Theoretical and Technological Analysis of Smart Manufacturing Systems

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Article Info
Journal of Journal of Enterprise and Business Intelligence (http://anapub.co.ke/journals/jebi/jebi.html)
Doi: https://doi.org/10.53759/5181/JEBI202404002
Received 20 March 2023; Revised from 15 May 2023; Accepted 10 Jul 2023.
Available online 05 January 2024.

Abstract – This study presents a comprehensive evaluation of the current status of smart manufacturing systems (SMS), with a specific emphasis on their theoretical significance in the context of technology management and technology development. The paper examines the theoretical underpinnings of development of technology through the lens of Rogers' Diffusion of Innovation (DoI) theory. Additionally, the paper employs Rieck and Dickson's Technology Strategy Model (TSM) to emphasize the importance of technology management. By incorporating the Management of Technology (MOT) theory, the paper aims to provide a comprehensive framework for understanding and shaping technology development. The integration of several technologies inside the SMS system has been the subject of discussion in relation to patenting. The features of Smart Manufacturing Systems (SMS) have been examined in order to analyze the comprehensive components of this emerging technological system. The suggested SMS model of the clothing manufacturing unit has been used to represent the global textile complex. This research incorporates recent scholarly publications and advancements in technology to provide a comprehensive understanding of future manufacturing system views. The objective is to minimize human involvement and enhance production efficiency within the manufacturing business. The primary components of the SMS have been identified as the cyber-physical system, artificial intelligence (AI), digital twin, enterprise resource planning, additive manufacturing, and big data.

Keywords – Smart Manufacturing Systems, Cyber-Physical Systems, Rogers Diffusion of Innovation, Rieck and Dickson's Technology Strategy Model.

I. INTRODUCTION

An envisagement of future manufacturing goods autonomously navigating their way throughout the production process. In the context of intelligent factories, there exists a cooperative communication system between machines and products, which facilitates the driving force behind production. This system is characterized by the interconnectivity of raw materials and machinery within an overarching network known as the Internet of Things. Currently, there are factories that incorporate networked machines and products. However, in the future, these previously isolated systems will be interconnected within a comprehensive network. All devices, machines, and materials will be equipped with sensors and communication technology, enabling them to establish connections with one another. These interconnected systems are commonly known as CPS. One notable aspect is their ability to engage in cooperative communication and control. The concept of Industry 4.0 is grounded on the rules of cyber-physical systems.

Smart manufacturing enables plant managers to autonomously gather and evaluate data in order to enhance decision-making processes and improve production operations [1]. Smart manufacturing revolves on the use of data, which serves as a guide for determining optimal actions and their appropriate timing. The aforementioned phenomenon has considerable disruptive capabilities and holds the potential to significantly reshape the existing competitive framework within the industrial sector. Industrial industrial equipment often experiences gradual wear and tear. Hence, the implementation of autonomous and in situ monitoring and maintenance methods poses significant challenges. Given the need to observe surroundings that may be difficult to access while maintaining uninterrupted production, industrial processes provide ideal opportunities for the use of remote monitoring methods. The deployment of sensors in industrial processes is seeing a fast growth mostly attributed to the notable decrease in sensor expenses, developments in sensing technology, and the emergence of sophisticated analytical tools capable of extracting and uncovering valuable insights from the collected data. The phenomenon of increased sensor use has been designated as the IIoT (Industrial Internet of Things) in recent times.

a) The IIoT integrates big data and machine learning technology, using the sensor data, M2M (machine-to-machine) connectivity, and technologies of automation that have been present in industrial environments for an extended period.
b) The underlying principle driving the IIoT is the belief that intelligent robots possess superior capabilities compared to people in effectively and consistently collecting and transmitting data.
c) The utilization of this data may facilitate firms in identifying inefficiencies and issues at an earlier stage, resulting in time and cost savings, as well as bolstering business intelligence endeavors.
d) In the realm of manufacturing, the Industrial Internet of Things (IIoT) presents significant opportunities for enhancing quality control, implementing sustainable and environmentally friendly practices, ensuring traceability throughout the supply chain, and improving overall supply chain efficiency.

The transmission of data from sensors and equipment to the Cloud is facilitated by Internet of Things (IoT) connection solutions that have been implemented inside the factory. The data is subjected to analysis and then integrated with contextual information, after which it is sent to stakeholders who possess the necessary authorization. The Internet of Things (IoT) technology, which utilizes both wired and wireless connection, facilitates the transmission of data. This allows for remote monitoring and management of operations, as well as the capacity to promptly modify production plans in real-time, if necessary. The use of this approach significantly enhances manufacturing results by effectively decreasing waste, expediting production processes, and enhancing both yield and the overall quality of the things produced. The implementation of smart manufacturing necessitates the integration of data both horizontally and vertically across the whole of the organization. Vertical digitization encompasses several aspects of business operations, such as production, product life cycle management, supply chain, procurement, logistical operations, and quality control. These elements are connected to provide a smooth and uninterrupted flow of data. Horizontal digitization encompasses the integration of data with suppliers, customers, and critical partners. The achievement of integration necessitates the enhancement and replacement of equipment, networks, and processes until the desired level of integration is attained.

According to Kharchenko [2], the IoT may be conceptualized as a global digital nervous system. The complete implementation of the IoT may be conceptualized as a dynamic creature that has the ability to perceive and interact with its surroundings via sensory capabilities, akin to a biological organism. When sensory input from a finger indicates that an object is too hot, it is essential for this information to be rapidly transmitted to the brain in order to prompt the withdrawal of the hand. Cameras and microphones are used as visual and auditory sensory devices, while other sensory organs are utilized to assess a wide range of phenomena, including temperature and pressure variations (see **Fig 1)**.

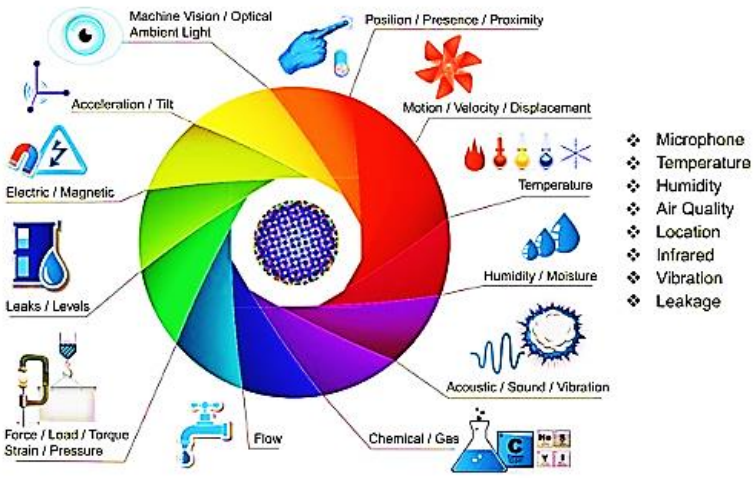

Fig 1. Digital Nervous System Comprising Super Sensors.

This research incorporates recent scholarly publications and advanced technological advancements in order to provide a comprehensive understanding of future manufacturing system views. The objective is to reduce human involvement and enhance production efficiency within the manufacturing sector. The primary components of SMS have been recognized as the cyber-physical system, artificial intelligence (AI), enterprise resource planning (ERP), digital twin, big data, and additive manufacturing. The remainder of the article has been organized as follows: Section II presents the research methodology employed in this research. Section III reviews different theoretical foundations for this research, such as Rogers' diffusion of innovation theory, phases of technology development, and model of technology strategy. Section IV presents the respective functions and components of SMS. These reviewed components include CPS, IoT, robotics, AI, advanced ERP, digital twin, additive manufacturing, cloud manufacturing, and big data. Lastly, Section V presents drawing remarks to the paper.

II. RESEARCH METHODOLOGY

This research includes a dual review. The first section primarily centers on two prominent theoretical frameworks, namely technology management and technology development. The innovation theory diffusion proposed by Rogers has been widely used as a fundamental framework for technology development. Similarly, the model of technology strategy developed by Dickson and Rieck in 1993 has been widely used as a foundational framework for reviewing technology management. The examination of these two ideas has been undertaken with regard to viewpoints on innovation and management. In the following section, the theoretical significance of SMS has been addressed. then, the primary constituents of the aforementioned subject matter are recognized and then expounded upon. A model patent workshop has been detailed, including its operational framework. The properties of SMS, being a novel manufacturing paradigm, have also been subject to scrutiny and evaluation. The practical implementation of Smart Manufacturing Systems (SMS) has been effectively shown by its use within the worldwide textile industry [3].

III. THEORETICAL ANALYSIS

Rogers' Diffusion of Innovation Theory

The Diffusion of Innovation Theory (DIT) framework developed by Rogers is a widely recognized empirical model that provides a conceptual understanding of the diffusion of innovation [4]. This framework can also be utilized to examine the adoption of educational technology within the field of education. Recently, the Diffusion of Innovation Theory (DIT) was used in a study conducted by Kharbat and Abu Daabes [5] to investigate the implementation of online proctored tests in response to the COVID-19 pandemic. Additionally, Baskerville and Pries-Heje [6] deployed DIT to explore the adoption of experiential learning via live-in-labs. It is important to acknowledge that although there are several theoretical frameworks that discuss the adoption of innovation, they all conceptualize the components that influence the utilization or acceptance of the innovation. However, the present research specifically concentrates on the whole process of innovation adoption. The TAM (Technology Acceptance Model), as described by [7], identifies two key criteria related to innovation: perceived ease of use and perceived utility.

The UTAUT (Unified Theory of Acceptance of Technology) is a comprehensive framework that integrates several theories, including the TRA (Theory of Reasoned Action), TAM, TPB (Theory of Planned Behavior), and Diffusion of Innovation. This framework examines additional elements related to innovation. In recent studies, researchers have used several theoretical frameworks to analyze the elements that influence the adoption and utilization of online educational resources during the COVID-19 pandemic. Upon thorough examination of these models, our attention was directed towards Rogers' Diffusion of Innovations (DIT) Theory. This theory was chosen due to its comprehensive coverage of the variables influencing the adoption of machine learning (ML), as well as its detailed description of the sequential phases involved in the adoption process, totaling five in number. Therefore, the DIT theory was determined to be the most appropriate framework for the purpose of this research, which aims to investigate the process of machine learning adoption.

The decision process for innovation adoption is comprised of five steps, as posited by the Diffusion of Innovations Theory (DIT). The Knowledge Stage encompasses the acquisition of cognitive knowledge. Within this stage, the learner is introduced to the innovation, develops an awareness of it (referred to as awareness knowledge), and actively seeks information on how to effectively use it (known as how-to knowledge). In order to enhance the probability of persons adopting the innovation, it is essential that they possess a satisfactory degree of procedural understanding prior to engaging in autonomous utilization of the innovation. The Persuasion Stage primarily focuses on emotions, since it is at this phase that individuals develop their attitudes about the invention. During this phase, the individual encounters a sense of ambiguity and, as a result, may be swayed by social reinforcement to use the novel technology, in addition to the positive subjective evaluations of the device by peers. The Decision Stage pertains to the individual's decision about the adoption or rejection of the innovation. The probability of deciding to accept the innovation is positively correlated with the frequency of previous chances to experiment with it. The ultimate determination is influenced by three distinct categories of motivations: individual aspirations, social influence, and/or influence exerted by a figure of authority.

The adoption of technology during the pandemic was influenced by the distinct social circumstances and often guided by authoritative individuals such as school principals and the Ministry of Education. Consequently, it is intriguing to analyze the impact of each factor on the process of adoption. The Implementation Stage refers to the phase in which a person puts the invention into practice and evaluates the resulting consequences. Therefore, it is crucial, at this juncture, for users to get feedback, as well as guidance and support, from the individuals spearheading the shift, as this will aid in reducing anxiety among the novice users. Another helping factor at this phase is the concept of "reinvention," when users modify and alter the tool to suit their own requirements. There is a positive correlation between the number of adjustments implemented and the probability of consistent use of the instrument. Considering the intrinsic use of diverse applications in machine learning (ML), there exist several approaches to making modifications, so rendering it an optimum platform. During the Confirmation Stage, users engage in a reflective examination of the decision-making process and its results. This stage serves as an opportunity for users to seek confirmation for their choice and solidify their final opinions.

Previous research has investigated the adoption of technology, including machine learning (ML), by employing Rogers' theoretical framework. More recently, a questionnaire was developed based on this theory to assess the implementation of ML in the education sector. However, it is important to note that there is little research on the adoption and implementation process of educational technologies among pre-service teachers (PSTs) and in-service teachers (ISTs) within school settings. Furthermore, there is even less research on the process of adopting machine learning (ML) during times of crisis, particularly in relation to the shift towards distant learning. The examination of the attitudes of pre-service teachers (PSTs) and in-service teachers (ISTs) in relation to the adoption of machine learning (ML) is of particular significance due to prior research indicating that instructors and pupils are impacted by distinct variables when using technology. In recent times, some scholarly investigations have contended that it is crucial to do a comparative examination of the perspectives held by educators and students who are involved in the process of adopting new technology.

Therefore, a research investigation that explored the perspectives of educators and students on the implementation of online education during the COVID-19 pandemic revealed both shared and divergent viewpoints. This highlights the importance of considering both groups' perspectives in order to gain a comprehensive understanding of the issue. In particular, the perspectives of students mostly revolved on factors pertaining to the learning process, such as concentration. Conversely, educators predominantly directed their attention towards organizational elements and study materials, including matters relating to copyright. Recent research has shown that instructors outperformed their pupils in terms of personal innovativeness when it comes to the use of information technology. The existence of such disparity has the potential to give rise to divergent expectations between educators and students. Recent comparative research conducted by Tahriri and Divsar [8] examined the similarities and variations in the perspectives of instructors and learners across three distinct educational levels.

According to Lundvall [9], the concept of innovation may be described as an idea, activity, or item that is recognized as novel by a person. Rogers' discourses primarily focus on technical breakthroughs, which may be defined as designs for instrumental action aimed at reducing ambiguity in cause-effect linkages involved in achieving desired outcomes. Technology typically has two fundamental components, namely hardware and software. Hardware refers to the tangible components or physical entities of technological systems, including transistors and semiconductors.

In contrast, software encompasses technological instruments that consist of programmed instructions and information. Holmboe and Batalden [10] proposed a conceptual framework consisting of five key stages in the innovation-decision process, namely: (i) information acquisition, (ii) confirmation, (iii) decision-making, (iv) execution, and (v) persuasion. These five processes facilitate the dissemination of information from the stage of invention through execution and subsequently to the process of adoption. Knowledge acquisition occurs when an individual entity is exposed to the existence of an invention and acquires a certain level of understanding of its functionality. Persuasion occurs when an individual or any other entity responsible for decision-making adopts either a favorable or unfavorable stance towards innovation.

The process of decision-making occurs when an individual or a collective decision-making entity engages in actions that lead to the selection of either accepting or rejecting an invention, and considering elements outlined in **Table 1**. The process of implementation occurs when an individual or a collective entity incorporates an invention into practical application. Confirmation is a cognitive process whereby an individual or a decision-making entity seeks validation for a previously made choice about the adoption of an innovation. However, this confirmation may be negated if the individual or entity encounters contradictory information pertaining to the innovation.

Table 1. Elements the Roger's Diffusion of Innovation Theory

Communication channel	The communication channel may be described as the mechanism via which messages are sent from one person to another. Rogers classified channels of communication into two distinct groups, namely interpersonal channels and mass media channels.
Time	Time is a crucial factor in the process of dissemination. The concept of time remains unaffected by any specific occurrence, although it plays a crucial role in the execution of many activities.
Social System	The social system may be described as a collection of interconnected entities that collaborate in resolving shared challenges with the aim of achieving a mutual objective.

A. Phases of Technology Development

The process of producing new technology in the industrial industry generally involves four distinct phases: innovation, imitation, technological rivalry, and standardization, as outlined in **Table 2.**

Table 2. Phases of Technology Development

Innovation	Innovation is characterized by a time of uncertainty and the use of trial-and-error problem-solving techniques, ultimately resulting in the development of new ideas or products. This process often takes place on a small scale, such as in a tiny facility resembling a garage, as seen in industries like bioengineering.
Imitation	Imitation is a common practice among firms, whereby they modify and enhance fundamental innovations via research and development (R&D) in response to market demands. Hence, business spinoffs give birth to new enterprises that engage in the introduction of novel products, such as the solar collector industry.
Technological rivalry	Technological rivalry involves research and development laboratory efforts aimed at enhancing innovation in order to maintain a competitive edge in the market by modifying the manufacturing process. The entry of tiny enterprises into the market is a formidable task, since established firms often exit owing to their inability to effectively implement imitation strategies, as shown in the semiconductor sector.
Standardization	Standardization refers to the developmental efforts aimed at enhancing the manufacturing process to create a durable product that has competitive pricing attributes. An example of an industry that exemplifies this concept is the pocket-calculator business.

Model of Technology Strategy

Gates [11] described a theoretical framework known as the utilitarian technology strategy model. This model pertains to the management of technology adoption and diffusion within organizations, emphasizing the integration of technology strategies into the broader vision of a corporation. The model referred to as the technology strategy model encompasses six key sequential tasks involved in the process of technology strategy. These tasks include: (1) establishing horizons, (2) managing technology (3) conducting industry forecasting, (4) appropriate technology (5) positioning technology, and (6) assessing technology availability. The six activities outlined include three fundamental tiers of strategy. Specifically, tasks 1 to 3 pertain to corporate strategic considerations, tasks 3 to 5 address business strategy matters, and tasks 5 to 6 focus on strategic operational problems (see **Table 3**).

Table 3. Tasks Included in the Model of Technology Strategy

No.	Tasks	Brief description
1	Setting horizons	Horizon setting refers to the process of publicizing the technical components of a company's strategy within the context of the sector or industry in which it works. Adopting a new technology or industry has both strategic and practical ramifications that must be carefully weighed before a decision is made.
2	Industry forecasting	Understanding the long-term threats to the sector and its overall trajectory of growth are the main points of this study.
3	Technology positioning	A company should position itself technologically where it will be the most successful. The strategic course and anticipated business climate in the future will determine where the technology will be positioned.
4	Determining technology availability	By this point, the company will have learned all there is to know about the necessary technology and why it will be crucial in the future. The company's research and development plans are associated with the availability of technology
5	Appropriating technology	Once the necessary technology and resources have been identified, the company must put them to good use in their daily operations. Appropriateness is made up of two parts: efficient technology transfer in cases where technology is uncodified, and consideration of economy in cases where knowledge is costly to develop but cheap to transmit.
6	Managing technology	The last part of a successful technology plan is its management, which is what keeps everything running smoothly. It's an ongoing strategy where workers strive to better the business in every way possible.

IV. FUNCTIONS AND COMPONENTS OF SMS

A number of disruptive technologies, including CPSs, the IoT, big data analytics, cloud manufacturing, and AI, have been introduced to facilitate the smart manufacturing system (SMS) inside the sector. In their study, Kovalenko, Saez, Barton, and Tilbury [12] included more elements into the realm of SMS, including IIoT, virtual reality, simulation, augmented reality, reconfigurable manufacturing, and additive manufacturing. Furthermore, Dong and Qi [13] have highlighted the significance of simulation and the integration of the value chain, both vertically and horizontally, spanning from management to the shop floor, as crucial elements for the future of textile SMS. Based on the aforementioned analysis, the essential constituents of a Smart Manufacturing Systems (SMS) may be enumerated as follows.

Cyber-physical System

Cyber-Physical Systems (CPS) refer to a comprehensive framework that integrates compute, communication, and control technologies to effectively manage distributed and embedded computing systems. The primary objective of CPS is to facilitate dynamic and real-time cooperation between embedded and physical systems. The concept being described is the integration of the physical and virtual realms, whereby the physical world incorporates computational elements and vice versa. The forthcoming Smart Manufacturing Systems will be founded upon SCPS (Socio-cyber-physical system) based manufacturing. This approach amalgamates smart manufacturing, which enables additive manufacturing and mass customisation, which facilitates mass personalization. Additionally, this integration incorporates the social dimension. Roffeh [14] suggest that social dimensions include several aspects such as legal frameworks, belief systems, and cultural practices. In the context of SCPS-based manufacturing, there is a significant level of interaction between various entities such as the internet, consumers, social media, equipment, and producers. This interaction occurs in conjunction with smart and hybrid manufacturing processes.

Internet of Things

The term IoT pertains to a network of tangible gadgets, appliances, automobiles, and other physical entities that are equipped with software, sensors, and network connection. This enables them to amass and exchange data. These gadgets, also known as "smart objects," include a wide spectrum of technologies. They span from basic "smart home" devices such as smart thermostats, to wearable devices like smartwatches and clothes embedded with RFID technology, to intricate industrial equipment and transportation systems. Researchers are already imagining "smart cities" that are fully equipped with IoT infrastructure. The IoT allows for greater connectivity between smart devices and other internet-enabled gadgets such as gateways and smartphones. This creates a vast system of interconnected items that can communicate with one another, share information, and carry out a wide range of tasks without human intervention. This covers a wide range of uses, including but not limited to: the management of traffic patterns through the use of smart vehicles and other intelligent automotive devices; the control of machinery and processes within industrial facilities; shipments within warehousing operations and the tracking of inventory; and the monitoring of environmental conditions in agricultural settings.

The adoption of IoT has been shown to contribute to the improvement of product quality and manufacturing process efficiency. However, it is important to note that companies encounter significant uncertainty difficulties in the course of implementing IoT. Three major problems have been highlighted, one of which is to the prevailing reluctance of machine manufacturers and end users to effectively use this technology. One notable concern is to security concerns, namely the handling of industry-related data as big data inside an Internet of Things (IoT) oriented business, necessitating its sharing with collaborative partners. Ultimately, via collaboration with many industries, a select few sectors have the capacity to integrate all the necessary supporting enterprises into a unified and cohesive framework. The implementation of IoT and the creation of a connected industrial strategy are significantly hindered by the formidable task of system integration. **Table 4** illustrates the sustainability concerns associated with the IoT in the context of smart manufacturing.

Table 4. IoT in Sustainable Manufacturing

Sustainability Issues	Description
Reducing product miles	Smart product monitoring provided by the Internet of Things may determine the most efficient path for things to travel from origin to destination, ensuring that consumers get their orders promptly.
Increasing the durability of mechanical and tool systems	Tracking and continuously monitoring the performance of the product may considerably extend its lifespan. In addition to improving the product's efficiency, this makes it easy to ascertain the product's maintenance needs.
Preserving energy and water	Managers at an IoT-enabled factory will have a clearer picture of how much power each system, such as the HVAC system, is really using. This opens the door for more efficient use of energy in the future. Systems provided by the Internet of Things may also be used to properly manage garbage.
Create more efficient supply networks.	The Internet of Things paves the way for the remote monitoring and automated operation of devices situated in a wide variety of settings, including those of suppliers and customers, with the collected data then being uploaded to a central database for analysis.

Robotics

A robot is an automaton that is capable of executing pre-programmed instructions, hence accomplishing a certain job. On the other hand, the word robotics pertains to the academic discipline dedicated to the advancement of robots and automation. Robots exhibit varying degrees of autonomy. The spectrum of these levels includes bots that are under human control and execute designated duties, as well as bots that operate independently and carry out tasks without reliance on external factors. The advancement of technology is directly proportional to the expansion of the domain included by the term "robotics." In the year 2005, a significant majority of robots, namely 90%, were primarily engaged in the task of assembling automobiles within the context of automotive manufacturing facilities. The primary components of these robots mostly include mechanical arms that are assigned with the tasks of welding or attaching certain components onto an automobile. In contemporary times, there exists a refined and broadened conceptualization of robotics, including the advancement, construction, and utilization of automated agents capable of fulfilling a diverse range of functions. These functions include activities such as investigating the most inhospitable environments on Earth, aiding law enforcement efforts, optimizing surgical processes, and engaging in missions aimed at rescue operations.

Robotics refers to an autonomous system that encompasses several components such as sensors, programming, actuators, machines, microprocessor technology and digital electronics. This system has the capability to do certain tasks. Robots are often regarded as a fundamental component of intelligent manufacturing systems, especially in the context of vehicle and related component assembly. This is mostly because to the inherent risks and time-intensive nature associated with human engagement in these processes. According to Hedelind and Jackson [15], there is an expectation that industrial robots will have a broader scope of use within the manufacturing sector in the future. The garment sector has begun using robots in limited capacities, particularly in sewing processes, with expectations for substantial expansion in the future.

Artificial Intelligence

AI refers to the capacity of a computer-controlled robot or a modern computer to do activities often attributed to intelligent entities. The concept is often used to describe the endeavor of creating systems that possess the cognitive abilities inherent in humans, such as reasoning, comprehension, generalization, and the capacity to acquire knowledge from previous encounters. Since the advent of the 1940s modern computer, empirical evidence has shown that computers had the capability to execute very intricate operations, such as generating mathematical theorem proofs or engaging in chess gameplay, with remarkable efficiency. However, despite ongoing advancements in processing speed of computer and capacity of the memory, there currently exist no software applications that possess the same level of comprehensive adaptability as humans do, particularly in broader fields or activities that need extensive daily knowledge.

The concept of Industry 4.0 has gained significant prominence within the realm of industrial manufacture, being often regarded as the fourth industrial revolution. The revolution of 4^{th} industrial advent has facilitated the industrial transformation, hence driving the transition towards Smart Manufacturing. By incorporating cutting-edge technologies like IIoT, Cloud Computing, Big Data, and AI, the manufacturing industry can achieve a higher level of intelligence and autonomously execute intricate operations. These operations include predictive maintenance of machinery, real-time monitoring, and optimization of product quality. Based on the findings of Lu, Witherell, and Jones [16], the implementation of the IIoT in the context of Smart Manufacturing has the potential to result in a reduction in logistics expenses by 10-30%, quality management costs by 10-30%, and production costs by 10-30%. Currently, it occupies a central position within the context of Industry 4.0 and garners significant attention from governmental bodies, corporations, and scholars alike due to its potential for the implementation of Smart Manufacturing. In a recent study done by Yalcinkaya, Maffei, Akillioglu, and Onori [17], a comprehensive examination of technology pertaining to smart manufacturing systems was undertaken.

An essential attribute of the IIoT is the integration of sensors inside all the various components associated with the manufacturing process. The sensors function as sensory mechanisms for gathering data pertaining to the many stages of the supply chain, including supply, manufacturing, storage, distribution, and consumption. This data is used for the purpose of analyzing and optimizing industrial supply chains, ensuring product quality control, and facilitating active maintenance. The use of data obtained from these processes has facilitated the efficient operation of sophisticated computer technologies, hence enabling the integration of artificial intelligence (AI) into industrial processes. Smart production offers several benefits, including the optimization of all phases of the production process, waste reduction, and the development of innovative goods and services of superior quality. Artificial intelligence (AI) technology now assumes the function of a cognitive system in the context of Smart Manufacturing. The Smart Manufacturing implementation is a complex and time-consuming endeavor. This method requires a profound understanding of a variety of sophisticated and contemporary technologies that are included into it. The objective of this Special Issue is to provide a comprehensive analysis of the study area and present novel advancements in relation to the existing difficulties and potential uses of artificial intelligence in the field of smart manufacturing. The platform serves as a prominent venue for the widespread distribution of cutting-edge findings in theoretical investigations, technical advancements, and practical implementations of artificial intelligence within the realm of Smart Manufacturing.

Advanced ERP

ERP is a comprehensive management of information technology that facilitates the integration of many aspects of company administration, hence enabling a seamless flow of information throughout the firm. The successful implementation of SMS requires the incorporation of tailored and individualized connectivity and collaboration involving various technological and informational components such as DCM (Design Chain Management), MES, Artificial Intelligence (AI), IoT, intelligent algorithms, Supply Chain Management (SCM), and EDA (Engineering Data Analysis). This integration is made feasible through the utilization of an integrated information framework facilitated by Enterprise Resource Planning (ERP) systems.

Digital Twin

Refers to a physical things virtual representation that is used to imitate their actions. Its purpose is to facilitate the integration of cyber and physical elements and to enable the smart services, manufacturing processes, and optimization of product design. It provides a modern representation of the historical and current behavior of components inside a structural monitoring system (SMS). According to Hofbauer, Sangl, and Engelhardt [18], the digital twin has strong managerial qualities that facilitate the enhancement of system or product performance via process modifications and predictive design in the physical realm.

Smart manufacturing refers to a manufacturing methodology that integrates cutting-edge technology, including AI, the IoT, big data analytics, and robots, with the aim of optimizing processes of production and enhancing operational efficiency. The level of intricacy inside the production habitat is increasing, and the processes of manufacturing are becoming more tailored. Consequently, the system of production necessitates a significant level of cognitive abilities and learning aptitude in relation to the examination and alteration of manufacturing processes. Smart manufacturing offers several possibilities for product modification and personalization, along with the ability to manage supply chains in real-time. This capability allows manufacturers to promptly adapt to fluctuations in demand, shifts in market trends, and variations in client preferences. Additionally, it empowers them to develop customized goods that cater to the specific requirements of individual customers. The use of real data, automation, and interconnected devices are utilized to enhance quality, productivity, and efficiency, within industrial processes.

The objective of smart manufacturing is to provide a manufacturing environment that is characterized by enhanced agility, flexibility, and responsiveness. This environment should possess the capability to swiftly adjust to evolving market requirements while delivering goods of superior quality at reduced expenses. The user's text does not contain any information to rewrite. Consequently, it employs and incorporates modern software tools and information throughout the whole of the lifecycle of the product. In the context of smart manufacturing, the digitalization of all resources enables their analysis and modification inside virtual environments. The diagram in **Fig 2** illustrates the shift from conventional MSD to a modern twins-based SMSD strategy.

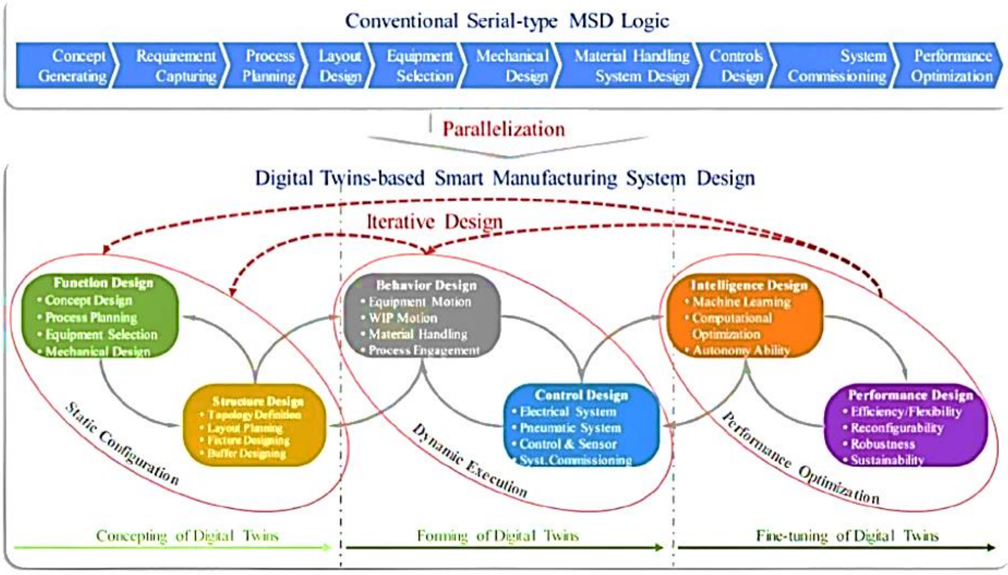

Fig 2. The switch from the traditional MSD strategy to the SMSD approach based on digital twins

Additive Manufacturing

Additive manufacturing refers to the method of fabricating three-dimensional items by sequentially depositing several layers of materials using a 3D printer. This technique involves the use of software programming to dictate the composition of each individual layer. According to Bhattacharya, Toombs, and Taylor [19], this technology has the capability to generate three-dimensional objects with intricate geometric structures, while also offering fine control over surface quality and dimensional precision. The method described involves the creation and delivery of solid objects using an additive manufacturing technique, which allows for the possibility of mass customization. This process integrates both cyber and physical systems.

Cloud Manufacturing

CM is a manufacturing system that leverages Ios and cloud computing to convert manufacturing assets and competencies into manufacturing services. This approach provides a range of value-added services and enables communication through multiple channels. The model of CM is based on the fundamental principle of leveraging manufacturing resources and skills via a cloud platform that has the ability to make informed choices, resulting in the provision of the most sustainable and resilient manufacturing pathway. The introduction of prior advanced manufacturing models has been limited by disadvantages in the processing power of a computer, security solutions, and analytics and data collecting. Cloud manufacturing, on the other hand, has the benefit of incorporating emerging technologies like big data, cloud computing the IIoT, which is the industrial application of the IoT. This enables cloud manufacturing to address several restrictions that were present in the past. Cloud manufacturing has the potential to emerge as a critical element within the future industrial environment. It serves as a complementary component to developing manufacturing techniques, like AM, in order to facilitate the production of consumer-customized goods by sustainable means. When Additive Manufacturing (AM) use 3D design data to construct a component by layer-wise material deposition, it is generally referred to as 3D printing.

Numerous research endeavors have been undertaken to explore various study issues and applications of CM. The National High-Tech Research and Development Programme was initiated by China in 2009 with the aim of facilitating research pertaining to CM. China has produced two influential and well referenced publications that are among the first contributions to the field of CM. Mcmanus and Scianna [20] provided a comprehensive exposition on the fundamental concepts of Configuration Management (CM), including its architecture, definition, features, and associated advantages. Xu conducted an analysis on the impact of cloud computing on the manufacturing industry and provided a clear distinction between cloud computing in the context of manufacturing and CM. The project ManuCloud was launched under the European Seventh Framework Programme. The primary aim of the project of ManuCloud was to examine and construct a cloud-based infrastructure that would enhance the efficiency and effectiveness of on-demand of supply chains of manufacturing within the automotive, organic lighting, and photovoltaic industries. Currently, there is a growing number of enterprises that provide cloud-based solutions for the manufacturing industry. One instance of a company that has created the SaaS, Plex Manufacturing Cloud, ERP used for manufacturing process management, is Plex Systems. The program has been specifically developed to provide engineers and managers immediate and continuous access to real-time production data.

Nevertheless, the whole ramifications of Configuration Management (CM) have not been completely actualized in the industrial sector. The term "Industry 4.0" originated in Germany and pertains to the digital transformation of the manufacturing industry, which is propelled by substantial growth in data quantities, computing capabilities, and the expanding interconnectedness of production facilities. Cloud manufacturing has the ability to operate within the context of Industry 4.0 by using on-demand access of manufacturing resources from a shared pool. This allows for the creation of temporary and adaptable supply chains that provide improved efficiency, lower production costs, and efficient allocation of resources.

Big data

The precise delineation of Big Data is a topic of ongoing scholarly discourse, with several proposals having been put forward. Johnson, Friend, and Lee [21] put up a proposal recommending the classification of Big Data based on three key dimensions, often referred to as the 3Vs: Variety of Data, Velocity of Data, and Volume of Data. This category (or definition) is generally acknowledged in academic circles. Additional definitions have included a fourth element, denoted as "veracity," which pertains to the quality of captured data. This factor introduces variability that might impact the precision of subsequent analyses.

Big Data in Smart Manufacturing systems refers to the huge quantities of information that are generated by different sources like manufacturing systems, controllers, ambient sensors (humidity, vibration, temperature, etc.) and machines. This data is available in various forms including manually entered operator data, signal streams, master data, and log files. In the context of Big Data analysis, it is plausible to include additional data sources derived from sales and marketing activities, enterprise-level systems, social media platforms, website browsing patterns, supply chains, PLM systems, and business projections. The smart manufacturing systems generate substantial volumes of data, often referred to as Big Data, which may be subjected to analysis. This analysis encompasses actual-time information streams, capturing short-term patterns, as well as comprehensive historical data repositories. However, it is significant to consider the process of data reduction while ensuring the preservation of significant information. The transmission of data from several sensors to a solution of data analysis inside a smart manufacturing infrastructure is not feasible at a millisecond interval.

V. CONCLUSION

Smart manufacturing systems have evolved from being logical and physical hierarchical encapsulated systems to being non-hierarchical structured, CPS, heterogeneous, loosely connected systems that engage in event-based communication and collaborate inside unified networks. From a collective perspective, these emerging ecosystems have the capacity to provide novel technical opportunities that may be well-suited to meet the complex needs, expectations, and aspirations of discerning customers. This entails the incorporation of various factors such as new key performance indicators, increased waste efficiency, advanced production and product visibility, and enhanced production flexibility. Additionally, it involves considering novel influencing conditions such as adaptations in the supply chain, customizable products, feedback from social media platforms, dynamic market trends, ambient conditions, and alterations in the life cycles of products, systems, or orders.

Theory provides a framework for comprehending the intricate elements of a given occurrence, enabling stakeholders to gain insight into its fundamental intricacies. Nevertheless, there is a significant degree of skepticism among researchers about the efficacy of theoretical relevance in comprehending technology. The Smart Manufacturing Systems (SMS) is a novel production system paradigm that incorporates several disruptive technologies, hence presenting unparalleled levels of complexity. The concept of theoretical viewpoints might facilitate the process of addressing its main challenges. Rogers' Diffusion of Innovation theory may facilitate the cultivation of inventive thinking among early adopters throughout many stages of technological advancement. However, the use of a technology strategy model may assist individuals in understanding and spreading the acceptance of technology inside a company. The incorporation of theoretical information into technical views enhances the comprehension of SMS, including its components and qualities, making it more widely accepted. This research integrates theoretical and technological information about the administration of Smart Manufacturing Systems (SMS), using a patented model of SMS inside a worldwide textile complex.

Data Availability

No data was used to support this study.

Conflicts of Interests

The author(s) declare(s) that they have no conflicts of interest.

Funding

No funding was received to assist with the preparation of this manuscript.

Competing Interests

There are no competing interests.

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