluntary forces involving the imitation of successful organizations or competitors' actions to replicate their successful paths [28]. Mimetic pressures, identified as drivers of MSME digitalization [14], tend to be stronger for organizations with similar objectives, producing similar products, targeting the same customers, and facing the same business challenges as their successful digitalized competitors [14]. [7] reported pressure from competitors as one of the key drivers of MSME digitalization in the retail sector.

Additionally, internal staff recommendations (internal drivers) have been found to drive MSME digitalization. Previous research has also demonstrated that employees' knowledge and abilities, encompassing critical thinking and problem-solving capabilities, are essential for the digitalization efforts of MSMEs [12].

2.3 Benefits of MSME Digitalization

Studies have demonstrated that digitalization and associated technology adoption enhance MSMEs' competitiveness [32]. One of the key benefits is the improvement in business processes, digitalization streamlines coordination between processes, optimizing their performance [12]. For instance, digital accounting and automated invoices have improved the speed of reporting by removing the time-consuming process of gathering and transferring paper-based data, and also made it more cost-efficient [27]. Likewise, social media presence and e-commerce platforms enable easy access to new global markets, and MSMEs can leverage them to provide products and services to a global customer base without the need for a physical presence in those locations [12, 27]. Blockchain-enabled smart contracts, which are self-executing, remove the need for intermediaries and thereby save related transaction costs (intermediary fees constitute a significant proportion of MSMEs' costs) [5]. Real-time data analytics enhance production speed, responsiveness, and adaptability, enabling swift responses to malfunctions and minimizing failures [27].

Digitalization also boosts customer satisfaction. For example, digital solutions enhance MSMEs' capacity to offer customized products and services and increase product delivery speed, dependability, and timeliness, ultimately leading to higher customer satisfaction [27]. Additionally, the use of digital technologies, including basic ones such as social media and websites, improves the brand image, awareness, reputation, and recognition, increasing sales and market share [27]. A testimony to this is that consumers place greater trust in online reviews on social media than other channels. On the supply chain front, digital technologies (IoT, Blockchain, etc.) enable real-time information sharing and visibility that help reduce operational costs, improve resource efficiency, and make the supply chain more agile [6]. Similarly, AI-enabled forecasting techniques facilitate efficient inventory planning and management. [11] emphasized the numerous advantages of digitalization for MSMEs, including increased productivity, enhanced product quality and process efficiency, improved decision-making processes, increased flexibility, reduced time-to-market, and business model innovation. Finally, the use of robotics and automation of business processes has been found to positively impact product quality and reduce customer complaints [6, 27].

2.4 COVID-19 Impact on MSME Digitalization

The evidence from the literature on this topic is limited. However, the available information suggests that COVID-19 acted as a catalyst for the digital transformation of MSMEs. This is because COVID-19 restrictions had a much more detrimental impact on MSMEs than on large firms, making digitalization critical for survival [3]. The need for the urgent strategic digital transformation of MSMEs during COVID-19 has been highlighted by some researchers, such as [11]. In fact, many MSMEs were able to do this and adopt digital technologies quickly despite their limited resources. This could be because MSMEs are typically agile and dynamic with a less bureaucratic mode of operation [3, 4]. It could also be argued that COVID-19 may have hampered the ongoing digitalization efforts of MSMEs due to the challenges and uncertainties it caused. However, given the limited number of studies, it cannot be conclusively established as to how and to what extent COVID-19 impacted MSME digitalization.

3 Methodology

A sequential mixed-method explanatory research design involving quantitative (survey) followed by qualitative (interviews) was adopted, with Thailand chosen as the case country. Thailand was considered because of its digital advancement as also the fact that digital economy has been identified as one of the key drivers of economic growth there. According to the European Center for Digital Competitiveness 2020 report, it is the second most digitally competitive country in East Asia and the Pacific region, based on its progress in developing the ecosystem and shifting the mindset towards digitization. Thailand also has a 4.0 strategy to transform itself into an innovation and knowledge-based digital hub in Southeast Asia. Another unique aspect in Thailand's case is the large proportion of MSMEs it has (more than 99%); they have to be taken on board with regard to any large-scale digitalization efforts. Finally, COVID-19 has had an adverse impact on Thailand's economy, and digital technology has been identified as key to bringing about the required recovery [31]. Therefore, Thailand provides an interesting setting for this investigation.

Regarding research methods, the literature review informed the development of the survey instrument. A 5-point Likert scale (High Extent (5) to Low Extent (1)) was used to assess the extent of adoption of various digital technologies. Similarly, a 5-point scale (Strongly Agree (5) to Strongly Disagree (1)) was used to assess the impact of COVID-19 on MSME digitalization. For enablers, and benefits, respondents were asked to choose relevant/applicable enablers and benefits from a list of options identified from the literature; they could then be ranked based on the proportion of respondents' choices. Additionally, several open-ended questions relating to each research question were included to obtain detailed qualitative insights. Qualtrics, a leading online survey research platform, was used to develop and administer the survey. A probability sampling technique was adopted in this study. The links were shared with MSMEs via email. After removing incomplete responses, a total of 585 usable responses were obtained (Table 2), of which 11 responses were excluded (where the number of employees was above 500) leaving 574 responses for the detailed analysis. Most respondents who participated in the survey were business owners, CEOs, COOs, Managing Directors, and those at senior manager levels with several years of experience. Demographic details of survey participants and their firms are provided in Table 2.

Table 2 Classification of survey respondents

	Responses	Percentage (%)
Firm size (number of employees)		
0–9	293	50.10
10–50	223	38.20
51–100	30	5.10
100–250	21	3.60
251–500	7	1.20
500+	11	1.80
Total	**585**	**100**
Firm age (in years)		
0–2	53	9.11
3–5	103	17.55
6–10	124	21.19
10–15	98	16.72
16–25	124	21.19
25+	83	14.24
Total	**585**	**100**
Work experience of respondents (in years)		
0–5	68	11.6
6–10	103	17.6
11–15	110	18.8
16–25	158	27.0
25+	146	25.0
Total	**585**	**100**

In the next phase, interviews with key stakeholders associated with MSME digitalization in Thailand (refer to Table 3) were conducted. The objective was to enrich the survey findings and develop deeper insights into the research themes. Purposive sampling was used to select the interviewees. This was because of the need to obtain high-quality, in-depth information from experienced suitably designated professionals who also represented a cross- sections of the stakeholders (i.e., government and digital service providers). A semi-structured interview protocol comprising enablers, benefits, and COVID-19's impact on MSME digitalization was used for this purpose. The participants were purposively selected since they had knowledge of MSME digitalization at the country level. The questions were shared with participants in advance to enable them to come prepared. The interviews were conducted virtually (due to COVID-19 restrictions) using the Zoom platform and lasted 60 to 90 min. All the interviews were digitally recorded and transcribed before analysis.

Table 3 Details of interview participants

Organization	Designation
Digital Economy Promotion Agency (DEPA)	Vice President, Northern Region
The Office of Small and Medium Enterprise Promotion (OSMEP)	Director, SME Knowledge and Service System Department
Digital Technology Platform Provider	Head, Public Affairs
Digital Technology Platform Provider	CEO

4 Findings and Discussions

The findings from the survey and interviews were combined to comprehensively understand the different facets of MSME digitalization. The organization and discussion of these findings are structured according to the research questions and presented in the following sections.

4.1 Digital Technology Adoption—Current Status

Figure 2 summarizes the current state of digital technology adoption across the three levels (basic, intermediate, and advanced) among MSMEs on a scale of 1 (low extent) to 5 (high extent).

Not surprisingly, the level of adoption for basic technologies is relatively high at $\bar{x} = 3.66$ (Standard deviation or SD = 1.16). However, for intermediate technologies, the adoption level is lower at $\bar{x} = 3.15$, SD = 1.13. The adoption is even lower for advanced technologies at $\bar{x} = 2.77$, SD = 1.21. The relatively high standard deviation (SD > 1) indicates that there is a significant high variation among MSMEs with regard to digital technology adoption. The extent of implementation (scale of 1–5) of individual digital technologies across the three levels is given in Table 4.

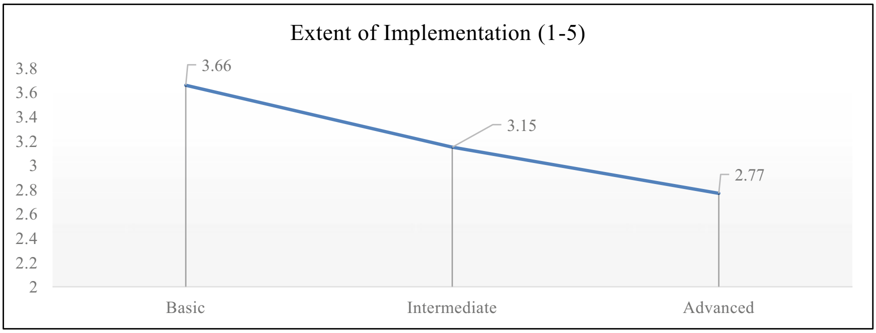

Fig. 2 Digital technology adoption levels in MSMEs

Table 4 The extent of implementation of digital technologies among MSMEs

Digital technologies	Mean ($\bar{x}$) (n = 585)	Standard deviation (SD)
Basic		
Basic software	3.98	1.13
Digital communication tools	3.80	1.13
Social media	3.76	1.12
Company website	3.42	1.21
Digital tools for storage and sharing	3.35	1.21
Intermediate		
E-payments, digital invoicing	3.37	1.27
E-commerce platform	3.10	1.23
Digital platform/software for supply chain	3.10	1.22
Enterprise resource planning software	3.04	1.19
Advanced		
Internet of things	3.20	1.31
Artificial intelligence	2.84	1.20
Process automation/robotics	2.80	1.16
Big data analytics	2.79	1.22
Virtual reality and augmented reality	2.60	1.21
Blockchain	2.38	1.17

As can be seen in the Table, basic software such as Microsoft Office ($\bar{x}$ = 3.98, SD = 1.13) emerged as the most adopted technology, followed closely by digital communication tools such as email and WhatsApp ($\bar{x}$ = 3.80, SD = 1.13), and social media ($\bar{x}$ = 3.76, SD = 1.12). Company websites are relatively lower among basic digital technologies adopted ($\bar{x}$ = 3.42, SD = 1.21), followed by digital tools for storage and sharing, such as Google Drive and OneDrive ($\bar{x}$ = 3.35, SD = 1.21). The results support previous studies that have highlighted the significance of basic office software for employees (e.g., Microsoft Office, Google Drive), instant messaging tools like WhatsApp for direct contact with customers, social media for marketing (e.g., Facebook, Twitter, Instagram, LinkedIn), and websites to provide detailed information on products and services offered by MSMEs [9, 27].

In terms of intermediate technologies, e-payments and digital invoicing emerged as the most adopted ones ($\bar{x}$ = 3.37, SD = 1.27). This appears to be due to the COVID-19 pandemic and the need to reduce the risk of virus spread from physical cash transactions. One of the interviewees from a technology solution provider highlighted that *"MSMEs sales during the COVID-19 lockdown relied on postings on Facebook to enable customers to see the products, and then buying them* via *online* *applications, including online payments to reduce physical contact"*. Similarly, other interviewees emphasized the increasing use of QR code-based payments to make it easier for customers to pay. E-commerce emerged as the next most adopted technology in this category ($\bar{x} = 3.10$, SD = 1.23). According to the interviewees, its adoption is expected to increase further in the coming years. One of the respondents from a government department highlighted that 35% of the total revenues of MSMEs now come through e-commerce platforms. Additionally, digital platforms/software for supply chain management, such as e-procurement, warehouse management, transportation management, and CRM, are seeing increasing uptake among MSMEs ($\bar{x} = 3.10$, SD = 1.22). ERP systems emerged as the least adopted technology in this category with $\bar{x} = 3.04$, SD = 1.19) though they are still in the Intermediate range.

In terms of advanced technologies, with the exception of Internet of Things (IoTs), all other technologies were found to have low levels of adoption with $\bar{x} < 3$. The relatively high level of IoT adoption by MSMEs could be because it improves their supply chain's reliability through real-time data, information sharing, and object visibility [6], also, the fact that it is relatively earlier to implement than other technologies. Blockchain emerged as the least adopted technology in this category. This could be because blockchain requires the participation of various stakeholders in the supply chain, and MSMEs, with their lower bargaining power, struggle to convince others (the larger ones) to participate. Regarding the lower levels of adoption of other technologies such as robotics, virtual and augmented reality, automation, and big data analytics, interviewees attributed it to the high upfront cost of implementation and lack of knowledge and awareness about them. In the words of one of the interviewees, *"Learning how to implement and use these Industry 4.0 technologies is challenging for MSMEs"*. As evident from the literature, one of the main challenges facing MSMEs in the ASEAN region is the shortage of expertise in implementing digital technologies [13]. Without skilled human resources, implementing digitalization becomes a significant challenge, especially when MSMEs aim to move from basic adoption to digital sophistication. It is also not easy for MSMEs to bridge this gap, given that skilled IT professionals are expensive [13]. Addressing these challenges is critical for transitioning MSMEs from basic digital technologies to intermediate and advanced ones.

4.2 Enablers of Digital Technology Adoption

Figure 3 provides a summary of the survey results regarding the enablers of digital technology adoption.

As illustrated in Fig. 3, coercive pressure from consumers emerged as the most significant enabler. Over 51% of the MSMEs highlighted customer suggestions/requirements as critical to adopting digital technologies. The results echo the findings in a recent Mastercard study, which reported that 43% of MSMEs are digitizing their businesses to respond to changing customer needs, such as demand for online services [24]. One example of this is customer preference for contactless payment, which

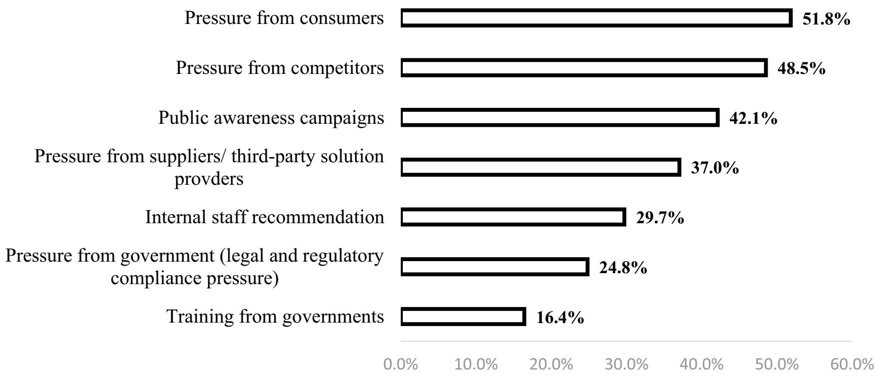

Fig. 3 Enablers of digitalization or digital technology adoption by MSMEs

accelerated the implementation of related solutions, including cashless payments for deliveries. Likewise, customers have already altered their purchasing behaviors in relation to digital sales channels and services [7]. The increasing role of customers in enabling MSME digitalization is echoed in the interviewee responses below:

> Purchasing behavior has changed. Customers are increasingly interested in paying online and prefer to use online applications and Facebook for communicating with firms

> More customers are turning to online payments. MSMEs need to accept this change in consumer behavior to support that requirement

> MSMEs are increasingly interested in using digital systems in their businesses to meet the trends and needs of customers and service users

Mimetic pressure to follow the actions of successful competitors (48.5%) emerged as the second most significant enabler for MSME digitalization. The results echo the findings of previous studies, such as [7], who reported such pressure as one of the key drivers of MSME digitalization in the context of the retail sector. Public awareness campaigns (42.1%) emerged as the third critical enabler of MSME digitalization. According to one of the interviewees from a government agency, the various public awareness campaigns urging firms to offer digital payments and online shopping during COVID-19 could have contributed to this. Previous studies have highlighted the role of the government in raising digital transformation awareness among MSMEs [3].

Pressure from suppliers and third-party digital platform providers emerged as the fourth significant enabler of MSME digitalization (37.1%). According to the interviewees, this is likely due to the increase in the number of IT vendors and digital platforms as well as their greater pressure on MSMEs to adopt digital technologies. One-third of the MSMEs (29.7%) highlighted that their internal staff recommendation was one reason for embracing digitalization. This is similar to the findings in [13], where internal staff recommendations were found to have influenced 35% of the MSMEs in ASEAN countries. However, contrary to the literature, compliance or coercive government pressure (24.8%) did not emerge as the main driver of MSME digitalization. This was not surprising to the interviewees, as per whom the government's role there is more of a facilitator than an enforcer. Although training from the government emerged as the least important enabler of MSME digitalization (16.4%), it is higher than the 10% reported in the study by ERIA on ASEAN countries [13]. This again highlights the emerging role of government as a facilitator in providing technical support/assistance for MSMEs.

4.3 Benefits of MSME Digitalization

Figure 4 summarizes the survey results concerning the benefits of MSME digitalization.

Approximately 85% of the MSMEs highlighted improved business processes as one of the main benefits of digitalization. The results are in accordance with previous studies. For example, [12] emphasize how adopting e-procurement systems improves the speed, efficiency, and transparency of the procurement process. Similarly, [27] describe how digitalization allows convenient access to data from any location in real-time, minimizes redundancies, enhances business flexibility, lowers the likelihood of transcription errors (improving data quality), and promotes more effective sharing of high-quality information. Improving customer satisfaction (68.5%) emerged as the second most cited benefit for MSMEs adopting digital technologies. This is also consistent with the literature discussed previously on how MSME customer satisfaction is improved through the implementation of e-payment systems and other digitalization-based systems that enable tailored or personalized products to be produced and subsequently delivered reliably in a timely manner [27]. An increase in sales due to an expanded customer base emerged as the third most highlighted benefit of MSME digitalization (67.6%). From an operational standpoint,

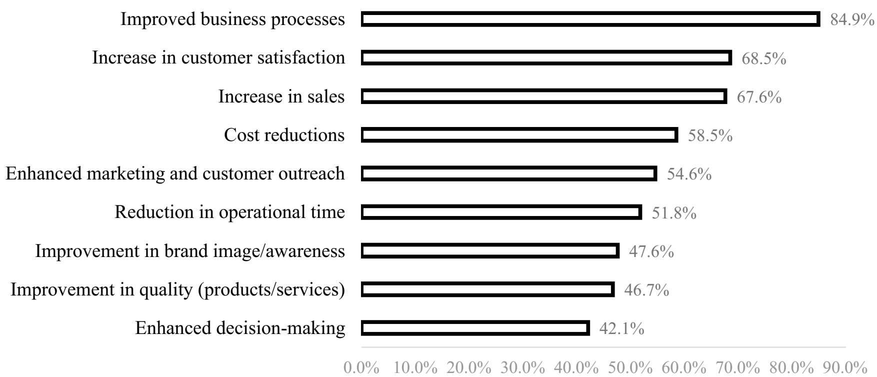

Fig. 4 Benefits of digitalization for MSMEs

cost reduction (58.48%) and reduction in operational time (51.82%) emerged as the fourth and sixth most highlighted benefits of digitalization, respectively. From a marketing and branding perspective, enhanced marketing and customer outreach (54.6%) emerged as the fifth most cited reason for digitalization. It is not surprising that more than half of the MSMEs highlighted this because online marketing can reach a large number of customers with only a fraction of the cost of traditional marketing.

Similarly, e-commerce platforms provide MSMEs with new marketing/distribution channels, including foreign markets, enabling them to reach an expanded customer base and sales area [27]. Improvement in quality (46.67%) and empowering information-based decision-making (42.12%) emerged as the least two important reasons for digitalization. However, they are still relevant, given that more than 40% of respondents in both cases have highlighted them as benefits. Overall, the results are aligned with the literature that suggests that digitalization and technology adoption increase MSMEs' competitiveness [32].

4.4 Impact of COVID-19 on MSME Digitalization

The survey findings on COVID-19's impact on MSME digitalization measured on a 1 to 5 scale (strongly disagree to strongly agree) are presented in Table 5.

The findings are consistent with existing literature which suggests that COVID-19 acted as a catalyst for the digital transformation of MSMEs [3, 11]. Respondents agree that COVID-19 accelerated the adoption of digital technologies ($\bar{x} = 4.05$, SD = 0.97). Notably, MSMEs now consider digital technologies to be a source of competitive advantage ($\bar{x} = 3.90$, SD = 0.98). This clearly demonstrates a shift in mindset towards digitalization. Moreover, COVID-19 prompted MSMEs to refocus their entire business model around digital technologies, such as transitioning from brick-and-mortar retail to e-commerce. Previous studies have also highlighted the emergence of new business models enabled by digital technologies [6]. Finally, it

Table 5 Impact of COVID-19 on MSME digitalization

Statements	Mean ($\bar{x}$) (n = 585)	Standard Deviation (SD)
COVID-19 has accelerated the adoption/use of digital technologies in my organization	4.05	0.97
In response to COVID-19, my organization now see digital technologies as a source of competitive advantage	3.90	0.98
In response to COVID-19, my organization is refocusing the entire business around digital technologies	3.54	1.03
COVID-19 has increased the investment in digital technologies in my organization	3.51	1.08

is encouraging to see that MSMEs have invested their scarce financial resources in digitalization, albeit to a somewhat moderate extent ($\bar{x} = 3.51$, SD $= 1.08$). According to one of the interviewees, the COVID-19 pandemic accelerated the drive towards a cashless economy, and MSMEs also recognized the benefits of such an economy. Another interviewee mentioned that MSMEs had little choice but to digitalize to adapt to the realities of the market and remain competitive. The results also echo the findings of a recent study by Mastercard in which 70% of SMEs globally accelerated their adoption/use of digital technologies during the COVID-19 pandemic to ensure business continuity [24].

5 Conclusion

This study highlights the current state of digitalization in MSMEs with respect to technology adoption, the role of key enablers, the various benefits realized, and the challenges faced during implementation. The study is timely, given that digitalization of MSMEs has become a top policy priority for most countries focused on building digital economies.

The results show MSMEs transitioning from basic digital technology implementation and usage to intermediate and advanced ones in a progressive manner. However, they often lack finances; as per the International Finance Corporation (IFC), 40% of registered MSMEs in emerging markets have an annual unmet financing need of $5.2 trillion [20], which would have worsened during the COVID-19 pandemic due to loss of income from lockdowns and border closures. Therefore, more support, such as access to credit and financial resources, is needed for them to accelerate this transition. However, if they are unable to do so, the digital divide between MSMEs and large firms will grow further. For instance, MSMEs that do not adopt digital technologies may continue to rely on manual processes, leading to higher operational costs, longer processing times, and increased chances of human error. Similarly, MSMEs that fail to digitize their supply chains may struggle with limited visibility, poor communication with partners, and inefficient inventory management. These challenges can lead to increased lead times, stockouts, or overstocking, negatively impacting customer satisfaction and profitability. Without a digital presence, MSMEs may miss out on opportunities to reach new customers and expand into new markets through e-commerce and other online channels.

In the case of Thai MSMEs, it is encouraging to see most MSMEs utilizing basic digitalization tools and an increasing number in the intermediate category, with COVID-19, significantly contributing to this transition. Finally, most MSMEs also face internal skill gaps as current employees may not have the requisite expertise in digital technology tools [24].

The implications of the study are manifold. None of the previous studies have conducted a comprehensive investigation on emerging economies, let alone Thailand, on understanding the enablers and benefits of digitalization among MSMEs. This study, therefore, makes a significant and novel contribution to the supply chain digitalization literature from an MSME perspective. For researchers, the study is expected to provide some degree of consensus regarding the digital technologies relevant to MSMEs, the enablers, and the benefits of digitalization. Future researchers could utilize the survey instrument developed for this study to assess the current status of MSME digitalization in other country contexts.

From a practical perspective, given that over 95% of all firms in most countries and regions are MSMEs, their digitalization is critical for innovation, economic growth, and job creation. It was evident from this study that the failure of MSMEs to adapt to technological changes is likely to deepen digital inequalities vis-à-vis large firms. Although the adoption of advanced digital technologies is relatively low among Thai MSMEs, the adoption of basic digital technologies is relatively high, and moderate levels of adoption are seen for intermediate digital technologies. The findings show that Thai MSMEs have a solid foundation to transition towards more advanced digital technologies. However, even with basic and intermediate levels of digitalization, some of the business benefits for Thai MSMEs, such as improvements in business processes, increase in sales, and customer satisfaction, are clearly evident. This is because customers increasingly expect seamless and personalized experiences. MSMEs that do not adopt digital technologies may struggle to meet these expectations, potentially losing customers to more digitally-savvy competitors.

However, for MSMEs, digitalization benefits such as enhanced decision-making are still relatively low. This is because, without data analytics and real-time information, MSMEs may find it difficult to make informed decisions quickly, impacting their ability to respond to market changes or capitalize on new opportunities. However, it is expected to improve as Thai MSMEs move towards adopting advanced digitalization technologies such as AI and automation. The study results are expected to provide a strong impetus for MSMEs looking to adopt digital technologies.

The study findings will also help practitioners and policymakers enact policy interventions and support mechanisms that could accelerate the digitalization of MSMEs. For instance, the study findings show that government support as an enabler of MSME digitalization is lacking. This is a concern given that the government plays a critical role in promoting the digitalization of MSMEs. For instance, a supportive legal and regulatory environment, such as laws on digital signatures and electronic authentication, is critical for MSMEs. Another trend found in this study is the Business Model Innovation of MSMEs. They have started to develop their entire business around digital technologies as they acknowledge digitalization as a source of competitive advantage. MSMEs that are slow to adopt digital technologies may be more vulnerable to industry disruptions caused by new business models or technological innovations.

It is clear from the study that the COVID-19 pandemic acted as an accelerator of MSME digitalization. However, it is important that this momentum is sustained in the present post-pandemic period. To achieve this, MSMEs need to invest more in advanced digital technologies to scale up their businesses. Additionally, more targeted awareness campaigns for MSMEs on the potential benefits of digitalization are required to increase uptake.

The study has a few limitations. First, it has been conducted only in Thailand, which may limit its generalizability. Second, the list of technologies, enablers, and benefits derived from the literature and subsequently used for the survey may not be exhaustive. Third, micro-enterprises are combined with SMEs based on the assumption that the nature of enablers, benefits, and challenges facing them would be similar to SMEs. This may not be true in practice. Future studies could address these limitations. However, despite these limitations, the study makes valuable contributions, as discussed above. The study framework and findings would encourage more researchers to investigate digitalization in MSMEs.

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A Preliminary Analysis of Blockchain Impact on Sustainable Supply Chains: Covid-19 Perspective

Ozlem Bak and Marina Papalexi

Abstract Transforming a more adaptable and resilient supply chains in the pandemic (Covid-19) environment and understanding how similar future events can be managed has been a great challenge faced by the sustainable supply chain (SSC) processes. With this aim, we have identified studies in sustainable supply chain (SSC) literature to tackle this specific challenge. Hence this research intends to determine and enhance the Blockchain technology research and practise of sustainable supply chain (SSC), making it less vulnerable to environmental risks, such as the pandemic. The preliminary review of the papers has indicated four themes presented across the literature which are as follows: benefits of utilising Blockchain in optimising sustainable supply chains; the role of digitalisation in sustainable supply chains; challenges in supply chains and the impact of Blockchain; and encouraging sustainable supply chains development. Positioned in the literature review we established a framework conceptually to evaluate the context of a hybrid blockchain in the context of SSC arena.

Keywords Blockchain · Sustainable supply chain · Covid-19 · Supply chain performance · Supply chain disruption · Supply chain management · Pandemic

1 Introduction

The COVID-19 impact has been diverse and unprecedented with its considerable impact on associated lockdown policies, limitations and restrictions on how supply chain operations will and can take place [1]. Disruptive environments are not new to the supply chain operations, in the last twenty years several disruptions have been faced and impacted how supply chains operate; ranging from disruptions such as

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the Japan 2011 earthquake, Indonesia, Tsunami in 2004, Fukushima Japan Nuclear Leak etc. However, these all mentioned disruptions were impacting at regional level, meaning they were localised in their impact. In comparison to these disruptions, the disruption caused by Covid-19 was more widespread to operations and impacted at a global level in most supply chains [2]. Such a global impact with a different level of disruptions moving from a regional disruption to global disruption not only impacted standalone industries and regions, but nevertheless, almost all industries causing food and labour shortages [1] and transportation challenges [3] just to mention some of the disruptions experienced. These aforementioned studies enhanced our understanding of the Covid-19 impact on supply chains, although they provided insight into particular supply chain areas or industries, the investigation of wide-ranging impact at a larger scale in the literature was limited. This is also partly due to the fact that the challenges faced were diverse in nature, due to the nature of products and their associated services and operations; distribution of perishable goods lead to obsolescence as well as delay in the lead times which lead to delay and high cost in transportation [4, 5].

Developing a digital future, which has been a priority within the Covid-19 environment, is the implementation of Industry 4.0 (I4.0). To name a few technologies; artificial intelligence (AI), blockchain, Internet of Things (IoT) and cloud computing, became a requirement. Manufacturing and service industries have adopted these technologies to reshape entire businesses, create value, facilitate real-time informed decision-making, save time and money, and ultimately improve lives [6, 7]. Specifically, the literature on supply chain underlines that blockchain technologies are capable to create proficient; adaptable; high quality; reduced cost and sustainable operations that are able to address the aforementioned process relevant challenges [8, 9]. As it can be seen from the above discussions, although the Covid-19 impact on sustainable supply chains in specific areas has been investigated, its wide-ranging impact at a larger scale on sustainable supply chain operations in the literature remains limited.

The development of sustainable supply chains is critical to achieve not only global market competitive advantage but a more resilient one [10]. Integrating innovative technologies, such as Blockchain, with the circular economy is important for developing sustainable supply chains [11]. Therefore, this chapter's aim is to investigate and analyse the implementation of blockchain technologies and their effect as facilitators in the context of sustainable supply chain (SSC) during COVID-19 and how it impacted the supply chain performance overall.

Sustainable supply chain (SSC) practises contribute towards competitive excellence [12]. Hence the global supply chains need systems to safeguard and control the effective and efficient distribution of products, ensuring that any type of waste is not created, therefore ensuring a more sustainable operations per se. Azevedo et al. [13] highlighted the importance of supply chain operations design considering their impact on sustainable development. The benefits of adopting Blockchain technologies within the supply chain included resource optimisation, enhancement of quality, employee work effectiveness, customer loyalty and cost reduction as well as generating sustainable supply chain operations as such [14, 15]. Wang et al. [16] suggested that the logistical innovation and its inherent operational capacity is reversely associated with supply chain risk [17]. However, the challenge that organisations have to consider when deciding to adopt this type of innovation is related to the establishment of a secure and confidential distribution and collection of information is presently generating a sustainable supply chain environment [18].

Blockchain implementation in this respect provides a critical role by producing an effective, speedy and secure answer for the supply chain members [8]; one example can be seen in food companies that adopted Blockchain technology to enhance food traceability [19–21]. After the New Zeeland earthquake in 2017, another example can be seen in the transport system supply chains such as (road, rail and port infrastructure) where a speedy and responsive recovery plan was established via the responsive use of information exchange and Blockchain [22]. In this chapter we will investigate the adoption of Blockchain and its benefits and to what extent these impacted during Covid-19 on sustainable supply chain. There has been considerable research on Covid-19 and its impact such as the closure of borders and trade limitations that has been introduced [17]. As a result, COVID-19 pandemic impacted most of the global supply chains, which has affected the design and evaluation of operations globally and managing extended supply chain networks as such. Therefore, organisations have been working on developing alternative supply chain strategies, which are related to the adoption of innovative solutions such as Blockchain as a potential solution to overcome the disruptions in their operations and the relevant limitations that it can bring.

The challenging situation generated by COVID-19 and its implications are still under investigation and there are some limitations regarding the sustainable supply chain impact of COVID-19 and how companies have responded with supply chain wide operational process and government restrictions considering their daily processes and operations [17]. Querioz et al. [23] and McMaster et al. [24] proposed blockchain as a tool for encouraging sustainability and resiliency of supply chain. Similarly, Magableh [25] notes that "Blockchains could be the solution to satisfy confidentiality and encourages suppliers to share information, contribute to supply chain, and increase visibility, thus leading to a resilient supply chain." Therefore, it is important to underline these specific limitations in the current research and address the need for new research areas related to the implementation of blockchain to mitigate the pandemic and develop supply chains that are sustainable.

The academic and practitioner interest, albeit high on the subject, with Blockchain being seen as one of the potential solution, there is still a need for further investigation to what extent this is impacting the development of sustainable supply chains [26]. Supply chains in their form are wide-ranging in its complex nature, existing structural setting, as well as worldwide span, and extended network, which amplified Covid-19 pandemic impact and provided challenges for supply chains to overcome. Therefore our main research question in this context remains.

'How has Blockchain technology impacted sustainable supply chains within the setting of Covid-19?

This chapter contributes to the analysis of the adoption of Blockchain as a facilitator in the SSC performance within the pandemic context. To achieve this aim, a systematic literature review (SLR) has been devised by adopting the analytical approach of Heinis et al. [27] and Denyer and Tranfield [28], which helped us to review and problematize the literature to set the foundation for theory development [29]. The output of the SLR is the descriptive analysis that provides an overarching understanding of the data; and the thematic analysis that synthesise the corpus of literature selected from the SLR by taking an inductive approach to establish the impact of Blockchain technology upon sustainable supply chains within the Covid-19 (or similarly uncertain) environment. This analysis leads to the identification of the main themes discussed in the current and relevant literature, which helped us to position our study within the field under investigation and develop an emergent model that set the ground for a case study or empirical research in future theoretical developments.

In this chapter the structure has been devised as follows; the following section will outline our methodological approach highlighting the choice of systematic literature review, which will lead to the next section looking into SSC and the adoption of blockchain theories and models based on the selected articles and provide insight into existing sustainable supply chain knowledge. The SLR findings are presented, and the emerged themes are discussed. Lastly, through this research agenda, a call for future research agenda is developed based on the key arenas lacking academic investigation and a conclusion provided for future research areas.

2 Research Design

This work has utilised the systematic literature (SLR) review, which helped the researchers to group, confer and compare the relevant chosen papers and categorise them accordingly. The inclusion of a SLR methods provided "a key tool …to manage the diversity of knowledge for a specific academic inquiry" [30] p. 208. The systematic literature review also provides a wider outlook considering specific research keywords set by the literature and developed by the research team. Our research has been guided by Denyer and Tranfield [28], which provides generic steps for undertaking the systematic literature review.

Based on the stages the following five stages have been utilised to carry out the systematic literature review:

1. Pilot research—this stage involved the establishing current literature and construction of the selection of keyword criteria for systematic literature selection.
2. Identifying the papers—Including a comprehensive, unbiased search, the inclusive search keywords string has been utilised. In this case, the selection of keywords strings utilised included the following keywords: ({Covid-19} OR {pandemic}) AND TITLE-ABS-KEY ({Sustainability} OR {blockchain}) AND TITLE-ABS-KEY ({supply chain management} OR {SCM} OR {logistics})) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE,

"English")) AND (EXCLUDE (PUBYEAR, 2018)) was used on Scopus, which has been considered a reliable database [31, 32].

3. Paper selection– inclusion/exclusion criteria: the search covers the studies published between 2019 to 2021 due to the relevance of Covid-19; only peer-reviewed journal was considered for the review; papers employ Blockchain within Covid-19 context; papers contribute to sustainability; they are written in English. Based on these criteria the papers have been listed and categorised based on the author's journals. Specifically, initially, our research was quite broad, and it identified 123 articles related to the subject area of Blockchain technology, sustainability and Covid-19. After the first relevance screening of titles, 102 potentially relevant articles and then by removing duplications resulted in a total of 92 unique sources. We conducted a final review round, where the titles and/or abstracts and/or a brief review of the full text were evaluated according to selected criteria. As a result, the total number of resources considered for the SLR is 37.
4. Elimination of duplicate studies: duplication of papers and any use of conference papers were eliminated.
5. Analysis and synthesis—Particularly, the analysis of the selected articles included a descriptive analysis [28]. The aim in this context was to analyse the selected papers, after examining the articles we identified revolving emerging themes. The discussion of these themes assists in identifying venues for further research venues.
6. Presenting the outcome—Whilst having discussed the papers, it is imperative to assess the existing and future areas for recommended future research. Specifically, the descriptive analysis provides information about the selected articles and the thematic analysis provides a comprehensive insight into the research under investigation uncovering 'what is and is not known' [28] pp. 671, and the main areas for further research.

After this stage, we incorporated an additional step as the intersection of the papers resulted in rather a limited number, we engaged in two stages involving 'snowballing technique' to evaluate whether papers in the subject matter were missed from our lists of papers identified due to keyword search as well as existing knowledge on subject areas as researchers were utilised. Especially, after the initial data collection patterns emerged around focal themes and content was discussed between authors until a point of agreement was reached [33].

3 Findings—Distribution of Paper Categories

This study conducted themes and analysis of papers identified to critically assess the systematic literature review. To evaluate the distribution and conduct the descriptive analysis of the existing papers the categories were established and utilised based on the coding categories including the description of the authors, keywords used, type/

classification of the paper, industries involved, sampling methods used in the paper and with which methods utilised.

The categories also provided us with an overview of the authors engaged, countries involved, research methods utilised, and also which journals were involved, providing us with a map of the existing literature environment. This was particularly useful, when the region, research methods and implication industries were discussed at a later stage.

Our research of the papers specifically highlighted that research was mainly carried out on computing, agriculture, and healthcare (see Fig. 1).

From the identified papers, 92% of them were published in 2021 highlighting the challenges of Covid-19 on sustainable supply chains and Blockchains. A significant number of studies were empirical in nature and qualitative or quantitative empirical research approaches had been utilised, followed by literature review papers, conceptual papers, and case studies (Fig. 2). The case study papers were limited to 3%, this is due to potentially the access to companies during Covid-19, while companies were dealing with the pandemic and perhaps also that the concept was rather new and was difficult to assess in a case setting.

The lack of case studies also would impact the in-depth understanding within a contextual setting, on the impact of Covid-19 particularly. Future research can address the challenges of blockchain upon SSCs during Covid-19 in diverse industries. Relating the case study category especially, the development and analysis of further case studies may bring a much better understanding of Covid-19 and the potential solutions for development and implementation in future potential endemics and/or pandemics. Hence, it would be interesting to see further case studies being developed retro-prospectively to provide further insights. The distribution of the studies whilst reflecting on the keywords found that Covid-19's impact on sustainable supply chain and blockchain comes in connotation with diverse contexts focusing with higher weighting on particularly digitalisation, the industry, the supply and the global impact (see Fig. 3).

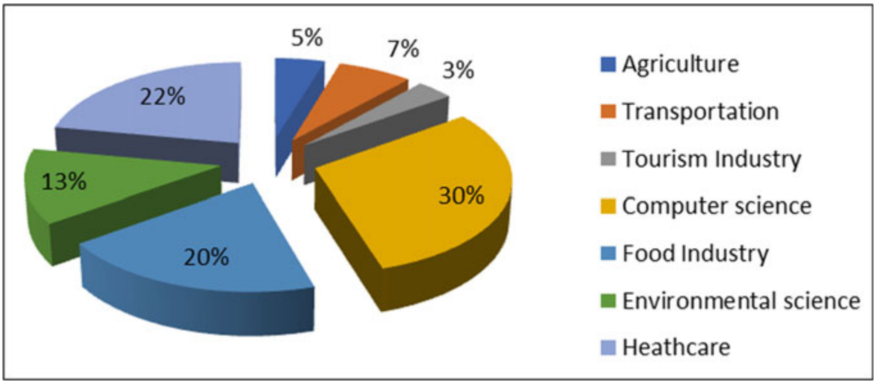

Fig. 1 Papers based on the sector

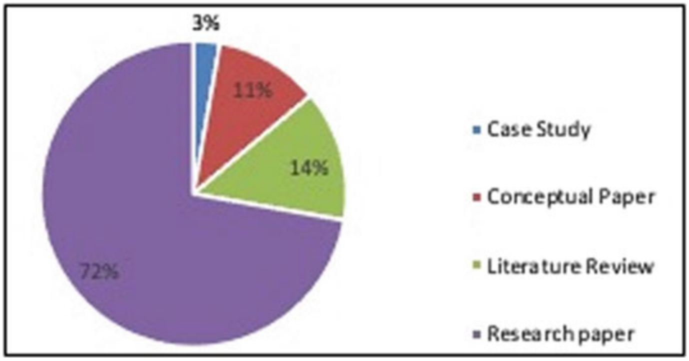

Fig. 2 Categories of paper types

Fig. 3 Categories of keywords chosen

This is rather noteworthy as Nandi et al. [34] noted that digitalisation enables the business and operations to be redesigned, which allows them to interact at diverse levels cross functional enabling are reshaping traditional business across time, location, and functions as such. Also, it was interesting to note that sustainability and

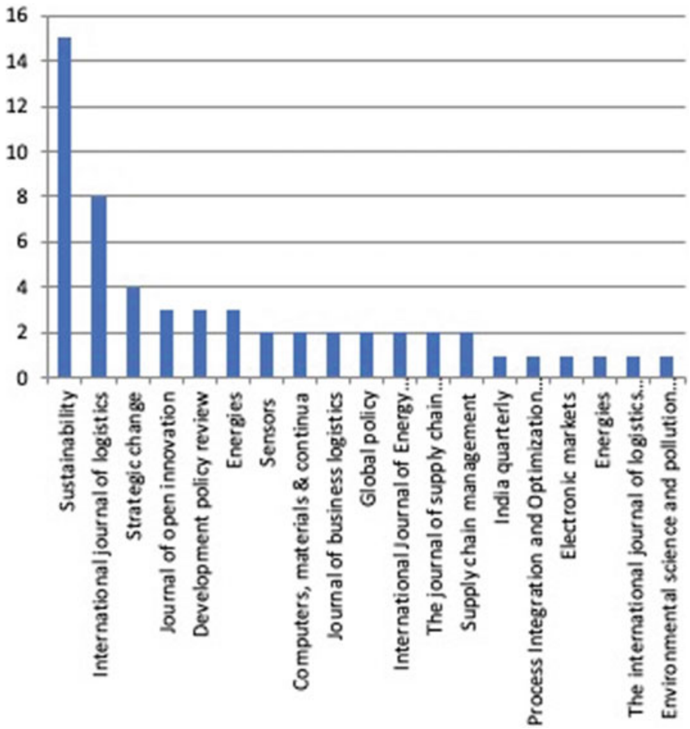

Fig. 4 Blockchain's first 20 journals

resilience seem to mention simultaneously highlighting their potential connotation as also referenced by authors such as Wieland and Durach [35].

Most papers were found in a specific journal, namely the Sustainability Journal followed by International Journal of Logistics Management and Strategic Change Journal. In the following Figure, we have presented the first 20 journals only, indicating the highest reliance on the concept of sustainable supply chains and the role of blockchain impact (Fig. 4).

4 Blockchain Technology Impact on Sustainable Supply Chain After Covid-19 Outbreak

Our SLR on sustainable supply chain impact during Covid upon Blockchain has highlighted four focal areas of Blockchain: (1) Benefits of utilising Blockchain in optimising SSCs; (2) role of digitalisation in supply chains; (3) challenges presented on supply chains and the impact of Blockchain; and (4) Encouraging SSCs development.

4.1 Theme 1. Benefits of Utilising Blockchain in Optimising Sustainable Supply Chains

The COVID-19 pandemic has created many socio-economic and environmental issues as stated by the World Health Organisation [36]. The measures set out to contain the pandemic has affected many industries across the globe and impacted worldwide logistics and supply; which led to also an increase in the numbers of unemployment [37]; increased risks of global poverty [38] generated healthcare and food security challenges across the globe [39, 40]. Studies highlighted that the use of Blockchain technologies in some cases became imperative with "Blockchain… an electronic cryptographic ledger [has the potential to]….operate [in a]… decentralised network model, instead of storing all information in a single database as in traditional cloud-based applications, the information is distributed and synchronised across all nodes in the network" [41] p. 1369. Blockchain technology has been identified as one of the 10 most effective innovative tools to combat COVID-19 and provide substantial benefits in containing the COVID-19 pandemic [42, 43]. Agbehadji et al. [43] study highlighted the wide-ranging use of technology which has been utilised across all the sectors ranging from higher education, to business to society, to manufacturing, which is something that has been reinforced by this study.

Blockchain has been increasingly adopted in healthcare, especially in the context of Covid-19 to mainly develop operative protocols and a proper basis to achieve an efficient and effective evidence-based decision-making process [44]. According to Lakhani et al. [45] the blockchain has provided benefits such as the creation of supply chain wide blockchain registry, a reliable record for all supply chain members providing up to date 24/7 information on supply chain wide collaborative planning and control, and process implementation with restricted right to change in case, if and when needed; alongside documentation such as "bill of lading" can be available whenever needed in digitised and recorded form. Li et al. [46] and Khan et al. [47] focussed on the implementation of artificial intelligence (AI), including blockchain (enhancing the electronic medical records), within healthcare sector for rapid diagnosis of COVID-19. The Blockchain application in healthcare can deal with the challenges of lack of advanced predictive systems in sharing large clinical data sets, which characterised the situation generated by COVID-19 [44]. COVID-19 has been utilised for medical trials, data aggregation and analysis, as well as tracing and tracking etc. [48]; Fusco et al. [44, 49]. For example, Pouye [50] p. 88 reported that through the use of blockchain, the companies have created "a partnership with pharmacies to deliver drugs to the patient using an accurate and reliable tracking system". The potential of tracking and tracing is not new in the academic literature however the decentralised validation increased its speed and potential for validated decentralised information sharing.

A number of solutions at a policy level have been suggested, which included the adoption of blockchain technology and its potential to mitigate the supply chain risks [51]. Similarly, in the study of Sharma et al. [52] we can see that blockchain technology had the capacity and capability to support supply chain vulnerabilities during

Covid-19, which created a much more transparent supply chain in a very disrupted environment. When investigating the food and beverages industry Menon et al. [53] and Mor et al. [54] also noted that using Blockchain in agrifood supply chain had the ability to facilitate and improve the development of trust among its stakeholders. Within Sustainable Business Models Gregurec et al. [55] investigated the impact of COVID-19 on Small-Medium enterprises (SMEs) and the impact of blockchain. Specifically, their research provided insights related to the innovative approaches, such as blockchain that companies adopted to overcome the crisis. Andiappan et al. [56] and Klemeš et al. [57] discussed post-COVID-19 world biomass supply chains' potential opportunities and improvements that may arise for example availability of supply and automation, collaborative work in supply chains energy production, and potential for regulation.

As seen in the above discussions based on the literature review the research undertaken exploring the impact of the pandemic indicated the benefits of using Blockchain technology as improving the decision-making based on a decentralised ledger, creating trust in a disruptive environment, improving the collaborative work across the supply chain as well as creating and leading to the development of innovative ways of managing the supply chain in a sustainable manner where the transparency and reliability of information and data have become imperative to manage the supply chains in a disruptive environment in a sustainable way.

4.2 Theme 2. The Role of Digitalisation in Supply Chains

The digital transformation focusses on the technology and tech-driven "placing an excessive level of concern on new technological concepts such as big data (BD), AI, internet of things (IoT), cloud computing (CC), social networks (SNs), blockchain …[than] on vision, strategy, structure, culture, human talent, resources and capabilities, business model, and competitiveness" [58], p. 423. As Nandi et al. [59] put it "[o]ne real practical concern is the feasibility of these solutions to be implemented. A question that will arise from managers is whether there is a payoff and benefit from utilising such a—currently—complex system and series of relationships." However, the challenging pandemic situation has forced decision makers in every sector to review and restructure their business supply chain operations and how to manage it effectively under the changing conditions [56] and consider digitalisation and implementation of several enabling technologies, such as blockchain as a response to Covid-19 disruption. Indeed, technologies such as Blockchain helped logistics companies to respond quickly, interact on delays and respond to the changing government regulations (regional and local restrictions), understand the bottlenecks in their supply chain, such as the financial challenges for industries and associated supply shortages [60]. With the increased decentralisation and traceability made possible by Blockchain technology, the trust level among the SC members increased in their transaction, especially where authority central to the transactions may not be required and hence potential for data security improved as data is saved in different blockchains across the supply chain network members [61, 62]. Thus, the presence of such transparency allows the generation of reliable data for its stakeholders in real-time [63].

The potential for use of digital technologies to overcome difficulties across supply chain wide operations, especially in a disruptive environment has led to the technologies, that provide a level of assurance, reliability and potential for flexibility in operations as the pandemic context and responses in regulations were changing rapidly. The theme also indicated that research has focussed mainly on the role of Blockchain and its potential use in generating SSC operations.

4.3 *Theme 3. Challenges in Supply Chains and the Impact of Blockchain*

There are a considerable number of challenges that have been identified regarding the implementation of Blockchain in the academic literature, such as data security and privacy, large data set analysis, management of data, sustainable operations and increasing the standard of contactless operations. Especially the privacy issue has been viewed as a wide-ranging concern, despite "many studies indicat[ing] that blockchain is safe in every aspect, some studies predict that blockchain is still hard to entirely ensure the transactional privacy and create more opportunities for hackers" [64] p. 208. Similarly, although Botene et al. [41] noted that blockchain adoption can enhance and increase the efficiency to how it can help in the context of coronavirus, however they have also identified several areas which required improvements, such as integration with legal issues, security risks, resource utilisation, automation and data control. They recommended the adoption of hybrid blockchain, collaboration and the use of adaptive technologies, big data analytics and multi-robot augmented reality to increase the efficiency and optimisation of the achieved output [41].

The issues such as privacy protection and network security, sharing sensitive data has been one of the major concern, especially in the healthcare arena where healthcare data in public blockchains affect the adoption of this technology. The privacy concerns are understandable due to the fact that "[a] blockchain network has no central authority. Since it is a shared and immutable ledger, the information in it is open for participants in the supply chain to access and see" [34, 59] p. 323, hence creating a rather open arena for security concerns and privacy issues as not all its supply chain members may not have the same or similar security capabilities and capacity to deal with the operations. Therefore, in this context, cyber security risk and its management need to be an integral part of Blockchain implementation discussions and decision-making [65]. Nevertheless, as [66] mentioned on a positive note, this can lead the blockchain to generate a consumer feedback loop for a demand forecast system. Pyun and Rha [67] p. 13 similarly highlight that based on their literature review a segment that needs to be embedded is "the need for a sustainable [and digital] supply chain by applying blockchain technology with high security".

However, how the security systems need to be embedded and to what level has been rather limited in the academic literature.

Another challenge has been addressed in Bahn et al. [68] study on the agricultural industry in Middle East and North Africa (MENA) highlighted that the adoption of digital agriculture is at early stages in MENA and issues related to transparency of use, data protection, and labour protections, despite the digital technologies having the potential for improving production, increasing the performance of supply chain and logistics, and optimising the utilisation of limited natural resources (e.g. agricultural water). Another example indicating less readiness for blockchain adoption has been seen from the shipping industry where "especially for partners who locate in developing or least developed countries where they are still not ready for blockchain adoption" [64], p. 208. In the same vein, Castañeda-Navarrete et al. [69] explored the impact of COVID-19 pandemic on the worldwide apparel supply chain based on developing countries. Their findings indicated that there have been several disruptions, such as supply chain and operations issues, reduced output of materials, reduced demand for products, job security and safety.

The academic literature reflected the challenges of the blockchain its adaption, use and context may have considerable impact in generating sustainable operations, another interesting challenge that was particularly of interest is the context of the blockchain technology and where it has been adapted. This challenge particularly highlighted the implication of country and political support context and relevant trust in the blockchain technology operations.

4.4 Theme 4. Encouraging Sustainable Supply Chains Development

Sustainability literature reports the connection between environmental aspects of sustainability and Industry 4.0 technologies, including blockchain, highlighting that the development of digitalisation process enhances the sustainable aspect of as production cycle and at the same time improves the value chain, through the reduction of energy waste, recovery and reuse and recycling of the material, etc. [55, 70, 71]. This in turn is enabled through enhanced transparency and visibility supported through blockchain [52, 72, 73]. Chen and Biswas [71] explained that the COVID-19 outbreak created opportunities for business to rethink their practises and forced them to become more sustainable by adopting innovative approaches such as the blockchain technology. Yin and Ran [74] also highlighted that during Covid-19 disruption and in any future forthcoming disruptions supply chains may be tempted and willing to invest adopt blockchain and other new technologies as it provided opportunities for the supply chain to operate effectively in a disruptive environment. Aysan et al. [75] presented useful insights regarding the implementation of blockchain-backed systems for sustainable development. Whereas Bekrar et al. [76]

focussed on circular economy examining the potential benefits of blockchain technology on various aspects of reverse logistics and transportation activities. These activities and studies are noteworthy to mention, however the studies do not present a holistic understanding of how sustainable supply chain operations across and in specific industries can be developed whilst benefiting from Blockchain. As seen in theme analysis the studies reflect upon standalone practises or effective gains in the area of recycling or transportation for example, however, what it meant for global extended supply chain networks is rather underdeveloped and calls for future studies.

Based on the themes and extant academic literature review the following Fig. 5 summarises the emerged themes and explains during the pandemic context how sustainable supply chains can be developed by adopting blockchain technologies; what are the benefices of such implementation, what are the challenges and potential solution, which is the adoption of hybrid blockchain—the integration of blockchain with other technologies e.g. artificial intelligence to optimise results and provide solutions to most of the challenges e.g., [41].

Based on the existing research and our understanding of the blockchain implementation a hybrid blockchain that creates a secondary layer to improve the attributes for achieving sustainable supply chain operations can be beneficial in involving the challenges faced by the supply chain members and opportunities that it may bring for them. The covid-19 environment disruptive environment has made it clearer for the industries the importance of having a decentralised ledger and hence the use of Blockchain technologies, in case there is a disruption in a particular node in the supply chain per se.

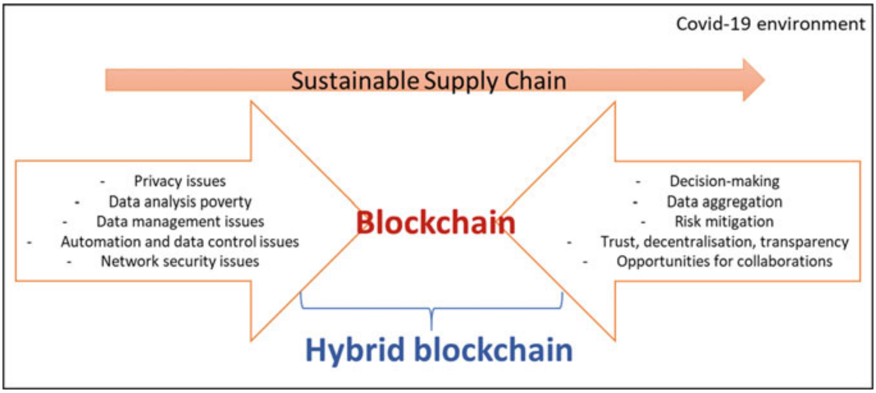

Fig. 5 Proposed framework-a hybrid blockchain in the context of sustainable supply chains

5 Conclusion and Future Work

Existing studies explored the Blockchain technologies focussing on the performance of sustainable supply chains [77] while evaluating blockchain adaption challenges [78]. This research focussed on Blockchain-technology impact in the context of sustainable supply chains during Covid-19. The findings highlight a positive stance of Blockchain upon sustainable supply chains. The impact is wide-ranging and dependent on diverse sectoral settings based on data-accuracy and supply chain transparency. The current study provides the first stage of assessing the impact of blockchain within the context of covid in relation to sustainable supply chain categories and developing further venues for potential research arenas. With this aim, the current research presents a first attempt in mapping the academic literature, which was carried out in January 2022. As a result of the SLR four undervalued themes in the literature were identified:

- Case studies have been underutilised as a research method, providing only limited insight into the company, its stakeholders and the interaction with its industry context. With the limited number of cases, therefore individual nuances of accounts, context and industries are under presented, calling for future studies focussing on single or multiple case studies.
- Second, existing studies have explored the impact areas of blockchain, such as supply chain risk and performance, tracking and traceability, trust between collaborative partners and integration of data, nevertheless still multiple case studies comparing and contrasting between sectors, regions the impact and effectiveness of blockchain during Covid-19 is needed. Most of the studies currently are based either on secondary data or industry data that is lacking industrial comparison. This is particularly noteworthy and understandable as during covid in such a disruptive environment data was varied and not easy to collect. Therefore, future studies are needed particularly focussed on primary data.
- Finally, although literature review categories presented authors located widespread in different locations across the globe, regions that were underdeveloped seemed South America and Africa, hence there are future studies required to assess the impact of diverse country contexts and relevant impact. This also leads us to a future call for studies looking at South America and Africa as Covid-19 had a diverse impact across the globe and the literature review indicated this to be an underdeveloped area.
- Industry wide analysis and cross industry analysis is missing in the literature calling for meta studies investigating respectively the impact of blockchain in the context of Covid-19 and how these studies also can shape and enhance policy for new technologies and its use in a disruptive supply chain environment [79].

Every study has its limitation, however revisiting the papers one of the limitations of the current study was that there were many papers present dating 2021 by mid-2022, hence this paper needs to be viewed as a preliminary attempt and needs to be revised with the delayed onset of the papers. Based on the initial proposed framework studies could assess whether these initial constructs have been present and to what extent, hence further studies are needed to explore the sustainable operations context in SCM and in disruptive environments. In addition, although Covid-19 impact has been viewed as an unforeseen event the differences between operations before, during and after the disruption may benefit later disruptions to be managed more efficiently and effectively in creating a more sustainable and operational supply chain even in a disruptive environment. In this context, further research is needed to assess and evaluate the shift from pre-Covid-19 to post-Covid-19 operational environments.

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Effective Supply Chain Management Using SEIR Simulation Models for Efficient Decision-Making During COVID-19

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Abstract The coronavirus illness epidemic of 2019 (COVID-19), the most devastating to world health, has affected not only demand but also supply. It has evolved into an economic shock that has had a significant impact on our daily lives and worldview. The economic fallout has posed significant challenges regarding raw materials and final product flow, thereby affecting manufacturing. In this paper, a simulation model of the susceptible-exposed-infectious-recovered (SEIR) network is built, which forecasts how infected and healed people will act. The graphs for each parameter are generated from the SEIR model output behavior, and the model is then used to identify the behavior of patients who are vulnerable, exposed, infected, and recovered. Analyzing the graph makes it simple to comprehend the behavior and prepare backup facilities, helping to reduce patient fatalities. With the help of the SEIR simulation model and its output behavior, an attempt has been made to establish a perfect supply chain mechanism in a different pandemic situation. These models can also be applied to predict the peak stage of any pandemic and improve the existing supply chain.

Keywords COVID-19 · Supply chain · SEIR model

1 Introduction

The World Health Organization (WHO) has recognized the coronavirus infection (COVID-19) as a disease outbreak [1]. It was first discovered in Wuhan, China, before migrating to other Chinese cities and all other countries [2]. As of August 5, 2020, there had been more than 18 million infections, many of which had resulted in fatalities. Moreover, raising public awareness and enforcing laws were important in attaining these objectives of limiting the spread of disease. Due to social, economic,

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and environmental factors like travel and intimate human contact, the COVID-19 virus was not only present in the country's capital, where it was first found, but also spread to other parts of the country. Travel by Indians and foreigners internationally was another aspect that had an impact. According to WHO data, there have been 1,755,653 fatalities and 80,133,093 confirmed cases globally since the disease was first discovered up until December 25, 2020 [3]. This virus results in infection problems in the respiration of the person, and slowly it results in the problem of breathing. It was found that the severe acute pulmonary sickness coronavirus 2 (SARS-CoV-2) was accountable for a cluster of pneumonia cases in Wuhan [4]. In order to predict how this pandemic might evolve in the future, many academics are now creating various mathematical and machine-learning models, which are concerned by the enormous and constant increase in the number of infections occurring every day across the world [5]. The new coronavirus has been mathematically modelled by a few authors, the Middle East respiratory syndrome coronavirus (MERS-CoV) infection mathematical model was utilized to predict the infection rates over two periods. The majority of nations imposed complete lockdowns to slow the disease's rapid spread because there was no possible treatment and no vaccine available at the time of the Covid-19 epidemic. Also, limiting social and professional interactions assisted in containing the Coronavirus outbreak, but regrettably, at a high economic and human cost [6]. In order to guarantee social isolation during the first surge, strict measures like curfews were imposed in addition to lockdowns. However, to continue implementing these measures seems impossible due to economic considerations [7]. Even though recent modelling studies have revealed that the easing of restrictions could have devastating penalties. A century ago, the second wave of the Spanish flu epidemic claimed substantially more lives than the first, decimating the country's population [8]. As a result, all nations' top priorities should be to adequately prepare for the second wave. South Korea was one of the first nations to declare that it had actually entered a second wave of infections, but because of its effective testing and tracking methods, it was able to deal with the issue [9]. Yet after the initial COVID-19 wave was eliminated, China and New Zealand also reported minor new outbreaks. By enforcing tight travel restrictions, several nations are living in virtually total isolation from the rest of the globe. The second pandemic wave, which is more severe than the first, is currently affecting Europe. Most European countries are notifying the authorities of more daily infections than they did at the beginning of the outbreak [10–12]. This research attempts to forecast the outbreak development under various quarantine constraints using a unique SEIR model. We were prompted to examine time-varying factors after preliminary attempts to discover such model parameters revealed that the constancy hypothesis is severely constrained (not much analyzed in the literature). Then, a set-membership forecasting algorithm is developed to realize an effective and trustworthy prediction for an SEIR model with time-varying parameters, fully fitting the scenario under consideration. Analytical evaluations are made of the predictor's stability and inclusion abilities. Numerical experiments for a few nations indicate how well the proposed approach performs.

Numerous people have died as a result of an outbreak of the deadly COVID-19 virus, which has also badly harmed the world's economy [13–15]. Manufacturing and logistical operations have been put on hold for several months due to the stringent lockdown. Due to the restrictions put in place as a result of the virus, it has adversely impacted the supply and demand for a variety of items and significantly harmed the supply chain [16]. Every type of unit from various sectors is experiencing the effects of COVID-19.

The most significant threat to world health in the twenty-first century has been determined to be the new coronavirus SARS-CoV-2. In most nations, viruses have been discovered in a range of heterogeneities. The infectious condition caused by this coronavirus is COVID-19. From December 2019 to the present, cases have been observed in almost all countries. The world faced a serious threat and an acute public health emergency as COVID-19 emerged and continues to spread as a global pandemic phase [17]. The first case was identified as a pneumonia case of unknown cause in China. COVID-19 cases were increasing due to many factors, including people's movements, international travel, cultural and socioeconomic factors, and status spread rapidly across most regions. The number of COVID-19 infections increased significantly across Asia, Europe, and America during the first quarter of the year (January to March) [18, 19]. Asymptomatic COVID-19 infected individuals may have triggered the rapid spread of COVID-19 infections. On January 27, 2020, India confirmed their first COVID-19 case, and in the initial phase, the number of infected cases increased gradually and erratically up until mid-March 2020. The number of new infections has dramatically climbed since mid-March, averaging 25.1% every day till March 26. [20, 21]. Government initiatives and associated public health measures have altered the pattern of confirmed positive cases. The dynamics and spread of the disease have been studied using a variety of models, including simulation models, mathematical modelling, and more. The SEIR model was applied as an additional concept of control, representing preventative actions such as social isolation, confinement, limitations on public movement, and masks. Precautionary steps have been taken to prevent the disease's spread in the absence of a vaccine. The objective was to support the healthcare system by delaying and lowering epidemic peak heights in the affected population. The SEIR model of infectious diseases is among the simplest compartmental models available [22]. It is a highly well-liked model that is frequently utilized in a wide range of environments. The SEIR model illustrates the relative proportions of four classes of people change over time: susceptible individuals (S), who are able to contract the illness and become infectious; exposed (or asymptomatic) individuals (E); infected individuals (I), who are able to spread the illness to susceptible; and recovered individuals (R), who become immune for life once they recover [23]. A related advantage of this straightforward model is the small number of parameters that must be determined (three transition rates σ, γ, and b). It provides a clear illustration of how epidemics often behave (as a succession of changes between several compartments) [24] (Fig. 1).

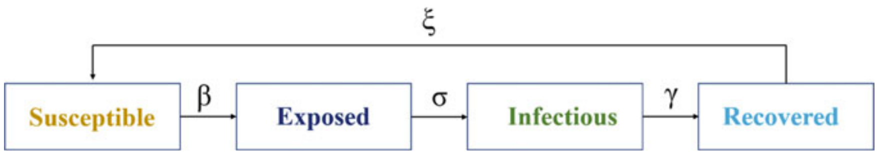

Fig. 1 Schematic diagram of SEIR model

2 Epidemic Model

In the Epidemic model, infection rate, recovery rate, and susceptible patients are the essential factors that help to take the decision regarding quarantine period, lockdown, isolation period, and social distance. Susceptible-Infected-Recovered (SIR) model is one of the effective models used in epidemic [25]. The population is split into three groups in this classic compartmental model: susceptible, infected, and recovered. The model makes the assumption that the population is homogeneous and that susceptible and infected people come into contact with each other directly. A population category for exposed individuals is added to the Susceptible-Exposed-Infected-Removed (SEIR) model, which is an expansion of the SIR model. [23, 24]. The exposed category represents individuals who have contracted the disease but are not yet symptomatic. Susceptible-Exposed-Infected-Asymptomatic-Removed (SEIAR) model is similar to the SEIR model but adds an additional asymptomatic category to the population. The asymptomatic category represents individuals who have been infected but are not showing symptoms. Compartmental models with age structure incorporate age-specific transmission rates, susceptibility, and mortality rates to simulate the spread of disease in a population with different age groups. Agent-based models are based on the simulating individual behaviors and interactions between individuals in a population to predict the spread of disease [26]. Network models use network theory to describe the interactions between individuals in a population and simulate the spread of disease through the network. There are also hybrid models that combine elements of these different models to more accurately predict the spread of the disease. The choice of the model depends on the specific outbreak and the data available. The SEIR model shows good results to model any pandemic such as novel coronavirus [27]. Another very useful model is SARIIqSq based on six dynamic factors Susceptible person (S), Asymptomatic infectious person (A), Recovered person (R), Symptomatic infectious person (I), Isolated infected person (Iq) and Quarantined susceptible person (Sq). The total size of the SARIIqSq model is the sum of all individuals ($N = S + Sq + A + I + Iq + R$) and shows the goods resulting for the COVID-19 pandemic. An asymptomatic person infected with COVID-19 is not traced easily or traced after 14 days, but that person has been infected with the virus [28]. Therefore, the time of actual infection (t) is greater than the time of infection count (t_o). Figure 2 depicts the relationship between the various SARIIqSq model parameters; S stands for the daily contact rate per unit of time, and βs represents the transmission probability per contact between the infective and susceptible

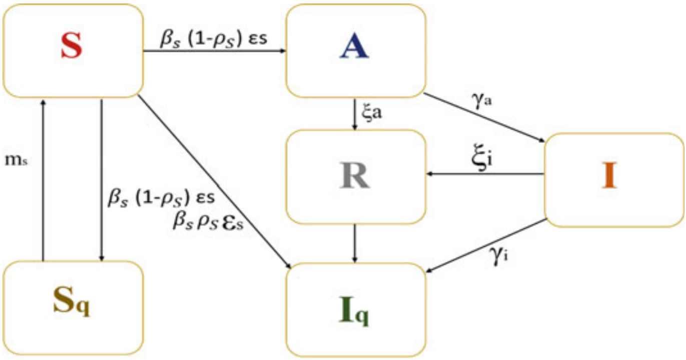

Fig. 2 SEIR parameters and relations

classes. Both the parameters are explicitly related and help to take decision reading Quarantine periods, lock-down periods and social distancing that help to control the infection rate of pandemics [29].

3 SEIR Model

The SEIR model is one of the simplest compartmental models of epidemics. It is a highly well-liked model that is frequently used in a variety of contexts. The SEIR model illustrates how, in a population of constant size, there are changes in the relative proportions of four types of individuals: susceptible individuals S, who can contract the illness and become infectious; exposed individuals E and symptomatic individuals I (infectious); who can spread the illness to the susceptible population; and recovered individuals R, who become immune for life after recovering [30, 31]. A set of differential equations that characterize the rate of change of each compartment over time is used to represent the transitions between these compartments. The SIER model assumes that the population is homogeneous and that the disease spreads through direct contact between individuals [32]. Based on inputs like the starting population size and disease transmission rate, the model can be used to forecast the occurrence of infections and the course of the epidemic over time. The SIER model has a drawback in that it does not take into account the impacts of interventions like social isolation, quarantines, or immunizations, which can have a big impact on the disease's transmission. Therefore, modifications to the SIER model have been developed to include these interventions and provide more accurate predictions of the spread of disease [33]. During infectious disease outbreaks, deterministic mathematical models can be beneficial tools for describing the dynamics of epidemics and, as a result, for assisting in the development of public health strategies. To predict the trajectory of the COVID-19 epidemic, the SEIR mathematical compartmental model is employed. The SEIR model outlines the temporal development of the Susceptible (individuals who have not been exposed to the virus and do not have resistance to it), Exposed (individuals who were exposed but are still in the incubation period and are not yet contagious), Infectious (individuals who are capable of transmitting the disease and symptomatic individuals who are already beginning to exhibit the first symptoms), Recovered (individuals who have been removed from the situation), and Isolated (individuals who may be treated, admitted to a hospital, or die) [34–36]. Mathematical models have produced quantitative data in epidemiology and offered helpful recommendations for handling outbreaks and formulating policies. For COVID-19, several modelling investigations have been carried out in particular.

The compartment model is a useful tool in the COVID-19 scenario. This effective mathematical model makes it easier for us to understand the intricate dynamics of epidemics. The well-known SEIR model is built in this study employing four compartments. Susceptible population S, exposed population E, infected population I, and recovered population R. The SEIR model is appropriate for disease transmission in which a contagious disease develops quickly in an infected person [37, 38]. Numerous studies have used the SEIR model to predict the dynamics of endemic and epidemic diseases like dengue fever [39]. The SEIR model effectively forecasts the situation after 14 days because this is the average incubation time for spreading the virus. In various studies, the SEIR model has been modified by including strategy elements like social distance and face mask usage to regulate and forecast COVID-19 situations [40, 41]. The use of vaccinations is a very efficient way to prevent and treat viral illnesses. Only a few of the SARS-CoV-2 vaccines that have been created including inactivated vaccines, subunit vaccines, DNA and RNA vaccines, live attenuated vaccines, and vector vaccinations. However, no vaccine or specialized antiviral medication has been available in the past for the treatment of SARS-CoV-2 patients [42–44].

The Susceptible-Exposed-Infectious-Recovered (SEIR) model is a practical tool for simulating pandemic behavior and reliably calculating the number of susceptible, infected, and recovered individuals. Population, disease transmission probability, recovery and fatality rate are the main input parameters required to compute the number of recovered, infected and dead through this model. The peak of infection, number of deaths per day, and number of individuals infected are accurately predicted through this model. Figure 3 shows the SEIR model developed in Anylogic software with various parameters connected to it.

(a) S is the percentage of susceptible persons
(b) E is the percentage of persons exposed with virus
(c) I is the percentage of infected Persons
(d) R is the percentage of recovered individuals.

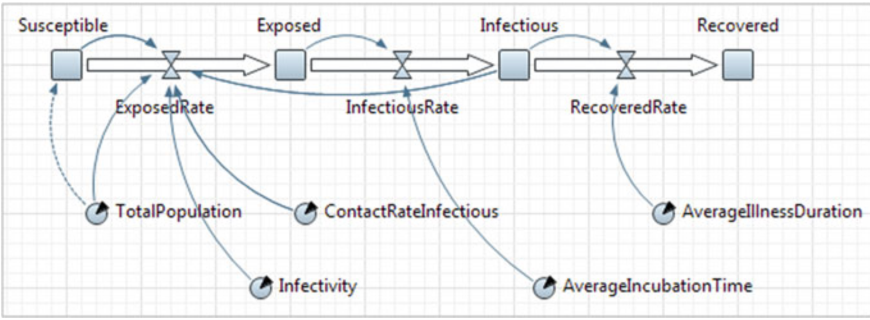

Fig. 3 Parameters interlinked in SEIR model

4 Limitation of SEIR Model

The group of unreported instances is likewise disregarded by the SEIR model. During a widespread pandemic, there is no assurance that all infected persons will be examined and reported due to a shortage of medical resources and variations in testing policies. These groups will likely infiltrate the community as covert broadcasters. Long-term simulation cannot be performed using the SEIR model with constant parameters. This is due to the requirement for a steady shift in the transmission rate and removal rate over time [45, 46]. Mathematical analysis and data fitting are made more challenging by the fact that the transmission rates of the existing COVID-19 models are frequently set as constants.

The economic effects of the pandemic have not traditionally been taken into account by epidemic models for COVID-19. The COVID-19 "suppression" and "mitigation" control strategies are the topic of a contentious debate. The suppression strategy, put into place in China and a number of other nations, employs the most drastic measures to drastically minimize disease transmission and swiftly contain the epidemic, at the expense of economic development during the outbreak control phase.

The ecology, genetics, microbiology, and pathology of the newfound virus are mostly unknown, which makes mathematical modelling more difficult. Yet, it is challenging to accurately reflect in a model a number of COVID-19-related factors, such as political and social difficulties as well as cultural and ethical norms. We must realize that such a mathematical model is a modification and estimate of reality by its very nature.

5 Methodology

In the SEIR model, infected covid-19 populations are separated from the susceptible populations before the development of further medical symptoms, and the terms called quarantine and isolation refer to the populations already infected by the virus and showing medical symptoms that must be separated from the rest of the populations.

Examining individuals under potentially dangerous circumstances, such as contact with someone who has COVID-19, may help find new cases. The first contaminated patient that contracts the illness and spreads it to others is the starting point of the model. Depending on the social activity of the COVID-19 positive person, there may be one or several people. The COVID-19 patient may pass the illness on to others one at a time or in numerous instances at once. The individuals who were contacted may not get the disease due to many factors like health status, personal hygiene, or environmental health measures. Using the Ministry of Public Health's data that are currently accessible, the rate of transmission might be determined. The characteristics of the COVID-19 disease, such as the incubation and infection times, were also examined. Using appropriate data, such as health statistics acquired from various government websites and published literature, the recovery and death rates were also computed.

On the other hand, machine learning forecasts can be validated using mathematical modelling, and it can also be used to guide the development of more efficient and reliable algorithms for data analytics and machine learning. The improvement of these two distinct quantitative techniques might thus be mutually advantageous, and their combination could result in potentially game-changing advancements in the research of COVID-19 and other topics.

The rate of change of populations from one compartment to another at any time is non-linear. Changing quarantined susceptible individuals into infected individuals or isolated infected individuals into recovered individuals in the case of COVID-19 takes very less time. The total size of populations is dynamically changing from one compartment to another compartment, and their mathematical expressions are shown below:

$$\frac{dS}{\partial t} = \Lambda - (\beta_s + \rho_S(1 - \beta_s)\Sigma_s S\frac{i}{N} - \delta S + m_s s$$

$$\frac{ds_q}{\partial t} = (1 - \beta_s)\Sigma_s \rho_S S\frac{i}{N} - (m_s + \delta)s_q$$

$$\frac{d\mathrm{A}}{\partial t} = \beta_s(1 - \rho_S)\Sigma_s S\frac{i}{N} - (y_a + \Sigma_a + \delta)\mathrm{A} \quad [35]$$

$$\frac{d\mathrm{I}}{\partial t} = y_a A - (y_i + \Sigma_i + \delta)I$$

$$\frac{dIq}{\partial t} = \beta_s \Sigma_s \rho_S S \frac{i}{N} y_i I - \left(\Sigma_q + \delta\right) I$$

$$\frac{dR}{\partial t} = \Sigma_a A + \Sigma_i I + \Sigma_q Iq - \delta R$$

The following non-negative initial values have been included in the model:

$$\mathrm{S(t_0) = S_0,\ \ Sq(t_0) = S_{q0},\ \ A(t_0) = A_0,\ \ I(t_0) = I_0,}$$

$$\mathrm{I_q(t_0) = I_{q0}\ \ and\ \ R(t_0) = R_0}$$

βs = Probability of transmission per contact (between susceptible and infective populations)

εs = Contact rate per unit of time (per day)

β = βs·∈ s is explicitly related to taking decisions regarding lock-down time, supply and demand, and cautionary precaution.

ρs = Proportion of population exposed to the virus, this proportion of the population is identified through contact tracing and must be quarantined. It is put in Sq or Iq compartment based on the degree of infection and clinical symptoms.

1−ρs = Proportion of population exposed to the virus but not identified in contact tracing. This proportion of the population is moved to infectious class I (0nce infected) or susceptible class S (if unaffected).

(1 − βs) ρs ∈ s (or βsρs ∈ s) = Rate of uninfected (or infected) quarantined population move to Sq (or Iq) categories.

βs (1 − ρs) ∈ s = Rate of asymptomatic infectious individuals (not quarantined) moves to the asymptomatic noninfectious categories.

γa = Rate of asymptomatic individuals moving to infected individuals.

1/γa per unit time = Average time (time spent in asymptotic categories)

1/γi = Mean Time (infected individuals)

This model must include some geographical factors by taking proportional natural decay for all six individual compartments.

6 Simulation Data

Data simulation is the process of recreating or replicating actual situations while using a lot of data to make predictions, choose the best course of action, or test a model. Various data are required in the SEIR model for the output purpose, and few data are taken from different research papers, and the previous trend of Covid-19 for three months is taken from the Indian government website for COVID-19. It enables the creation of the SEIR model as a complex and dynamic system and also empowers data-driven decision making. The SEIR model utilizes the data to generate synthetic data to represent a specific trend by predicting the various components. This SEIR model utilizes the data taken from April 1st, 2020, to June 30th 2020 and provides the output of the SEIR model by predicting the different components like the suspect, Exposed, Infectious, and recovered people. Following are the data used in SEIR model.

(a) Total Population = 100,000 [47]
(b) Infectivity = 0.87 [48]
(c) Contact Rate Infection = 3.2 [49]
(d) Average Incubation Time = 14 [50]
(e) Average Illness Duration = 25 [50].

7 Covid-19 Cases in Dhanbad

After Jamshedpur, Dhanbad has the second-highest population in the Indian state of Jharkhand. It is the 33 biggest urban cluster in India, with over one million people, and it is among the 42 largest cities in the country [51].

Dhanbad, located in eastern India, is one of the most well-known industrial cities in the state of Jharkhand. It is highly renowned throughout the world for its rapid development and urbanization. According to the Indian Census of 2011, it is the most populated city in the state of Jharkhand, with a population of over 2 million people. As a result, it is critical to provide enough healthcare services for everyone, and Dhanbad excels at this. Throughout the region, competent healthcare services are available, and several government and private facilities provide healthcare to people in need.

The daily number of infected patients in Dhanbad from April 1st to June 30th 2020, was used in this study. Data were obtained from the government of Jharkhand, India website [52] to research the COVID-19 pattern and patterns calibrated using the simulation model for the exact outcome. The following graph represents the daily COVID-19 cases recorded April 1st to June 30th 2020, as per the data provided by the Health and Care Department (Fig. 4).

8 Calibrated Model

In order to use the SIER model to precisely predict the spread of a particular illness in a given population, the model must first be calibrated. Calibration entails changing the model's parameters to fit the observed data to make sure the model appropriately reflects the dynamics of the disease. Model parameters include the disease's transmission rate, incubation period, infectious period, and recovery rate. These parameters can vary, depending on the specific disease and population being modeled. The SIER model is fitted to the observed data by adjusting the model parameters until the model output matches the observed data as closely as possible. Once the model is calibrated, it needs to be validated to ensure that it accurately reflects the disease

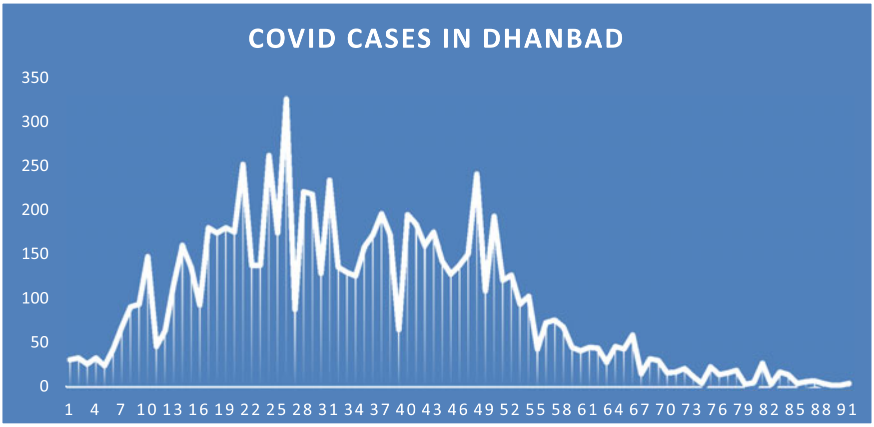

Fig. 4 COVID-19 cases in Dhanbad [52]

dynamics in the population being modelled. This is done by comparing the model's predictions with new data that was not used for calibration. It is standard procedure to do a sensitivity analysis to see how the model's inputs affect its output. This aids in determining which inputs have the greatest influence on the model and where further data is required to increase model accuracy.

The various parameters of the model may be made with some minor adjustments so that it can fit the previous pattern of infection. The two major factors, Infectivity and contact rate, must be calibrated with past data to maximize the model's accuracy. When this model is fitted with previous data after calibration, it shows the same pattern of past infection. The calibration data of Infectivity and contact rate are used in the present model to ensure that the model predicts the pattern of infection more accurately.

9 SEIR Model Outputs

The output graphs of each parameter obtained from the simulation model predict the behavior of susceptible, exposed, infected, and recovered patients. By analyzing the graph, it can be easily understood that the behavior of infection can be predicted and backup facilities can be prepared, which can minimize the death of patients. The behavior of each parameter, the peak of infection, and forecasts of the types and number of the population in each compartment are obtained from the SEIR model. These data are very useful for taking decisions regarding the supply chain of various products required in a particular time period. Maintaining particular supplies of essential items such as oxygen, ventilator set-up, and essential medicines saves the lives of millions of people.

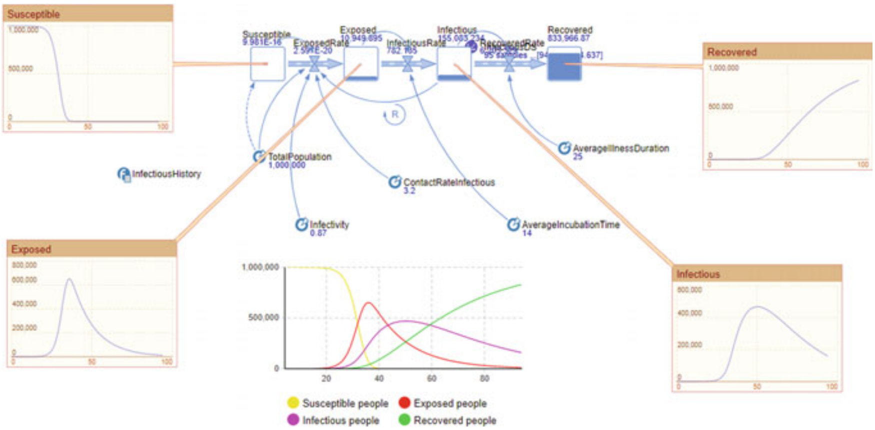

Fig. 5 SEIR Model running with output graphs

These output graphs represent the behavior of each parameter and predict the nature of the curve. With the below model outputs, the variation of change can be predicted whenever the same pattern repeats itself in the future. The curve helps in predicting the peak, which helps determine the priority of necessity. The population parameter is linked with the susceptible and exposed rates, as shown in Fig. 5. The infectivity parameter is interrelated with the exposed rate. Also, the contact rate for infectious disease is connected with the exposed rate, which helps in calculating the exact number of exposed patients. From the data provided by Total Population, Infectivity, and Contact Rate Infectious, the number of exposed patients are calculated. For calculating infectious patients, parameters like infection rate and average incubation time are interrelated with the infectious compartment.

Figure 6 shows the behavior of output that is concluded by the SEIR (susceptible-exposed-infectious-recovered) model. Figure 6 includes all four graphs, where the X-axis represents the number of days and the Y-axis represents the number of people. Figure 6b, c shows the population of exposed people and infectious people are almost equal at peak, showing the high rate of infection.

The output of the SEIR model is divided into three categories: normal situation, moderate situation, and worst situation. The supply–demand decision is taken on the basis of these three divisions, and each division has a different priority of items. In a normal situation, there are no positive cases in the present area, but there are positive cases present in nearby cities, and the demand for immunity boosters, oximeters, sanitizers, masks, etc. is normal. In the moderate situation, the positive case started to identify itself, and the demand for essential medicines, oxygen cylinders, ventilators, etc., increased. The worst situation refers to the high demand for all items, especially medicine and medical items. The simulation's findings are highly beneficial in enhancing the strategy's capacity to limit the number of COVID-19 cases in Dhanbad (Fig. 7).

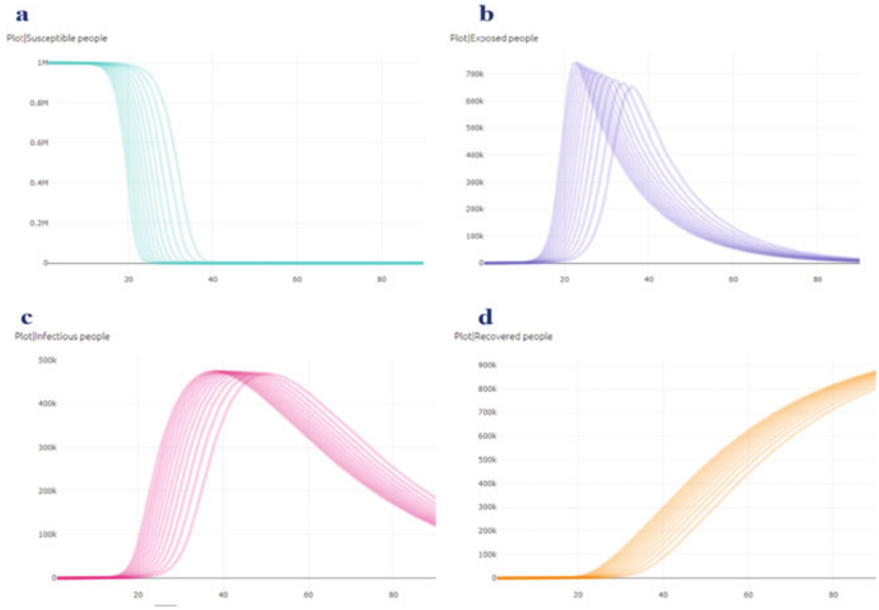

Fig. 6 Output graphs from SIER model

Fig. 7 Categorization the output in three parts

10 Results

The purpose of this study was to develop a modified SEIR compartmental mathematical model that would estimate COVID-19 pandemic dynamics while taking various intervention options into account. This model might be able to offer the most effective solutions for lowering the risk of an outbreak. The SEIR model helps in forecasting the different parameters, such as the number of suspects, exposed, infected, and recovered, and helps us to know the pattern and behavior of the patients for the preparation of all the essential items at the time of the pandemic. The factors of vaccinations and isolating are not included as simulation results in this SEIR model.

Figure 8 represents the behavior of all four parameters, which are susceptible, exposed, infectious, and recovered, and helps in predicting the peak of the pandemic.

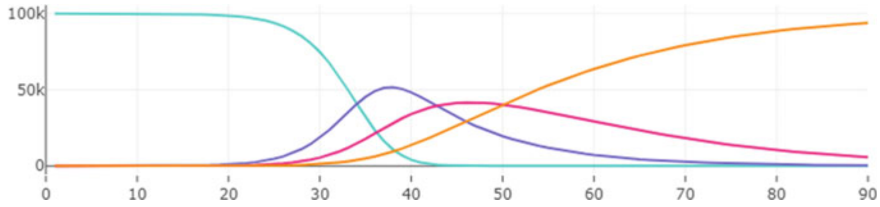

Fig. 8 Output of the simulation model

The graph will predict the peak so that we can prepare for all the emergency situations, before the peak reaches. In addition, getting data on the number of infected patients at a certain time period helps to arrange all the required components as per the various situations like normal, moderate, and worst situations. Hence, the focus should be on the supply of essential medicines in the phase of normal conditions. As the graph indicates the pattern of recovered patients, it can fetch the data on the number of beds required at a certain time period. As the graph indicates, the number of exposed patients suggests a home quarantine for a certain number of patients, which helps to decrease the rush on medical hospitals. In addition, the output graph predicted that the peak would be obtained in 35–40 days.

11 Conclusion

The SEIR model is the mathematical equation that most often describes how an epidemic disease spreads (as per current research). Based on contacts, the probability of disease transmission, the incubation and infectious periods, and the disease fatality rate, the model is used to calculate the number of infected, recovered, and dead people. In addition, it helps to prepare a strong supply chain and inventory of essential medicines and lifesaving equipment before the peak. Output graphs show the behavior of suspect, infected, exposed, and recovered patients, which helps to maintain an efficient number of beds, ventilators, and other medical facilities. The behavior of all components is predicted as per the observed graph. The simulation demonstrates that over a specific time frame, the peak of the infectious population was greatly flattened. The study's findings led to the conclusion that the SEIR model may serve as a benchmark for COVID-19 transmission in Dhanbad. The SIER model can shed light on how measures like social exclusion, quarantines, and immunizations affect the disease's spread in the Dhanbad region. The model can assist decision-makers in selecting the most effective course of action to impede or stop the spread of the disease.

(a) This model can estimate the potential number of infections in a population, which can help public health officials allocate resources and plan for the surge in demand for medical care in the Dhanbad region.

(b) The SIER model can help identify which groups of people, such as the elderly or those who have underlying medical conditions, are most vulnerable to the COVID-19 infection. Public health officials can use this to target their interventions better to safeguard vulnerable populations.
(c) The result predicted from the COVID-19 SEIR model of this paper shows a very close to the actual pattern of the pandemic, and it can be used in future for any other type of epidemic or similar situation.

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Digital Twins an Enabler of Digitalization in Supply Chain

R Bargavi and Deepak Mathivathanan

Abstract Digital twins, the virtual replicas of physical assets and processes are revolutionizing supply chain management by improving overall visibility, enabling accurate data-driven decision-making leading to operational efficiency. The chapter discusses the various definitions of digital twins, their types, and their potential benefits in specific to supply chain management are explored. Specific areas where digital twins have a significant impact on supply chain management such as how digital twins enhance supply chain visibility, increase efficiency and productivity, enhance collaboration and communication, and help in risk management and mitigation and contribute towards better customer satisfaction with lowered overall costs are detailed. Further, a ten-step process of implementing digital twins in existing supply chains and the associated challenges in implementation is presented in this chapter. To summarize, this chapter showcases the importance of digital twins as an enabler of digitalization in the supply chain by highlighting the potential benefits of using digital twins and how managers can unlock new opportunities for supply chain optimization and innovation in the digital era.

Keywords Digital twins · Supply chain · Digitalization · Implementation · Challenges

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1 Introduction

There is significant increase in usage of digital twins as an effective tool for improving operational efficiency [1–3], reducing costs [4–6], and enhancing decision-making [7, 8] in various industries over the recent years. So, what is a Digital Twin? It is a virtual representation of a physical object, system, or process that mimics its real-world behavior and characteristics in real-time. Existing literature throws multiple definitions for digital twins, and the term digital twin is often used in different contexts and specificity. However, there are some common definitions of digital twins that are frequently mentioned in existing literature by industrial practitioners and academicians. Here are some of the commonly used definitions: According to the Industrial Internet Consortium, a digital twin is "*a virtual representation of a physical asset, process, or system that uses data and models to understand and predict the asset's performance*" Gartner defines digital twins as "*a software representation of a physical asset, system, or process that allows you to understand and simulate its behaviour in the real world in a virtual environment*" The Digital Twin Consortium defines digital twins as "*a virtual representation of physical assets and processes that is used to monitor, analyse, and optimize the performance of the asset or process*". Siemens defines digital twins as "*a complete digital replica of a physical product or process that is used to simulate the behaviour of the system under various conditions*". According to Deloitte, a digital twin is "*a virtual model of a physical object or system that enables companies to visualize, analyse, and optimize the performance of the object or system in a digital environment*." In summary the common understanding is that digital twins are virtual representations of a physical system or asset that uses real-time data and other information to provide insights and predictions about its performance and behavior in a digital environment. Digital twins are best suited for real-time monitoring and optimization and are often associated with industrial IoT and data analytics applications [9]. Since, digital twins are a dynamic digital representation of a physical asset, process, or system they can be used as a tool for continuous improvement and optimization and are often associated with supply chain management and other operational applications [10]. Though the above-mentioned definitions differ in emphasis and scope, they share a common theme on using digital technology in creating a virtual representation of physical systems or process to improve its performance, optimize the operations and/or enhance decision making.

Though simulation models and digital twin look similar they actually differ from each other in many ways. Prime difference is simulation models typically study one particular process, but a digital twin can run multiple numbers of useful simulations in order to study multiple processes [11]. Second, digital twins are built around the mutual flow of information that first happens between object sensors and the system processor, whereas simulations often do not depend on or benefit from having real-time data. [12]. With a constantly updated wide range data combined with the computing power and an accompanying virtual environment, digital twins are far more superior to standard simulations in terms of insights they can provide on the

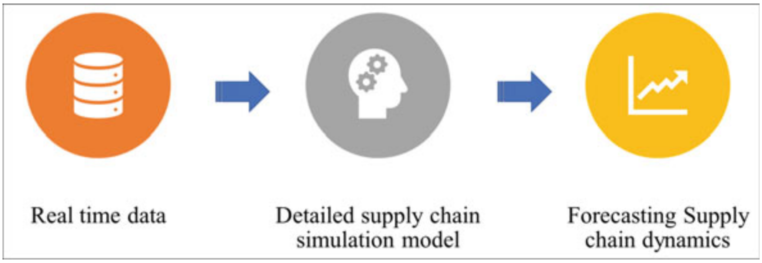

Fig. 1 Supply chain digital twin

dynamically varying system [13]. As shown in Fig. 1, a Supply Chain Digital Twin in this context would be a thorough simulation model of an actual supply chain that uses real-time data/snapshots to forecast supply chain dynamics.

The ever-growing pressure to optimize the operations and responding to volatile markets in today's business makes the concept of digital twins increasingly important in the field of supply chain management [14]. Using digital twins, supply chain managers can create a virtual replica of their physical supply chain, to identify potential bottlenecks, optimize processes, and improve efficiency [15]. Leveraging real-time data collected via sensors, IoT devices, and other sources, digital twins can provide accurate and detailed picture of the supply chain performance [16]. This enables firms to make informed decisions which focus on improved product quality, reduced lead times, and enhanced customer satisfaction. Further, digital twins enable supply chain stakeholders to collaborate more effectively by providing a common platform to share information, communicate, and identify issues well in advance [17]. Furthermore, digital twins allow businesses to test new ideas and evaluate potential risks before implementing changes in their actual physical supply chain [18]. Thus, digital twins present today's businesses the opportunity to achieve digitalization in their supply chain management. The key benefits of using digital twins in supply chain management are improved visibility, increased efficiency and productivity, better risk management and mitigation, enhanced collaboration and communication, higher customer satisfaction and lower costs (Fig. 2).

2 Types of Digital Twins

Before getting into how these key benefits can be achieved it is necessary to understand the types of digital twins. Based on the area of application and levels of product magnification there are several types of digital twins namely component twins, system twins, process twins and asset twins and so on. Though, when one

Fig. 2 Benefits of digital twins in supply chains

looks at the fundamental differences, there are overlaps in the features, but they can be classified in to three distinct categories namely,

I. Physical Digital Twins
II. Virtual Digital Twins
III. Hybrid Digital Twins

Physical digital twins: These are the digital representations of real-world physical assets or items that are made by collecting and combining data from sensors, IoT devices, and other attached sources [19]. They provide a real-time reflection of the current state, behavior, and performance of the physical object thus enabling monitoring, analysis, and optimization of physical assets such as machinery, equipment, vehicles, and infrastructure. For instance, a physical digital twin of a manufacturing machine captures data on its operational parameters, performance metrics, and maintenance history. Based on the collected data, insights into its current condition, the digital twin helps in predicting potential failures, and enables proactive maintenance planning [20].

Virtual Digital Twins: These are purely digital representations of objects, systems, or processes created using computer models, simulations, and algorithms to mimic the behavior and characteristics of a physical counterpart [21]. Virtual digital twins are used for testing, analysis, and optimization of the system in a simulated environment, without the need for a physical presence during the design and development stages of a component or object or a system [22]. For instance, in a new product scenario, the twin design allows engineers to simulate its performance, conduct virtual tests, and optimize its features and functionalities before the actual physical production starts.

Hybrid Digital Twins: Combination of elements of both physical and virtual twins integrating real-time data from physical objects with virtual models and simulations are called the hybrid digital twins [23]. They provide a more comprehensive and accurate representation of the physical system by augmenting the real-world data with predictive analytics and simulations [24]. They also enable real-time monitoring, analysis, and optimization of complex systems and processes [25]. For example, a hybrid digital twin of a transportation system in a smart city would combine a virtual model with real-time information from traffic sensors, schedules for public transportation, and weather conditions. It is possible to monitor traffic in real-time, forecast congestion, and improve traffic flow using simulations and predictive analytics.

3 Benefits of Digital Twins in Supply Chain

By leveraging digital twins, businesses may increase the efficiency of their supply chains, cut costs, and provide their customers with better goods and services, giving them a competitive advantage. In this sub-section we will discuss each of the key benefits of digital twins presented the introduction section in detail in a supply chain context.

3.1 Enhanced Visibility

Supply chain management with digital twins extensively increases supply chain visibility. Sensors, Internet of Things devices, business systems, and other real-time data sources from various points along the supply chain are all integrated by digital twins [26]. This allows the firms to have a comprehensive view of the supply chain, provided with up-to-date information on inventory levels, production status, transportation, and other relevant metrics [15]. By providing visual representation of the entire supply chain through simulation of the physical assets, processes, and flows in a virtual environment, the digital twins enable stakeholders to view and understand the interactions between different components of the supply chain [27]. Using historical data and real-time information, predictive analytics can anticipate potential issues or disruptions in the supply chain. Digital twins also aid in the monitoring of deviations from intended supply chain performance by comparing real-time data with predetermined models on a regular basis [28]. Doing so, digital twins can flag variations in expected performance, such as delays, quality or capacity issues. This allows supply chain managers to plan and execute corrective actions preventing further disruptions. The simulation capability of the digital twins helps in optimizing supply chain processes and improving visibility into the potential outcomes [18]. Digital twins provide a centralized platform with access to a common virtual representation of the supply chain, enabling teams to communicate, exchange insights, and jointly analyze the data [29]. This shared visibility promotes better coordination, alignment, and decision-making across the supply chain network. This visibility enables companies to make data-driven decisions, identify optimization opportunities, and respond effectively to changing market conditions or customer demands.

3.2 Increased Efficiency and Productivity

Digital twins in supply chain management can effectively contribute to increased efficiency and productivity in several ways. Supply chain managers can simulate and analyze different scenarios, and hence work towards optimizing existing processes for maximum efficiency [11]. This optimization leads to improved operational efficiency and increased productivity throughout the supply chain. Real-time visibility into the performance of assets, processes, and systems within the supply chain helps in monitoring and using digital twins, supply chain managers can have timely insights, to quickly intervene, take corrective actions, and prevent or minimize any negative impact on efficiency and productivity. Digital twins enable predictive maintenance, and this proactive approach reduces unplanned downtime, improves asset utilization, and enhances overall productivity [30]. Leveraging historical and real-time accurate demand forecasting and planning, analyzing customer behavior, market trends, and supply chain data, digital twins can help in optimizing inventory levels, production schedules, and logistics [31]. This reduces the risk of stockouts, excess inventory, and associated costs, leading to improved productivity. Further, by analyzing data and performance metrics, supply chain managers can identify areas of improvement, test alternative scenarios, and implement changes in a virtual environment before applying them to the physical supply chain. Providing a shared platform for collaboration and data-driven decision-making stakeholders can collaborate more effectively, exchange insights, and jointly analyze data enabling quicker and more informed decision-making, leading to improved efficiency and productivity.

3.3 Better Risk Management and Mitigation

Digital twins in supply chain management help in better risk management and mitigation by leveraging real-time data and predictive analytics to monitor the performance of assets, processes, and systems within the supply chain [32]. On continuously analyzing this data, digital twins can identify potential risks and anomalies before they escalate into significant issues [12]. The simulation of different scenarios and what-if analyses and creating virtual representations of the supply chain, managers can test the impact of potential risks and disruptions in a controlled simulated environment. Insights into the vulnerabilities and dependencies within the supply chain can be studied between different components, systems, and suppliers, to identify critical failure points and potential bottlenecks [33]. Digital twins enable real-time monitoring of the supply chain, thus allowing early detection of risks and immediate response [34]. Analyzing data from various sensors and IoT devices, digital twins provide visibility into the performance of assets, transportation, inventory levels, and other critical parameters [35]. A collaborative environment provided by a shared digital platform enables effective risk mitigation by facilitating information sharing, coordination, and joint decision-making. Further, digital twins support continuous improvement in risk management by enabling capturing and analyzing of data of various performance metrics and implement changes in a virtual environment [36]. This iterative process allows testing and refining risk mitigation strategies, leading to enhanced risk management practices over time ultimately enhancing the supply chain's resilience and minimizing the impact of potential disruptions.

3.4 Enhanced Collaboration and Communication

Digital twins in supply chain management enhances collaboration and communication among supply chain stakeholders by providing a common centralized data platform where stakeholders can access and share data related to the supply chain [32]. The stakeholders will have access to the same information, which helps in fostering collaboration and alignment, eliminates silos and enables better-informed decision-making [29]. Creating a virtual representation of the supply chain, digital twins allow stakeholders to have a shared understanding of the entire system for effective communication, discussions, analysis, problem-solving and eliminates misunderstandings [37]. The integrated real-time data from various sources within the supply chain, from sensors, IoT devices, and enterprise systems ensures that stakeholders have access to the most up-to-date and accurate data to track the progress of processes and monitor key performance indicators. Collaborative analysis and decision-making by providing are possible for stakeholders as the platforms allow them to jointly analyse data, simulations, and scenarios allowing for consensus-based decision-making [38]. Digital twins also facilitate efficient issue resolution by enabling faster and more effective communication among stakeholders on issue and exception that arises in the supply chain [14]. These capabilities strengthen collaboration among stakeholders, leading to improved coordination and alignment in the overall supply chain.

3.5 Higher Customer Satisfaction

Digital twins in supply chain management can significantly contribute to higher customer satisfaction as they provide improved visibility and transparency to track and monitor the status of orders, shipments, and inventory levels on a real time [39]. Keeping customers informed and reducing uncertainty, digital twins enhance customer satisfaction. Firms can optimize their order management processes by streamlining workflows, reducing errors, and improving accuracy [15]. Using real-time data and simulations, firms can better anticipate demand, allocate resources, and optimize production schedules [7]. Integrating customer data and preferences data with the supply chain processes firms can personalize customer experiences by offering tailored products, services, and delivery options. Enabling real-time monitoring of the supply chain, allows firms to detect and respond to customer needs more rapidly and if necessary, take immediate corrective actions and communicate proactively with customers [40]. Monitoring and analyzing product quality throughout the supply chain, firms can detect and address quality issues promptly, ensuring that customers receive products of high quality and reliability. Firms can collect feedback from customers and integrate it into their supply chain processes using digital twins. Analyzing customer feedback, areas for improvement can be identified, and the necessary process optimization can enhance the customer experience. This continuous improvement loop ensures that the supply chain is aligned with customer expectations, leading to higher customer satisfaction.

3.6 Lower Costs

Digital twins in supply chain management have the potential to lower costs by improving the operational efficiency. Simulating different scenarios and analyzing real-time data, firms can optimize processes such as inventory management, production scheduling, transportation routes, and warehouse operations leading to reduced costs by minimizing waste, improving resource utilization, and increasing overall operational efficiency [41]. Predictive maintenance facilitated by continuous monitoring of physical assets within the supply chain can help firms to predict maintenance needs and identify potential failures before they occur and thus lowering maintenance and repair costs. Further, analyzing real-time demand data, historical trends, and market forecasts, digital twins can optimize inventory levels based on customer demand and lead times more accurately preventing overstocking or stockouts, and thereby reduce inventory holding costs, and also minimize the risk of obsolete inventory [42]. Generating more accurate demand forecasts using digital twin data enables better production planning, procurement strategies, and resource allocation, reducing the risk of overproduction or stockouts and optimizing costs. Digital twins help optimize transportation operations by analyzing real-time data on routes, traffic, and delivery schedules [43]. Simulating different transportation scenarios, firms can identify the most efficient routes, reduce fuel consumption, and optimize delivery schedules [3]. Further, the digital twins also contribute to cost reduction by helping to mitigate risks within the supply chain. By leveraging these cost-saving opportunities, digital twins in supply chain management help firms to lower costs and improve profitability throughout the supply chain.

4 Implementation of Digital Twins in Supply Chain

Implementing digital twins in the supply chain is a challenging task that necessitates collaboration across several functions and stakeholders. For the successful implementation of digital twins, a well-defined plan, the provision of appropriate resources, and organizational commitment are required. This section discusses the

10-step process presented in Fig. 3, for successful implementation of digital twins in the supply chains. The steps are as follows,

(i) *Define clear objectives*: Clearly define the objectives and expected outcomes for digital twins' implementation in the supply chain. By identifying the specific areas, processes, or assets where digital twins are to be deployed and the goals to achieve are to be identified clearly for successful implementation.
(ii) *Identify Key Processes and Assets*: Identifying the key processes, systems, and physical assets within the firms' supply chain that will benefit from digital twins includes identifying the manufacturing equipment, transportation systems, inventory management, or demand forecasting. This should be followed by prioritizing the areas that will have the most significant impact on your supply chain operations and customer satisfaction for successful implementation.
(iii) *Data Collection and Integration*: Data sources required to create a digital twin for each identified process or assets including data from sensors, IoT devices, ERP systems, and external sources. Determining and defining the data collection mechanisms, ensuring data accuracy and quality, and establishing protocols for data integration into the digital twin platform are key activities.
(iv) *Technological Infrastructure*: Assessing existing technological infrastructure and identifying gaps for implementing digital twins considering the need for cloud-based platforms, data storage and processing capabilities, connectivity requirements, and security measures are critical. Selection of appropriate tools and efficient technologies will support the creation and management of digital twins effectively.
(v) *Accurate Model Development*: Developing accurate representation models involve creating computer-aided design models, simulation models, or mathematical models depending on the type of digital twin. Ensuring that the models capture the relevant parameters, behaviors, and performance metrics required for analysis and decision-making is needed for successful implementation.
(vi) *Data Visualization and Analytics*: Leveraging advanced analytics, machine learning, and AI capabilities to gain insights, predict outcomes, and optimize supply chain operations and implementing algorithms to support real-time visualization use of appropriate visualization tools help in meaningful presentation and provide platform for effective analytics.
(vii) *Integration*: Digital twins should be integrated with existing supply chain systems, such as ERP, warehouse management system, and/or transportation systems is the next step. Firms should ensure seamless data flow between the digital twin platform and these systems to enable real-time monitoring, analysis, and decision-making.
(viii) *Testing and Validation*: Once integration is complete, firms need to pilot test the digital twins in a controlled environment and validate its effectiveness and performance. Further monitoring and continuous measurement of the impact on key performance indicators such as efficiency, cost reduction, and customer satisfaction are required. Based on the feedback received from stakeholders,

necessary corrections need to be incorporated to optimize the performance of digital twins.

(ix) *Scaling and Deployment*: Post successful pilot testing, firms should go for scaling up the implementation of digital twins across the supply chain. Deployment on a broader range of processes, assets, and stakeholders through gradual adoption should be coupled with established protocols for ongoing maintenance, data updates, and continuous improvement of the digital twins.

(x) *Training and Change Management*: Final step towards successful implementation is provide training and support to the entire supply chain teams involved in working with digital twins. Firms should ensure that stakeholders understand the purpose, benefits, and functionalities of digital twins and how to effectively utilize them in their day-to-day operations.

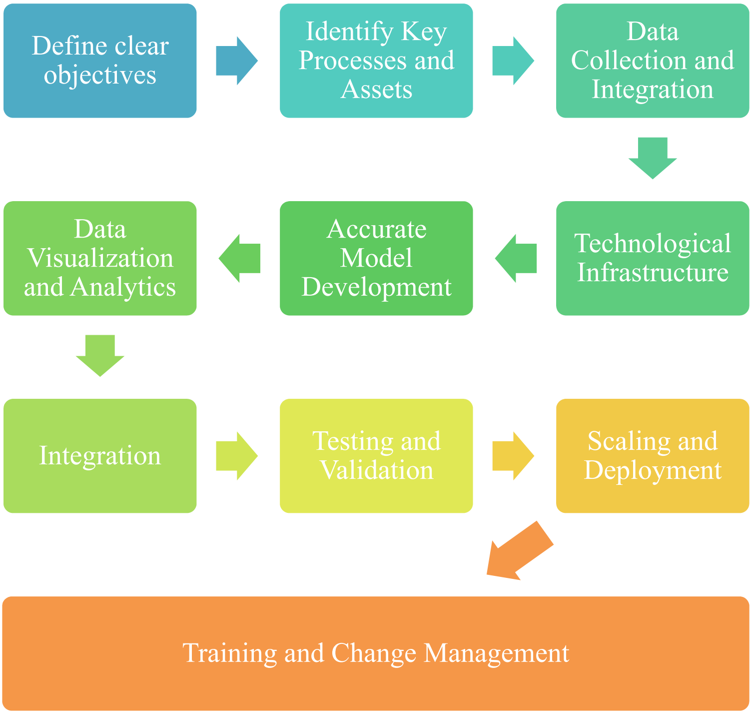

Fig. 3 10-step model implementation model for digital twins in supply chains

5 Challenges in Implementing Digital Twins in Supply Chain

Though implementing digital twins in the supply chain provides several benefits to stakeholders, it also comes with several obstacles and risks. This section discussed some of the common challenges and risks associated with implementing digital twins in the supply chain.

(i) *Data Integration and Quality*: Integrating the data acquired from various sources, ensuring date accuracy, consistency, and reliability is a significant challenge [44]. Digital twins require reliability on real-time to provide meaningful insights and predictions and hence, ensuring proper data integration, data cleansing, and establishing overall data governance processes is critical to address this challenge.

(ii) *Infrastructure and Connectivity*: Robust technological infrastructure, including hardware, software, and network capabilities supporting data collection, storage, processing, and real-time connectivity are essential for seamless integration [45]. Lack of adequate infrastructure and connectivity can hinder the effectiveness and responsiveness of digital twins.

(iii) *Model Development and Validation*: Developing accurate and reliable digital twin models that adequately represent the system requires domain expertise, data analytics capabilities within the organization [46]. Ensuring the accuracy and reliability of models is necessary for accurate predictions and decision-making and hence this is an important challenge.

(iv) *Organizational Culture*: Introducing digital twins require a significant change in existing processes, workflows, and organizational culture in traditional organizations [45]. Hence, resistance to change and lack of acceptance from employees can hinder the successful implementation of digital twins. Effective change management strategy should be in place to address these challenges.

(v) *Capital investment and ROI*: Significant upfront capital investment, including technology investments, data infrastructure, and expertise is required for successful implementation [47]. Assessing the return on investment (ROI) and justifying the cost can be challenging, particularly in the initial stage and organizations need to carefully evaluate the potential benefits and weigh them against the costs to ensure a positive ROI.

(vi) *Data Security and Privacy*: Connectivity and data sharing involved in digital twins, data security and privacy are critical concerns [48]. Protecting sensitive data, adhering to data protection regulations, backed up with robust security measures to prevent unauthorized access or data breaches are crucial to ensure data security.

(vii) *Scalability and Integration*: Scaling digital twins across the entire supply chain and integrating them with existing systems can be challenging [3]. Compatibility issues, data synchronization, and ensuring seamless integration within the existing network systems require additional effort and resources

[44]. Hence, organizations need to account for scalability and interoperability requirements as early as possible during the implementation process.

(viii) *Skill and Knowledge Gap*: Implementing and managing digital twins requires expertise in data analytics, simulation, modeling, and technology [49]. Organizations may face challenges in finding and retaining skilled professionals with the required knowledge and experience to develop, deploy, and operate digital twins effectively.

(ix) *Vendor Selection and Partnerships*: Selecting right technology vendors and establishing partnerships are crucial to the success of digital twin implementations [44]. Evaluating vendor capabilities, establishing reliable support and maintenance frameworks and building long term partnerships are critical in mitigating risks and ensuring successful implementation.

To address the above-mentioned challenges and risks, organizations should set up functional teams prioritizing risk management, invest in necessary resources, and continuously monitor the implementation process.

6 Conclusion

Though digital twins for supply chain management are not developed so long ago, it is fair to accept that they have emerged as a critical tool for supply chain digitalization. Digital twins offer immense potential for operational excellence and efficient decision-making in supply chain management. This chapter explored the importance and the potential benefits offered by digital twins, and the challenges involved in the successful implementation in a supply chain context. Digital twins not only provide a virtual representation of physical assets, processes, and systems in the supply chain, but also enable real-time monitoring, analysis, and optimization of the entire supply chain. With enhancement in visibility offered by digital twins, organizations can track and manage their supply chain operations more effectively. The potential benefits include increased efficiency and productivity, efficient resource utilization improved risk management, better collaboration, and higher customer satisfaction. Looking forward, digital twins offer a promising future in the field of supply chain management. With advancing technology, digital twins will only become more sophisticated, leveraging artificial intelligence, machine learning, and big data analytics. This will further improve predictive capabilities and enable organizations to anticipate and prevent supply chain disruptions more accurately. Future digital twins will also play a crucial role in enabling end-to-end supply chain visibility and traceability, supporting sustainability efforts, and facilitating the integration of emerging technologies like blockchain and advances in the Internet of Things. Though digital twins pose several advantages, to fully harness the potential of digital twins in the supply chain, organizations must address several implementation challenges such as data integration, infrastructure requirements, model development, and change management. Investing in right technology infrastructure, data governance processes, and skilled resources, selecting and collaborating with the correct technology vendors and building long term partnerships will be key to success. To summarize, digital twins are a game-changer in supply chain management which can enable organizations to leverage data and technology to drive efficiency, collaboration, and customer satisfaction. The future of digital twins holds even greater potential, which can empower organizations to achieve end-to-end supply chain visibility and adopt emerging disruptive technologies. By embracing digital twins, organizations can competitive and in fact stay ahead in the digital era and unlock new opportunities for supply chain optimization.

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Requirements for the Adoption of Industry 4.0 in the Sustainable Manufacturing Supply Chain

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Abstract The commencement of Industry 4.0 is dramatically changing the method of working in the manufacturing sector and it is anticipated to lead the way for forthcoming intelligent industries with smart machines and interconnected networks to accomplish higher productivity, profitability, and operations flexibility without affecting the ecosystem and society. The adoption of Industry 4.0 are crucial to achieving sustainable development. This is because the technological developments in Industry 4.0 not merely encourage the sustainable initiatives to increase the financial benefits besides diminishing the impact on the environment and exerting an influence on the development of society nearby. But the Industry 4.0 adoption in the manufacturing sector to limit non-eco-friendly practices have substantial challenges to face. To address the above problem, this chapter attempts to elucidate the dimensions and requirements available from the literature for Industry 4.0 adoption in the manufacturing supply chain. The identified requirements from this chapter were categorized into five dimensions from the context of sustainable, organizational and technological. The requirements identified from this study can assist managers and policymakers for the adoption of Industry 4.0 especially helpful to organizations keen to enhance their sustainability from the aspect of competitive advantage.

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1 Introduction

In the contemporary global environment, several organizations are incorporating innovative technology into their production systems, thereby enhancing their productiveness, producing better quality products, and at the same time mitigating the risks and ensuring environmental sustainability [1–3]. The Industry 4.0 (I4.0) concept is becoming more popular across organizations due to its benefits in production and manufacturing processes along with protecting the environment [3]. Industry 4.0 tries to completely automate manufacturing systems irrespective of the types of production systems. It uses all the latest hardware and software technologies available to connect machines, products, materials, material handling systems, and labour so that the entire process is completely self-driven with minimum human intervention. There has been a revolution in manufacturing after bringing forth I4.0. The perspective itself is very new, as manufacturers collaborate with emerging technologies to acquire the utmost yield with minimal input in terms of utilization of the above-said resources. I4.0 was a terminology that stemmed from a German project that married manufacturing with Information technology [4].

I4.0 is a system depending heavily on integration and connection between machines and humans and this information is also being continuously monitored online from anywhere and at any time [5]. Though the manufacturing sector is prepared for adopting technological advancements, they are pending at the connectivity stage [6]. I4.0 is a technology-driven phenomenon to transform the production and manufacturing systems throughout firms. It is the foundation that provides the strength in advancing technology for the manufacturing sector's products and processes [5, 7, 8]. The following are key essential enablers of this transition for the manufacturing sector, namely Cyber-physical systems (CPS), big data, Artificial Intelligence (AI), Cloud computing, Internet of Things (IoT) and Augmented reality [8, 9].

The wider application of cutting-edge technologies in the production division has eased the movement toward I4.0 [10]. For instance, AR is evolving in all domains, right from entertainment to the lifesaving healthcare sector. It is also a challenging area as new AR gadgets which were luxury and affordable are becoming more accessible to the overall population [11]. Big data in businesses are exponentially increasing in volume, originating from the Internet of Things and information services [12]. The CPS is an inalienable part of making the entire smart factory adaptable [4, 13, 14]. For example, in the case of manufacturing, machines like lathes, grinders and millers are connected to a computer processing unit [4, 15, 16]. Industry 4.0 tries to automate manufacturing systems which are somewhat similar to Enterprise Resource Planning (ERP) in automating business processes and decision-making. ERP needs a lot of enablers and factors for implementing it in organizations. Similarly, I4.0 also needs some basic requirements as a form of change management in manufacturing systems and supply chains to become sustainable [3, 17, 18]. Identifying the requirements of the manufacturing divisions becomes very important for implementing Industry 4.0 in their concern to minimize the environmental and societal impact [3]. Hence there is a dire need to identify the requirements in implementation for the smooth conduct of I4.0 for the manufacturing supply chain [8].

The present chapter attempts to delineate the key requirements for the I4.0 adoption in sustainable manufacturing supply chain. The rest of the chapter is structured in this way. The linkages between I4.0 and sustainable manufacturing supply chain are presented in Sect. 2. Section 3 detailed the various technologies of I4.0 and their application in the manufacturing supply chain. The need for requirements for the I4.0 adoption is addressed in Sect. 4. Section 5 clearly explained the dimensions and requirements identified from the literature for the adoption of I4.0. Section 6 summarizes the conclusion and directions for the future.

2 Connecting Sustainable Manufacturing Supply Chain and Industry 4.0

According to a holistic concept of sustainability (Brundtland [19]) and based on recent literature by Ansari and Kant [20], the sustainable manufacturing supply chain should be built on the triple bottom line concept (TBL) and should have three components of social, ecological, and economical. The sustainable manufacturing supply chain can be divided into four components namely sustainable sourcing, sustainable manufacturing, sustainable logistics and sustainable consumption and disposal. This above component encompasses methods and procedures that can make products of high quality and services through utilizing minimal resources from the environment, responsible sourcing, existence of a secure atmosphere for consumers, workers and the nearby community, being be-eco-friendly in terms of logistics and distribution, capable of alleviating the impacts on social and environmental across the entire lifecycle and sustainably making a profit.

There has been a great development in the operations and decision of manufacturing organizations after the initiation of I4.0 [3, 21]. Exponential growth in the last decade in the domain of Information and Communication Technology (ICT) and IoT has tremendously helped to adopt novel techniques in industrial firms in automation [3]. As a consequence of amalgamation of technology in manufacturing sector results in the emergence of "smart factories". These smart technology platforms impart great advantages for manufacturing companies to control environmental impact using IoT and ICT [3, 21, 22]. The advantage of these smart factories is highly efficient resource utilization, meeting the management goals by adapting quickly concerning current scenarios in the industry [4, 23].

3 Industry 4.0 Technologies

The world is encountering advanced technologies like I4.0 in manufacturing industries. I4.0 or Smart manufacturing has gained popularity in recent years [24]. It blends the IoT with smart factories to create an information technology platform that is driven by industrial processes for actual data on machines, the components flow, production, data integration for decision-making, monitoring and tracking of products [2, 25, 26]. The technologies of I4.0 such as cloud computing (CC), machine learning (ML), big data analytics (BDA), augmented reality (AR), autonomous robots, blockchain technology, cyber-physical systems (CPS), simulation, additive manufacturing (AM), cybersecurity, cloud manufacturing, Internet of Things (IoT) and drones are the applications found in the manufacturing process, logistics and supply chain [3, 27–29]. The advantages of these technologies are efficiency, transparency, traceability, sustainability, collaboration, and cost reduction [29].

Big Data Analytics (BDA): BDA analyses the real-time data to improve efficiency and reduces the variability in the process of making decisions [3, 30]. It also assists to monitor customer choices for better decision-making using analytical tools and computer algorithms [29, 31]. BDA aids in long-term achievements, corporate advantage [29, 32], product quality, and flexibility in manufacturing and equipment services through predictive maintenance [4, 33, 34]. Hence it is extensively used in manufacturing industries to control and identify faults.

Cyber-Physical Systems (CPS): CPS, one of the advancements of data processing and information technology is believed as a significant technology in Industry 4.0. It aims to integrate physical and virtual environments in controlling, planning tasks and procedures, and utilizing information by assessing and processing data [15, 35, 36]. The implementation of CPS in manufacturing, logistics and supply chain leads to industrial transformation [36]. Thus, CPS is a built in system that interacts with an intelligent network to share information and allow smart production.

Autonomous Robots: Autonomous Robots are environment-friendly machines capable of sensing their movement without human intervention [29]. It is used for transporting the components to their respective assembly line [37]. The robots aid the firm to work precisely in the area where workers are restricted or not able to operate [3, 27, 28]. It allows to minimize the working time, costs, and the emission of gases dramatically [37–39]. It is used for long distances along with the operational level of the supply chain [29]. Furthermore, the robots enhance work efficiency as it is accurate, cooperative and flexible.

Cloud Computing (CC): A program that offers internet services with storage space for storing data [40]. The cloud is located far away from the production area [29, 41]. The cloud provides services to the user like hardware, software and IT infrastructure. The user uses resources based on application needs and storage systems [42]. It is a computing technology with low cost, fast service, accessibility and high performance [29, 42].

Augmented reality (AR): AR is a service system that supports the industry through the communication device. It helps to gather real-time information and data from consumers thus improving the work facility and multiple decision-making in the manufacturing sector [3, 38]. AR supports many services such as maintenance procedures and improves work and assists virtual training [37, 43, 44]. It helps in repair operations and instructs workers in the industry related to repair operations [3].

Simulation: Simulation is a technology to plan, develop and optimize decision-making in the designing and operations of smart and complex production systems. It aids manufacturing industries to analyse the costs, risks, barriers, and operational performance [45]. Thus, it improves plant operations in the real-world related to humans, products, and machines [3, 38]. Two-dimensional and three-dimensional simulations are used widely in manufacturing industries to simulate the industrial process like cycle time, material use, and energy consumption [46]. Simulations help to reduce the generation of waste, production downtime, and production failure [3].

Additive manufacturing: Additive manufacturing aids industrial firms to produce a diminutive number of custom-made products with optimized design [38]. It reduces material wastage, production time [37, 47, 48] stock on hand and transport distances [3, 38]. The change in demand can be easily adjusted using additive manufacturing by frequently changing the product design [3]. Hence additive manufacturing is very useful in the manufacturing industry.

Machine Learning (ML): A computer-aided technology that extracts data from big data, both unstructured and structured that are achieved from a business [3, 49]. ML assists the manufacturing industry in monitoring defects and predicting the future thus helping in better performance in making decisions [28].

Cyber Security: Cyber Security is amongst the most significant requirement in the implementation of Industry 4.0 due to the increased risk of attacks on data in the industry [37, 50]. It is essential to utilize and connect protocols for communication, especially for operational purposes. Hence to safeguard the industrial system against the risks, there is a need for more sophisticated, reliable and secure frameworks for operating the machines [3, 30, 38].

Cloud manufacturing: It is the method of allocating manufacturing facilities and assets through the Internet and establishing a virtual environment [29]. It is a service-based activity that assists to interact with the consumers and providers for selling and acquiring the services such as simulation, product design, assembly, and production [29, 41].

Block Chain Technology: It is a emerging technology that shares data on a peer-to-peer network [29]. It reshapes the business model with the amalgamation of Industry 4.0 by creating and keeping records across industries. Block Chain helps in creating reliable information as it is irreversible, transparent, and flexible [51, 52].

Internet of Things (IoT): IoT has played a major role in industries as it facilitates production due to the integration of the Internet of Manufacturing Service (IoMs), Internet of Service (IoS), Internet of People (IoP), and communication technologies [3, 30, 37, 38]. It helps to change supply chain management communication through offering human-to-thing communication [53]. Ben-Daya et al. [53] defined IoT as "The Internet of Things is a network of physical objects that are digitally connected to sense, monitor and interact within a company and between the company and its supply chain enabling agility, visibility, tracking and information sharing to facilitate timely planning, control and coordination of the supply chain processes". The IoT integrates the data from virtual space and assists production activities for continual improvement [3, 54]. IoT systems are intelligent as they operate accurately and effectively with equipment from far places [29, 55]. IoT software aids in machine controlling and intelligent planning [3].

Drones: Drones are used for sudden inspection to map, survey, and transport lightweight material from one location to another [37, 56]. It supports the acquisition of real data for various studies and maintenance and repair activities. The major benefits are reduced human error, fast and accurate results in a short time, and flexible and easy identification of defects [37].

4 Need for Requirements of Industry 4.0

This section focuses on the need for requirements in the concept of Industry 4.0 and its implications. Though there are a lot of terms that might overlap like enhancers, enablers, key factors, key resources, key components, determinants, readiness framework, competencies, critical success factors and requirements, basically they mean the necessities for adoption and execution of I4.0. The requirements for Industry 4.0 are explained briefly under the different heads in the next section.

5 Requirements Identified for the Adoption of Industry 4.0

After a careful review of existing literature in the journal from various databases like Web of Science, SCOPUS, and Google Scholar, using keywords "requirements for adoption of Industry 4.0", "implementation of Industry 4.0", and "sustainable manufacturing", overall, the requirements can be classified under few generic dimensions.

The dimensions of social, technical, work organizational, and environmental dimensions were considered by Marcon et al. [57]. Narula et al. [58] added the dimensions in the directions of manufacturing from design to quality management. On a complimentary note, there is also the effect of I4.0 on sustainable development which includes Economy, Social and environmental dimensions [59]. Driving, facilitating, and impeding dimensions were considered as requirements for integrating positive and negative factors in better decision-making [60]. The existing studies on I4.0 adoption have mainly concentrated on analysing the technological and organisational impact, with little attention paid to the societal and environmental perspectives [61–64]. But a comprehensive dimensional coverage is incorporated for this study from the adaptation of Sharma et al. [65]. A comprehensive list of the dimensions and requirements which is partially adapted from the work of Bermudez and Juarez [66] is presented in Table 1. A brief explanation of each of the dimensions is given below.

Table 1 Dimensions and requirements identified for the adoption industry 4.0 in the sustainable manufacturing supply chain

S. no	Dimensions	Requirements	Source
1	Technological	Controlling and monitoring of Current production planning Cloud manufacturing Management of software for managerial activities e-Leadership skills Flexibility in the production process Automation of processes for cost reduction Additive manufacturing Robotics Virtual Reality (VR), mixed reality, and augmented reality Standardized internal and external connectivity for communication Use of IT-enabled technologies to deliver and provide digitization	Liu and Xu [41] Bermudez and Juarez [66] Sanders et al. [69] Ivanov et al. [70] Oesterreich and Teuteberg [71] Kamble et al. [72] Agarwal, Ojha [73] Cuevas-Vargas et al. [93] Bo-Hu [94]
2	Organizational	Strategic development of policies to address employer resistance to smart revolutions Stronger leadership tools Innovative management systems Long term investments Inventory control systems, Strategic organisational policies Welcoming corporate and organizational culture Employees strategically aligning with the leadership Readiness for organizational change Developing inter-functional teams Effective organization cross cycle Cross-sector collaboration Continuous monitoring of employee adoption Preparatory and training activities Create constant knowledge in the team especially with respect to I4.0 adoption Progressive mentality to address issues pertaining to process transformation Developing inter-functional teams Encourage continuous learning Develop skills and improvement processes Processing capability Exchange information and knowledge Empower workers Encourage participation in decision-making	Müller et al. [62] Bermúdez and Juárez [66] Liao et al. [67] Agarwal, and Ojha [73] Luthra and Mangla [75] Hirsch-Kreinsen [76] Kamble et al. [77] Jayashree et al. [78] Bag et al. [79]

(continued)

Table 1 (continued)

S. no	Dimensions	Requirements	Source
3	Economic	Network architectures and the design of effective global production networks and comparison using various cost-optimized settings Information and Digital Technologies knowledge and competency Open to change Reduction in manufacturing costs Greater flexibility, Introduction of simulation models Predictive analytics to automate manufacturing processes and aid in quicker fault discovery Knowledge about lean philosophy Increasing process transparency and retrofitting existing production equipment Circular product design and production Traceability of process and product Autoconfigured workstation layout Assembly control systems Problem-solving Adopting novel models of work and organization Strategic road-mapping for manufacturing digitalization	Bermúdez and Juárez [66] Sanders et al. [69] Oesterreich and Teuteberg [71] Bag et al. [79] Schuh et al. [84] Ramadan et al. [85] Yuan et al. [86] Belhadi et al. [87] Tortorella and Fettermann [88] Lorentz et al. [95] Tamás and Illés [96] Ghobakhloo and Ching [97]
4	Environment	Smart energy systems Environmental knowledge Awareness about eecosystem Knowledge about reverse logistics Green human resources Reduced emissions Environmental cooperation Reducing production waste Image of green branding Implementing green initiatives Energy savings Better human–machine interaction Strengthened human-learning through smart and intelligent assistance unit Environmental effects reduction Environmental accidents reduction Reducing penalty of environmental disasters Flow in lean production Thinking adaptively Cognitive load management and virtual collaboration Computational thinking Literacy in new media Product lifecycle management enhanced by intelligent manufacturing settings Transdisciplinary Design mentality Design of smart products Intercultural competencies End-of-life resource management	Machedo et al. [44] Thakur and Mangla [64] Sharma et al. [65] Bermúdez and Juárez [66] Ivanov et al. [70] Kamble et al. [72] Bag et al. [79] Gardas et al. [81] Skilton and Robinson [89] Kamble et al. [90] Ding et al. [91] Davies et al. [98]

(continued)

Table 1 (continued)

S. no	Dimensions	Requirements	Source
5	Social	Ability to generate new management practices Protection of price Local Markets Development of youth Developing individualised incentive programmes to enhance external motivation based on worker performance Applying technologies to enhance the employees skills through training Conversing with them to better understand their needs Ensuring user-friendly manufacturing and maintenance technologies Decentralized planning and execution with global standards, Managing legal and bureaucratic hurdles Development of community Ergonomic and safety improvements Establishing novel practices through formulating innovative strategies Association with foreign affairs Non-invasive interactions Corporate Social Responsibility (CSR) Social regulatory factors	Sharma et al. [65] Bermúdez and Juárez [66] Agarwal, and Ojha [73] Cuevas-Vargas et al. [93] Camisón and Villar-López [99] Wang et al. [100] Govindan et al. [101] Roldan et al. [102]

5.1 Technological Dimension

The technological dimension is important for I4.0 as most of the requirements are dependent on this technology for the successful adoption of I4.0. Using IT-enabled smart manufacturing, I4.0 connects people and machines, facilitating communication across all participants in the value chain [44]. In a smart manufacturing unit, the communication between machines and manufactured goods facilitates smooth production flow. According to Liao et al. [67] and Theorin et al. [68], intelligent systems are fitted with sensors that allow for secure connections between devices, machines, products, and things. Real-time production planning and monitoring are made possible by the revolutionary changes in operation execution in the manufacturing environment [69, 70]. Additive manufacturing, robotics, Virtual Reality (VR), mixed reality, and augmented reality are still in their blooming or formative stages, while a great deal of crucial technologies, such as modularization, mobile computing, and cloud computing, are currently moving closer to market maturity [71, 72]. The technologies required for cloud manufacturing software, management of software for managerial activities e-Leadership skills required for a manager are important requirements of information and communication technologies [66]. Flexibility in the production process, automation of processes for cost reduction, standardized internal and external connectivity for communication, use of IT-enabled technologies to deliver and provide digitization as a technology for the adoption of I4.0 [73].

5.2 Organizational Dimension

The organizational dimension is another important dimension for the successful adoption and implementation of I4.0. I4.0 needs to solve the serious issues it faces, such as collaboration, monitoring, and training where more direction and instruction are needed [67]. It is crucial to recognise that I4.0's organisational dimension necessitates "digital transformation" (Tesch et al. [74]), which also calls for a fresh, progressive mentality to address issues pertaining to process transformation [75]. Employer not welcoming smart revolutions should be addressed by organisations through the development of policies [76]. To promote the adoption of Industry 4.0, businesses must also develop their competencies, such as stronger leadership tools, strategic organisational policies, workforce knowledge, and a welcoming corporate culture [77]. I4.0 is being fuelled in large part by top management initiative and involvement, which is essential and is seen as one of the key requirements [75]. The management should encourage organizational learning, developing inter-functional teams, often conducting prior preparatory activities, and training activities [78]. The teams should be having good organizational culture and have required project management resources. An effective organizational cross cycle and cross-sector collaboration must be encouraged. Innovative management systems, investing in long-term projects and having better inventory control systems are also necessary requirements. It is crucial for employees to strategically align with the leadership, readiness for organizational change, and gain knowledge and skills related to I4.0 adoption and processing capability [73, 79]. Government assistance is also noted as a key motivator throughout the early phases of I4.0 adoption [62].

5.3 Economic Dimension

Sustainability has three main pillars namely economic, environmental and social aspects [80]. According to Gardas et al. [81], the goal of sustainable manufacturing is to manufacture and supply items while using the least amount of resources possible. This reduces emissions, production waste, and other harmful elements. Kazancoglu et al. [82] added that sustainable manufacturing should additionally lead to enhanced safety standards, ergonomics practises, and a reduction in energy use. According to Stock and Seliger [2] and de Jesus Pacheco et al. [83], I4.0 should answer the needs of the manufacturing industry and contribute to the production of sustainable value. In the literature, the economic dimension is covered by the way of cost of migration between network architectures and the design of effective global production networks and comparison using various cost-optimized settings [71, 84]. A few additional studies (Ramadan et al. [85]) also highlighted the advantages of reduced manufacturing costs and improvements in economic performance. The literature also supported the use of predictive analytics to automate manufacturing processes and aid in quicker fault discovery [86]. Additionally, Industry 4.0

assists manufacturing companies in becoming "lean" by lowering production costs. From an economic point of view, it's important to note that I4.0 lowers logistical costs by increasing process transparency and retrofitting existing production equipment [69, 87, 88]. Circular product design and production, product and process traceability, self-configured workstation layout, and assembly control systems act as important requirements concerning the adoption of I4.0 [79]. However, Ghobakhloo [6] coined a term called "Smart Manufacturing-related Information and Digital Technologies (SMIDT)" and based on this, perceived value, perceived costs, perceived compatibility, information processing requirements, knowledge and competency of Information and Digital Technologies, and strategic road-mapping for manufacturing digitalization, were considered under economic requirements for adoption of I4.0.

5.4 Environment Dimension

The environment dimension is a very important pillar of sustainable development. The length of the multi-tier supply chains affects environmental and social variables in addition to economic performance metrics including cost, responsiveness, quality, and resilience [89, 90]. One of the key advantages of I4.0 is better human–machine interaction and strengthened human-learning through smart and intelligent assistance units [64, 72]. Additionally, smart energy systems aid in reducing energy usage [91]. Product lifecycle management is enhanced by intelligent manufacturing settings, which also results in waste reduction, greater resource utilisation, and reduced greenhouse gas emissions. Social intelligence, thinking adaptively, design mentality, computational thinking, intercultural competencies, management of cognitive loads and virtual collaboration, encourage environmental aspects [66]. Environmental knowledge, awareness about environment, knowledge about reverse logistics, green human resources, and environmental cooperation are few other important requirements under environmental dimensions for the adoption of I4.0 [79].

5.5 Social Dimension

The Social Dimension is also critical concerning the triple-bottom approach of the third pillar of sustainable development. It is important with respect to the adoption of I4.0 as well. In manufacturing environments, the social dimension focuses on increasing operator satisfaction [92]. The ability to generate novel management practices, collaborating with the external suppliers, creativity in strategic designing for introduction of new practices, and public institutions and research encourage social dimensional requirements [66]. Technology-process-people are the pillars behind organizational culture changes, ensuring supply chain capability to digitally comply. Few approaches were suggested by Stock and Seliger [2], on dealing with social issues, they are developing individualised incentive programmes to enhance external motivation based on worker performance, arranging training to increase workers' competence by integrating emerging IT technologies and conversing with them to better understand their needs also ensure social aspect. Ensuring user-friendly manufacturing and maintenance technologies, decentralized planning and execution with global standards, and managing legal and bureaucratic hurdles also act as requirements for I4.0 technology adoption [73].

These requirements are provided to help managers accomplish the adoption of Industry 4.0, especially with respect to sustainable manufacturing. This not only helps in obtaining sustainable benefits but also helps the industrial managers to improve the technological and organizational aspects based on the guidelines followed.

6 Conclusions

This chapter contributes to the requirements for the adoption of I4.0 for a sustainable manufacturing supply chain by using the technological advances of Industry 4.0 to accomplish the benefits of sustainable development. Furthermore, the concept of sustainability and I4.0 are clearly explained through the literature coupled with the links between I4.0 and sustainable manufacturing supply chains. In this chapter, the identified requirements from the literature were grouped into five dimensions from the aspect of sustainability, organization, and technology. The requirements identified may act as a framework for industries that are in changeover in the direction of smart factories. Also, the identified requirements will assist researchers, practitioners, and policymakers to form a holistic strategy for transformation towards I4.0 and ascertain that they embark on the right foot. Moreover, this chapter offers some beneficial recommendations to practitioners such as concentrating on establishing infrastructure for Information Technology (IT), management flexibility, and building reliable execution teams to expedite the adoption of I4.0 and sustainable transformation.

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