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TOPICAL REVIEW

Recent Technological Progress to Empower Smart Manufacturing: Review and Potential Guidelines

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ABSTRACT With growing evidence of advanced technologies-assisted smart processes, it is fundamental to comprehend whether manufacturing systems are adequate to manage flexibility and complexity to enhance the monitoring of smart factories. Smart manufacturing (SM) is evolving as a new version of traditional manufacturing, revealing the magnitude and power of smart technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT). The wide applicability of these technologies is allowing important innovations across all industries. As the manufacturing industry has gained benefits, the current boosts of Smart Manufacturing are experiencing exceptional levels of interest. However, providing suitable SM systems and identifying the priority of requirements may vary according to different scenarios. To this end, this study presents a systematic survey of the current SM research trends. Furthermore, this paper aims to present a consistent and comprehensive vision of existing efforts in smart manufacturing and discussed the remaining open issues.

INDEX TERMS Smart manufacturing, industry 4.0, Internet of Things, artificial intelligence.

I. INTRODUCTION

Standards of living are changing rapidly over time. These changes involve technological enhancements to guarantee the growth and competitiveness of the global markets. During the past decades, the global economy has grown noticeably due to technological and industrial advances. In our study, we emphasize the role of technological development in smart manufacturing (SM). SM has become a crucial sector that promotes global economics [1] and expands people's standards of living. SM offers smart solutions based on the integration of human efforts, digital devices, and intelligent technologies for better development.

In recent years, many countries have been focusing on the importance of upgrading and transforming their manufacturing sector, stimulating significant attention by society and managers toward digitalization and connectivity importance, as well as smarter solutions in factories. Researchers and manufacturers have built two main paradigms to define the great interaction between manufacturing and innovative information technologies, especially artificial intelligence (AI) and the Internet of Things (IoT) [2], [3], [4].

In manufacturing systems, accurate information and communication techniques are required to meet the ongoing development of industrial systems and smart technologies [5], [6], [7]. The advent of Industry 4.0 (I 4.0) highlighted the importance of various disciplines [8], [9], [10] i.e.: big data analytics, cloud computing, IoT, AI, cyber security, etc. Numerous innovative manufacturing concepts have been suggested, based on these technologies to improve the efficiency of manufacturing systems. Global growth entails smart technological signs of progress, which emphasizes one of the significant milestones in our daily lives: SM. As a recent paradigm, SM has known a speedy evolution to enrich industrial intelligence [11].

SM is a modern manufacturing paradigm. In SM, machines are completely connected through networks, supervised by sensors, and monitored by developed computational intelligence to enhance system productivity, and product quality, and ensure sustainability while decreasing costs. The

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recent development of IoT, AI, and related technologies provide key strengthening solutions to improve modern manufacturing [12], [13], [14]. The adoption of new technologies in the manufacturing sector improves data collection and processing at different manufacturing stages [15], [16]. With the high speed of the manufacturing process, advanced data-driven intelligence can convert important volumes of data into insightful information for better SM management, as illustrated in Fig. 1.

The use of the Internet broadly ensures the communication of various industrial devices, which expands the connectivity of billion machines [17]. These connected devices allow the collection and sharing of data to perform the given manufacturing tasks [18]. SM systems remain a key concept to providing nowadays services in an intelligent way. For that, SM is knowing a growing interest in research as well as industrial communities. SM implementation can be affected by growing social or industrial needs, global economic variations, and technical advancement. This encourages the integration of innovative technologies to strengthen the upcoming SM solutions.

This study investigates SM's previous state-of-the-art and offers a strong analysis of all the research works in this context. The objective of this study is to assess the level of interest and current efforts regarding the incorporation of advanced technologies into the modern-day manufacturing sector by measuring the occurrence of these concepts in the present literature. Moreover, this paper seeks to discover the prominent areas related to the use of these intelligent technologies. With the availability of research publications, it is currently possible, using automated techniques, to search a wider scope and depth within the SM sector. This work outlines a comprehensive survey of recent SM research works. The main contributions of this paper are advanced as follows:

- Studying the advanced technologies for SM.
- Analyzing the SM-related challenges.
- Comprehensively analyzing the importance of SM implication in different sectors.
- Discussing the open issues and reviewing the future research challenges.

The rest of this paper is structured as follows: In Section II, a brief description of the background of SM is presented. The applied methodology in this survey is described in Section III. In Section IV, the advanced technologies for SM are reviewed. The taxonomy of SM challenges is provided in section V. Section VI underlines the importance of SM. Research questions are discussed in Section VII. Finally, Section VIII concludes this paper.

II. REVIEW METHODOLOGY

To survey the literature, in a specific sector, means to explore and examine the systematic, and reproducible works that investigate, identify, and evaluate the prior approaches [58]. In this study, we analyze previous scientific works dealing with SM. As SM is a concept, which is still progressing, it has earned growing interest in both the scientific as well as industrial communities. For that, scientists studied its implementation considering all the related fields, for instance: AI, Big data analytics, cloud computing, management, optimization, etc.

TABLE 1. Adopted search statements for the study.

Search statement
Smart Manufacturing
SM
"Smart manufacturing" or "SM"
("Smart manufacturing" or "SM") and ("Artificial Intelligence" or "AI")
("Smart manufacturing" or "SM") and ("Internet of Objects" or "IoT")
("Smart manufacturing" or "SM") and "challenges"
("Smart manufacturing" or "SM") and "trends"
("Smart manufacturing" or "SM") and "technologies"
("Smart manufacturing" or "SM") and "applications"
("Smart manufacturing" or "SM") and "Security and Privacy"

As there is no unified resource, for academics to shape the literature and gain a transparent picture of the current state of the art, this paper presents a thorough and analytical analysis of the SM state. To specify the main objectives of this survey, various questions have been raised.

Based on the recent growing manufacturing needs, raised in previous works such as Zhou et al. [2], Zhou et al. [5], Tao et al. [7], and Evans et al. [8], we aim to investigate the relevant SM studies and respond to the following research questions:

Q1. What characterizes SM environments?

Q2. What are the most important SM challenges investigated by researchers?

Q3. What are the remaining open issues?

To define the road map of this study, we build three key steps, as follows:

- Step 1. Analyzing SM studies.
- Step 2. Defining the selection criteria.
- Step 3. Exploring the SM works, examining the selected papers, and answering the raised questions.

The relevant works are provided and shared to develop information decentralization and to enhance the introduction of innovative paradigms. Our method is focused on studying SM from different perspectives.

A. EXAMINING SM STUDIES

Researchers explore different databases and other resources to make sure that they get all pertinent works. To study the trends of SM, we investigated various scientific databases (WoS, Scopus, ProQuest, etc.) using different search statements, as indicated in Table 1, and following different stages as illustrated in figure 2.

The collection of research papers has been made in September 2021. As the label "SM" is the abbreviation of a different term such as 'small molecules', 'smart

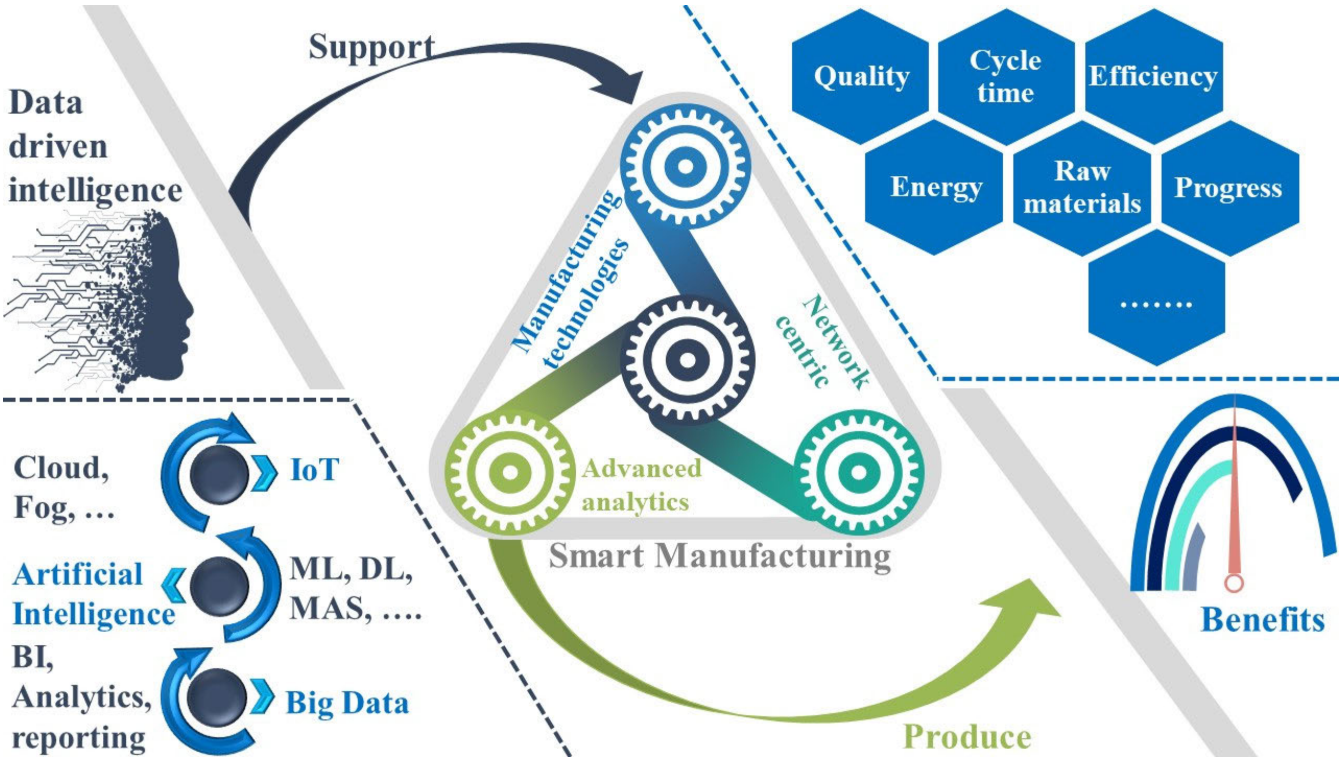

FIGURE 1. Driven intelligence in smart manufacturing.

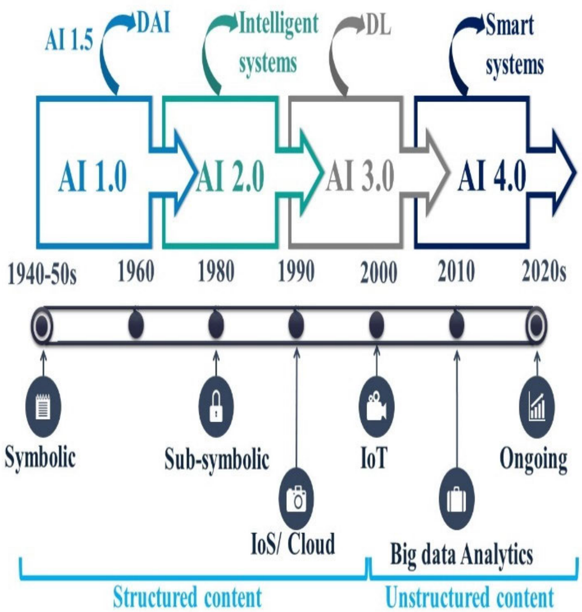

FIGURE 2. AI evolution.

materials', 'smart mobility, and 'smart modeling', we upgraded our research and thoroughly inspected each paper to filter the collected works and only pick the most relevant ones for our study.

B. SELECTION CRITERIA

The selection criteria are defined in our study to gather and filter the state of artworks. To include the suitable former papers, we examined the published papers in the specified database in table2. In this stage, the paper collection was done according to titles to select more accurate studies. Given the elimination criteria, many of the collected papers are removed from the inspection process. In this survey, the papers were eliminated because of:

- They lack abstract or full text.
- They were published before 2012.
- They only present a summary of the conference, table of content, keynote talk, tutorial, technical reports, short papers, and editorial papers.
- They were not written in English.
- They are not related to the suggested research questions.

III. SMART TECHNOLOGIES IN MANUFACTURING

As an emerging paradigm, SM is attracting growing interest in both industrial and academic communities. The SM requires the intensified adoption of innovative intelligence practices to manufacture new products in a faster and more dynamic way while ensuring real-time optimization of the manufacturing and supply chain.

A. AI PROGRESS

As a revolution in the industrial sector, AI demonstrated outstanding performance in several applications to improve decision-making and afford smarter solutions to tackle traditional issues (e.g.: image processing, translation, test questions & answers, prediction, etc..). AI allows automatic data processing towards extremely complex and nonlinear feature abstraction through various techniques, instead of

TABLE 2. Main principles of a smart manufacturing.

	PRINCIPLES	DESCRIPTION
P1	Modularity	Designing system components can define the capability of SM system components to be divided and combined easily and speedily. SM components should be loosely coupled and could be reconfigured easily on a plug-and-play basis [44]. For instance, some modules can be added, modified, reordered, or repositioned in the manufacturing line. SM should procure high modularity, allowing the quick incorporation of components that can be provided by multiple suppliers [45]. Modularity empowers the real-time ability to respond to growing and varying customer requirements and tackle internal SM failures.
P2	Interoperability	The ability to communicate technical information within SM components, and to share business information among manufacturing companies and customers [46]. IoT and semantic technologies had shown promising results in ensuring interoperability for SM[47].
P3	Decentralization	SM elements (materials, modules, products, etc.) should have the ability to make decisions autonomously in real-time, without violating the whole organizational purpose. In SMC systems, employees can make decisions about conventional matters, at the needed time, and change their strategy according to the variations of business environments [48]. Such interactions allow the adaptation of SM processes to each order, ensuring low-cost, and accurate custom-customized products [46].
P4	Virtualization	Creating both an artificial SM environment with a cyber-physical system (CPS), like the real SM environment, to supervise and simulate real SM processes. CPS allows information transparency along with the aggregation of sensor data to ease the creation of SM environments [49]. Virtual systems supervise the physical aspect, which transmits data, to update the virtual model in real-time [50]. These virtual systems support the SM design implementation and the creation of digital prototypes [51]. Furthermore, virtual systems are effective to simulate and analyze various issues such as workforce training, workforce guiding, and manual processes performed to diagnose and predict flaws and manage maintenance tasks.
P5	Service orientation	SM industries could move from only selling products to selling both products and services. SM industries are becoming currently service suppliers as their products have achieved competitive equality. Instead of seeking profit from selling their product, companies focus on selling also the services [52]. Today, SM industries outsource some services, to focus further on their core businesses [53]. Such a strategy promotes innovations and contributes to the improvement of the SM core process. In turn, an SM can sell its core processes as a service to other companies [54].
P6	Responsiveness	(Real-time capability): The SM system's ability to respond to variations on time, such as customer requirements or the internal manufacturing status [55]. The SM system should have a strong ability to examine the requirements meeting using current resources either through reconfiguration or collaboration with other factories [56]. For that, the SM systems should have an adequate modularity degree to achieve such needed reconfiguration.

handcrafting the best representation of data to reach greater knowledge. With AI and its high-volume modeling abilities, it is possible to provide advanced analytics tools for smart manufacturing. AI models can learn the data representations corresponding to various levels of abstraction, which then offers excellent potential to raise data-driven manufacturing functionalities [19], [20].

Since AI is a fundamental way to develop environmental intelligence, it is considered the lead top 10 strategic technologies [10]. AI has experienced numerous lifecycles, from the early years era (the 1940s), through the first expansion (1960s) and the second rise phase (1980s), and the current third growth period (since the 2000s). Figure 2 illustrates the evolution.

At the first movement, in the 1940s symbolic intelligence had gained enormous success at simulating high-level reasoning in small programs for solving miniature problems. Meanwhile, AI approaches based on cybernetics or neural networks took much time to be considered. In 1969 Minsky and Papert outlined the limits of perceptron [21]. In the 1980s, knowledge-based systems, or expert systems, got massive success. Expert systems used knowledge bases, which allow the processing of high-level knowledge obtained from domain experts and express the needed information in specific structured formats. Knowledge-based systems were adopted in manufacturing to resolve complex problems such as machine issues while multiple tools work instantaneously on the same workpiece [22]. In the mid-1980s, sub-symbolic approaches were proposed without specific representations of knowledge (e.g.: statistical and genetic algorithms (GA), neural networks (NNs), fuzzy algorithms, etc..).

Distributed Artificial Intelligence (DAI) got an increasing interest in the 1990s, along with the rise of multi-agent systems (MAS), which made prior AI systems in hierarchical and centralized, control structures become smoother and relieved by a set of agents cooperating, communicating through messages, and learning mutually from previous experiences. The 2000s have known the emergence of web intelligence (Web 2.0) and IoT. The prevalence of the Internet allowed the transfer and processing of huge volumes of data online, that need to be stored and processed [23]. The ongoing AI trends started around 2010, encouraged by three main factors related to each other [24]:

- Big Data analytics includes social media variations, e-commerce, the research community, data government, democratization, etc.
- Machine learning advances have been dramatically increased based on information provided by Big Data resources.
- Powerful computers support the processing of a large volume of data.

The current disruptive growth is converting traditional AI (AI 1.0), which is characterized by symbolic approaches, structured contents, and centralized control, to a more innovative version, (AI 2.0), which is based on deep learning techniques to handle unstructured content in decentralized structures. AI can offer intelligent connected systems [9], especially with the ongoing advances of IoT. The adoption of AI in manufacturing offered many specific intelligent industrial platforms with new scheduling approaches, design and modeling, manufacturing systems, prediction and inspection tools, diagnosis and monitoring, and decision-making [25], [26]. Many research works studied the implementation of AI in manufacturing.

Earlier, Teti and Kumara [26] examined the important AI methods used in manufacturing. These intelligent manufacturing systems attracted much more interest, so new AI approaches were presented [27]. Expert systems were presented efficiently in manufacturing components for large companies [28]. In the 1990s, MAS found its way for intelligent manufacturing [29], followed by web services and IoT [30] as well as Enterprise 2.0 [31] and crowdsourcing [32] in the 2000s. MAS-based methods offered potential solutions for manufacturing systems especially with the wide adoption of distributed AI (DAI) to manage the issues of software applications working in a highly dynamic and uncertain context [33], [34].

B. INTELLIGENT TECHNOLOGIES IN MANUFACTURING: APPLICATIONS AND ROLES

With innovative technologies, factories are becoming increasingly intuitive, connected, and crowded with sensors. The manufacturing sector is growing quickly. But to adapt effectively to the changes, companies should face different challenges.

Recently, the most important challenge is to be able to adapt properly to intelligent technologies. The last decades have proven that technical innovations have improved people's lives [4], [5], [6]. As SM reality continues to evolve, business owners and manufacturers must focus on advanced technologies. With SM, industrials can analyze trends in the data to assess their processes and detect the production issues such as slowing down or using materials inefficiently [8]. Examples of SM systems include computer-integrated manufacturing, prominent levels of adaptability and rapid design updates, digital information technology, and more adaptable training of the technical workforce. The main SM technologies can be classified into three categories.

1) DATA AND CONNECTIVITY

Deploying IoT sensors, in manufacturing processes and the supply chain; allows companies to collect enormous amounts of data at an unprecedented scale [9], [11]. As a result, IoT systems can now provide greater visibility into the entire production process. Thus, the decrease in peak/cloud computing, storage as well as bandwidth costs has brought the digital twin within reach [16], [17]. The digital twin consists of a digital representation of physical and behavioral characteristics; associated with production machines and finished products; permitting companies to promptly detect problems; achieve accurate simulations and determine operational inadequacies in real-time.

2) DIGITIZED STANDARD OPERATING PROCEDURES

Advanced analytics allow manufacturers to dive deep into historical process data; identify patterns and relationships between inputs and outputs and optimize the factors that have the greatest impact on performance [2], [3]. For example, the implementation of new AI analytics platforms in 2020 resulted in an estimated; 20% reduction in cleanroom investments; as well as a 10% reduction in production time and a return on investment of up to 300% [8]. In addition to its application to improve manufacturing processes; data analysis has also been leveraged to improve worker productivity and safety through the analysis of health; injury and incident data.

3) ADVANCED HUMAN–COMPUTER INTERACTION

The adoption of virtual reality (VR), augmented reality (AR), and collaborative robots (cobots) has enabled a new level of human-machine interaction for manufacturers, improving factory throughput, accelerating worker training, and reducing workplace risks [6]. For example, the application of VR has allowed Ford to simulate the car manufacturing process and reduce workplace accidents by up to 70% [6], [7], [8].

With AR, technicians can quickly understand how to service and repair faulty devices by overlaying schematics or instructions on the physical object. Indeed, cobots (safe enough to work alongside humans) facilitate work processes performed in collaboration with human workers to improve productivity - in some cases by up to 50% [6], [7]. Thus, to fully realize the benefits of this emerging paradigm; manufacturers should look beyond traditional sources to proactively co-develop solutions with startups and other external partners [7]. So, thoughtful and focused adoption of smart manufacturing technologies is essential to prepare workers and businesses for long-term success in the decade ahead. Indeed, it will be crucial to adapt and capitalize on key developments, including artificial intelligence and the offshoring of manufacturing.

C. SM AND INDUSTRY 4.0

In the 2010s, instead of integrating symbolic AI in manufacturing, the parallel convergence of smart technologies in manufacturing radically enhanced the management of manufacturing businesses in the manufactured goods cycle to offer further options for customers [35]. They used AI technologies for manufacturing comprising a wide range of fields, which are initially stated as the IoT technologies [36], and their numerous related techniques (i.e.: Cyber-Physical Systems (CPS), Internet of Services (IoS), etc.). These advanced technologies are the main keys to smart manufacturing. The recent rise of IoT and deep learning has made products more accessible. Furthermore, the generated data allows precise customer targeting and enables proactive management through timely in-depth decision performance [35]. Moreover, the combination of humans, data, and smart approaches has far-reaching impacts on manufacturing efficiency.

The ubiquitous use of data all over the entire manufacturing process, from manufacturing lines to supply networks, can provide new services and improve business growth [37]. Thanks to breakthroughs in information technology, mobile communications, and robotics, digital technologies are increasingly being used in businesses around the world. Over the past few years, there has been a lot of media coverage about the transformation called Industry 4.0. Yet, many entrepreneurs do not know what it is. Beyond the concept, it is quite important to know that the transition to Industry 4.0 could propel productivity, significantly reduce costs and greatly improve product quality. At its core, Industry 4.0 is about monitoring and controlling all machines and equipment in real-time by installing sensors at every stage of the manufacturing process.

The term Industry 4.0 derives from the high-tech programs proposed by the German government, which arises from the smart factories paradigm. Industry 4.0 is the most recent evolution in manufacturing. Over the past 250 years, several industrial revolutions have transformed the way goods are made (mechanization or Industry 1.0 around 1780, electrification or Industry 2.0 around 1870, automation or Industry 3.0 around 1970, globalization or Industry 3.5 around 1980, digitalization or Industry 4.0 in short). Like the mechanization, electrification, automation, and globalization that preceded it, this fourth industrial revolution promises to have a remarkable impact on the way we produce and sell goods [38], [39].

As shown in Figure 3, SM covers multiple levels, from physical to social, and produces data from (i.e.: social systems and social media networks, crowdsourcing communities, Web 2.0, SM digitalization, simulation, virtual manufacturing, sensors, smart objects, etc..).

Industry 4.0 and SM are empowering each other [40], [41], [42]. Yet, SM systems, which are, by their very nature, a socio-technical environment, require smart approaches to meet the increased demands of customized products and ensure sustainable manufacturing [43]. The previous industrial revolutions attempted to focus on mass manufacturing, as Industry 4.0 aims to enhance mass customization. Thus, Industry 4.0 represents a novel revolution, converting the preceding technical revolutions into a strong socio-technical one by introducing SM to combine human/social intelligence and technological innovations [4].

SM integrated IoT, and IA in traditional manufacturing contexts. Thus, most of the new evolving manufacturing models emphasize one or two aspects of IoT, for instance, smart factory, cloud computing, crowdsourcing, or predictive manufacturing [3], [38], [41].

The integration of AI and IoT fields in manufacturing has the advantage to accelerate the growth of available data sets, which overwhelms many companies. All these emerging manufacturing models have Big Data issues in common. As data-intensive computing, Big Data offers a new paradigm further than theoretical, experimental, and research studies [3] to rethink what can AI provide to smart manufacturing. On the other hand, Big Data is one of the biggest challenges of the 21st century. Therefore, companies need urgently to turn Big Data into actionable knowledge for the evolving manufacturing models. The development of SM integrates not only AI and its related smart technologies but also higher connectivity services due to IoT, more specifically mixing all efforts to support human intelligence in the manufacturing sector [2], [8], [35].

1) DEFINITION OF SM REQUIREMENTS

Before starting the survey of the literature, it is essential to identify and describe the SM system according to the requirements that should be fulfilled to boost its smartness. Most of the previous works have focused on the design principles of smart manufacturing. For that, we have tried to study the current situation as well as experts' expectations as possible. We considered these assumptions, which are described below, as guidelines for our proposed requirements.

2) PRINCIPLES OF A SMART MANUFACTURING

The principles of SM help researchers, designers, developers, managers, and industrials to build new SM systems or upgrade the existing traditional SM systems [44]. To examine the SM literature, it is obvious to describe these principles respecting the goals of I 4.0 as shown in table 2.

3) REQUIREMENTS OF A SMART MANUFACTURING

As we analyze the remaining perspectives towards smart manufacturing, in both the research and industrial sectors, we classified the SM requirements to better understand the previous works and elicit the modern requirements. Previously, Gorecky et al. [57] have presented six requirements of the smart factory, in a general overview. To the best of our knowledge, this survey is the first attempt to gather and describe the SM requirements in this form for a better analysis of the advancements of SM. Table 3 shows these SM requirements and examines them in terms of SM principles.

In this study, the existing works on SM are analyzed according to the indicated requirements. Besides, an analysis of the current technologies for SM advances is presented. The paper surveys the SM challenges and analyzes the existing

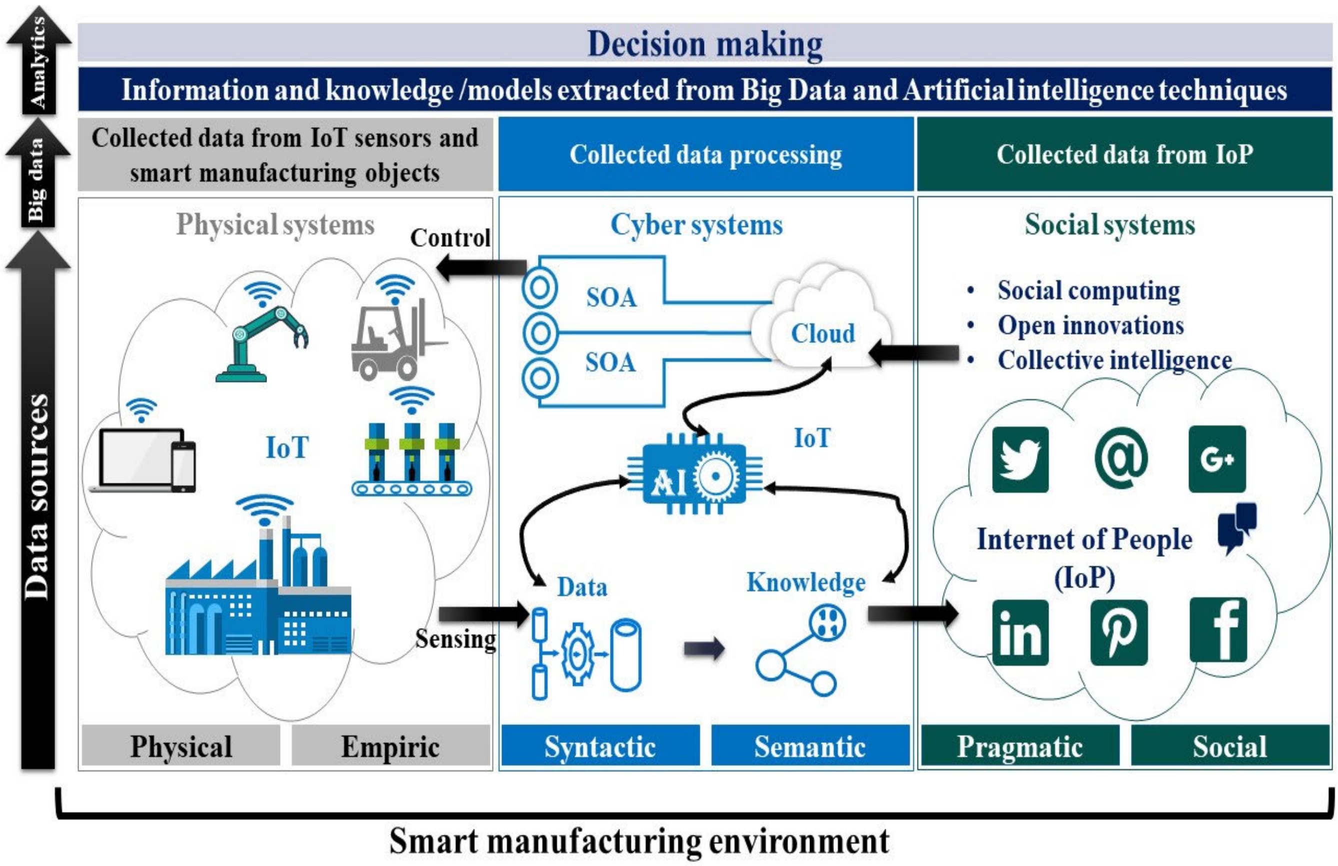

FIGURE 3. Description of SM components.

implications of SM. This paper aims to highlight the relevant literature that may promote future smart manufacturing.

IV. SURVEY OF SM STUDIES

The global output of scientific papers in AI has increased by a factor of 2.5 between 2010 and 2021. This trend characterizes the AI research of different countries but with great disparities. Since 2010, China has been the leading producer of scientific publications in AI. Between 2010 and 2021, it increased its number of publications by 3.6 times and its global share exceeds 25%, compared to 16% for the United States. India has quadrupled its production to become the 3rd largest producer in the world, ahead of the UK and Germany. France has ranked 12th in the world in 2021 and is ahead of Iran, Canada, Spain, and Australia.

An SM system gives an overview of a huge sector of research [59]. Several works have studied its adoption at enormous stopovers [60], [61]. Considerable research works in SM, have been dealing with one of the modernity pillars. SM is a discipline in speedy action to improve and invade all related sectors. By presenting new smart solutions into the heart of industrial manufacturing and scientific research, this survey intends to replicate relevant experiences, and interpret the results of previous works.

Firstly, 750 papers were the result of the first filtering stage. Secondly, applying abstract, title, and keywords criteria only

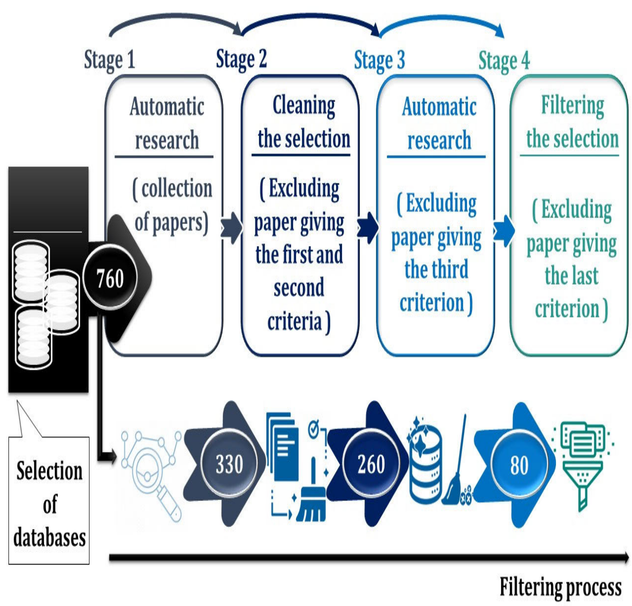

FIGURE 4. Collection of relevant literature.

250 papers were left. Finally, the final selection consisted of 80 papers selected for analysis. Figure 4 describes the adopted selection process.

TABLE 3. Main requirements of SM.

	REQUIREMENTS	DESCRIPTION AND USES	CORRESPONDING PRINCIPLES
R1	After-sale services	To outline products and services offered over the product life cycle [52, 53, 54]	Service orientation
R2	AI models	To produce smarter solutions and improve SM functioning [44, 45, 55, 56]	Modularity / Responsiveness
R3	Capturing actual factory	To capture the SM environment (using 360◦ cameras) as a real system [49, 50, 51]	Virtualization
R4	Cloud computing	To share product services, enhance factory functions, and manage SM data through cloud services [52, 53, 54]	Service orientation
R5	Cloud connection	To have to possibility to check the requirements of both service suppliers and customers [55, 56]	Responsiveness
R6	Collaborative behavior	System components (materials, agents, machines, etc..) act together to achieve system goals [46, 47]	Interoperability
R7	Customization and real-time capacity	To respond in real time and to reorder even a single unit [55, 56]	Responsiveness
R8	Data democratization	To make the SM digital information available to the normal non-technical users in the SM environment [46, 48]	Decentralization
R9	Deep learning prediction	To increase the speed of operations, the timing of slow tasks and to enhance the expected plans [49, 50, 51, 55, 56]	Virtualization / Responsiveness
R10	Embedded computer	To enable autonomous decisions and recover necessary information from cloud computing via CPS [46, 47, 48]	Interoperability/ Decentralization
R11	Fog and Edge Computing	Edge computing processes SM data at the network's edge, near the physical site producing the data, while fog computing is used as a mediator between the edge and the cloud services for better SM data filtering [52, 53, 54, 55, 56]	Responsiveness/ Service orientation
R12	Heal-ability	The SM environment should be able to recover after disruptions in real-time [55, 56]	Responsiveness
R13	Internet of Object	To collect significant manufacturing data and manages cloud software to extract insightful information from these data to improve the efficiency of the SM operations [52, 53, 54, 55, 56]	Responsiveness/ Service orientation
R14	Modular machine tools or workstations	Machines and workstations should be flexible to ease the reconfiguration in terms of adjusting the shop floor layouts and adapting the SM process functions [44, 45, 55, 56]	Modularity / Responsiveness
R15	Modular and decentralized control architecture	To identify the physical component plugged into the SM system and automatically activate its control elements without human intervention [46, 48]	Decentralization
R16	Modular material handling equipment	To reconfigure material handling kits or change equipment ability to transfer the needed product [44, 45, 46, 48]	Modularity / Decentralization
R17	Multi-skilled workforce	To perform several types of SM tasks (i.e: decision-making, supervision, maintenance, etc.) [44, 45]	Modularity
R18	Offering core processes as services	Offer the SM core functions to other factories [52, 53, 54]	Service orientation
R19	Online data analysis	To transfer customer requests to products and investigate the existing resource or services [55, 56]	Responsiveness
R20	Online monitoring and control	To monitor and control SM systems in real-time using reactive decision-making [55, 56]	Responsiveness
R21	Reconfigurable fixture	To adjust or fix a set of reconfigurable products [44, 45]	Modularity
R22	Reconfigurable tools	To offer useful tools in different tasks [44, 45, 46, 47]	Modularity / Interoperability
R23	Reinforcement learning tools	To automate decisions taken according to experiences and learned data [44, 45, 46, 47]	Modularity / Interoperability
R24	Secure communication	authenticating access requests for information in cloud computing [46, 47]	Interoperability
R25	Sharing meaningful information	a common framework that allows data to be shared and reused across application, enterprise, and factory boundaries in a meaningful manner (i.e., Semantic Web technology) [46, 47]	Interoperability
R26	Smart product	To provide all required information to achieve the production process [46, 48]	Decentralization
R27	Standard communication and CPS	To standardize, reorder, enrich, and manage the integration layer [46, 47]	Interoperability
R28	Standard infrastructure	To connect system components to all SM layers [44, 45, 55, 56]	Modularity / Responsiveness
R29	Standardized virtual modeling language	To enable manufacturers to build a virtual section corresponding to the physical section [49, 50, 51]	Virtualization
R30	Virtual interfaces with CPS	To enable retrieving and storing information from CPS and its related bases, for online simulation and diagnosis [49, 50, 51]	Virtualization
R31	Virtual reader	To provide a virtual SM system with online data	Virtualization
R32	Virtual system builder	To offer an engine to use the virtual system, allowing effective simulation [49, 50, 51]	Virtualization

As explained in the previous section, the in-depth investigation of the literature review was based on 80 articles. Table 4 lists the appealing papers regarding the selection criteria. The purpose is to analyze both the revealing publications and to present a descriptive study concerning the SM principles. The number of pertinent articles has grown considerably in the recent past decade, which indicates the expanded importance of the application of advanced technologies in SM. Furthermore, this growth strengthens the aim of this study to provide a current overview regarding the key evidence observed in the scientific debate.

Although the study of previous works showed that the majority focused on the management of SM for which they

TABLE 4. The studied publication according to SM principles.

Publications	P1	P2	P3	P4	P5	P6
Davis et al. [62]			✓			✓
Radziwon et al. [63]	✓					✓
Kolberg and Zühlke [64]	✓					✓
Stock and Seliger [68]			✓			✓
Rauch et al. [78]		✓				✓
Khan et al. [81]					✓	✓
Indrakumari [85]		✓			✓	
Zhang et al. [122]		✓	✓			
Gentner [65]			✓		✓	✓
Xun [74]			✓	✓	✓	
Erol et al. [76]		✓	✓			✓
Ben-Daya [87]		✓	✓		✓	
Fernández-Caramés [90]		✓	✓		✓	
Wang et al. [93]		✓	✓			✓
Qian et al. [106]		✓	✓		✓	
Fan et al. [107]			✓	✓	✓	
Tao et al. [110]		✓	✓			✓
Ferguson et al. [113]		✓	✓			✓
Zhang et al. [117]		✓	✓			✓
Fang et al. [121]		✓	✓			✓
Giannetti and Ransing [125]		✓	✓			✓
El Zaatari et al. [127]			✓		✓	✓
Xinyan Ou et al. [128]	✓				✓	✓
Jones et al. [100]	✓		✓		✓	
Lee [41]	✓	✓		✓		✓
Oesterreich and Teuteberg [66]		✓	✓		✓	✓
Robert et al. [67]		✓	✓		✓	✓
Sanders et al. [69]	✓	✓	✓			✓
Kannan et al. [70]	✓	✓	✓			✓
Arnold et al. [71]	✓		✓		✓	✓
Li et al. [72]		✓	✓		✓	✓
Hofmann and Rüsch [55]		✓	✓		✓	✓
Trappey et al. [53]			✓	✓	✓	✓
Dugenske and Louchez [75]		✓	✓		✓	✓
Qin et al. [77]		✓	✓	✓		✓
Vogel-Heuser and Hess [79]	✓		✓		✓	✓
Zhu et al. [80]	✓		✓	✓	✓	
Wang et al. [82]		✓	✓	✓	✓	
Das Almeida [84]		✓	✓		✓	✓
Shu-Hsien [89]	✓		✓	✓	✓	
Kamble et al. [95]		✓	✓		✓	✓
Lee et al. [97]	✓	✓	✓			✓
Zheng et al. [99]			✓	✓	✓	✓
Ghahramani et al. [101]	✓			✓	✓	✓
Mohseni and Tafreshi [103]	✓	✓	✓			✓
Xia et al. [105]			✓	✓	✓	✓
Kitagami et al. [109]		✓	✓		✓	✓
Hu et al. [111]			✓	✓	✓	✓
Huang et al. [115]	✓	✓	✓			✓
Isaja, Soldatos J. [116]		✓	✓	✓	✓	
Dibiano and Mukhopadhyay [119]	✓	✓	✓			✓
Huang et al. [123]		✓	✓		✓	✓
Liu et al. [129]	✓	✓			✓	✓
Popescu et al. [132]			✓	✓	✓	✓
Lăzăroiu et al. [133]			✓	✓	✓	✓
Wang et al. [136]	✓		✓		✓	✓
Hermann et al. [44]	✓	✓	✓		✓	✓
Yao et al. [54]	✓	✓	✓		✓	✓
Cheng and Cheng [73]	✓	✓	✓		✓	✓
Urbina et al. [83]	✓		✓	✓	✓	✓
Athul [86]	✓	✓	✓		✓	✓
Benjamin [88]		✓	✓	✓	✓	✓
Issaoui et al. [92]	✓	✓	✓		✓	✓
Barenjia et al. [94]		✓	✓	✓	✓	✓
Mohammadi, Minaei [98]		✓	✓	✓	✓	✓
Lin et al. [102]	✓	✓	✓		✓	✓
Tiburski et al. [108]	✓	✓	✓	✓		✓
Židek et al. [112]		✓	✓	✓	✓	✓
Jeong et al. [118]		✓	✓	✓	✓	✓
Wang et al. [120]	✓	✓	✓	✓		✓
Essien and Giannetti [124]	✓	✓	✓		✓	✓
Ren et al. [126]	✓	✓	✓		✓	✓
Wang et al. [130]	✓	✓	✓		✓	✓
Zhang et al. [134]	✓	✓	✓		✓	✓
Mabkhot [91]	✓	✓	✓	✓	✓	✓
Lee et al. [96]	✓	✓	✓	✓	✓	✓
Zheng and Sivabalan [104]	✓	✓	✓	✓	✓	✓
Lee et al. [114]	✓	✓	✓	✓	✓	✓
Andronie et al. [131]	✓	✓	✓	✓	✓	✓
Liu et al. [135]	✓	✓	✓	✓	✓	✓

mainly relied on quantitative analysis tools. The presented study is not only systematically different but furthermore covers an important timeframe witnessing the technological advances of Industry 4.0. These works suggest approaches, reviews, and surveys about SM systems or some of their enablers, in table 3.

The studied papers examine and analyze prior works that aim to provide innovative solutions for smart manufacturing. The studied papers were focused on manufacturing principles, with a higher interest in decentralization. However, virtualization and modularity are less considered in the literature. Meanwhile, interoperability remains an ultimate issue that may affect SM activities.

To continue, the analysis of table 4 reveals that several SM principles have been considered by researchers. Exploring modern technologies to enhance SM environments remains mandatory.

First, the flexibility offered by cloud computing platforms and virtualization allows the outline of advanced IIoT technologies, and to obtain measurable progress. The P4 dimension reflecting virtualization has received less interest in the studies (29 papers only discussed the issues related to P4) [41], [74], [77], [80], [82], [83], [88], [89], [91], [94], [96], [98], [99], [101], [104], [105], [107], [108], [111], [112], [114], [116], [118], [120], [131], [132], [133], [135]. This could be because it is necessary to start with pilot projects to define the SM benefits, and competencies and considerably respect timelines for future phases.

Second, the interest in the impact of P1 on SM is growing significantly over the last years, 37 papers have addressed the modularity in SM solutions [41], [44], [54], [63], [64], [69], [70], [71], [73], [79], [83], [86], [89], [90], [91], [92], [96], [97], [100], [101], [102], [103], [104], [108], [115], [114], [118], [120], [124], [126], [128], [129], [130], [131], [134], [135], [136]. SM systems impose requirements in terms of scalability and modularity. The continuous digital revolution as well as the growing use of connected objects are changing the way customers consume and the way companies are managed. This requires speed of execution and traceability associated with this action. Modularity, in this type of approach, the functionalities of new solutions are implemented in the form of modules. The latter represents the complementary functionalities of the basic system to reinforce its capacities.

Third P2 and P5 have received almost the same rate of interest. The biggest challenge in improving SM services is to get a whole set of tools, objects, and technologies to work together [44], [53], [54], [55], [65], [66], [67], [71], [72], [73], [74], [75], [79], [80], [81], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [94], [95], [96], [98], [99], [100], [101], [102], [104], [105], [106], [107], [108], [109], [111], [112], [114], [116], [118], [123], [124], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], [136]. Interoperability in SM environments reinforces the ability to make several solutions work together on the same system [41], [44], [54], [55], [66], [67], [69], [70], [72], [73], [75], [76], [77], [78], [82], [84], [85], [86], [87], [88], [90], [91], [92], [93], [94], [95], [96], [97], [98], [102], [103], [104], [106], [108], [109], [110], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [129], [130], [131], [134], [135]. This is essential to simplify the use and sustainability of production services. The emphasis on the interoperability dimension continues the trend of artificial intelligence, which makes the SM system even more practical. Unless SM solutions that combine the needs of connectivity, interoperability, and intelligence are put in place, the only way the promises of SM can be delivered. But other technologies are needed to go further and deliver on the promise of the current trend. Interoperability will help drive down prices and facilitate the adoption of new and different smart solutions.

Fourth, the P6 dimension reflecting responsiveness has gained much interest [41], [44], [53], [54], [55], [62], [63], [64], [65], [66], [67], [68], [69], [70], [71], [72], [73], [75], [76], [77], [78], [79], [81], [83], [84], [86], [88], [91], [99], [101], [102], [103], [104], [105], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [123], [124], [125], [126], [127], [128], [129], [130], [131], [132], [133], [134], [135], and [136]. Although the SM offers many advantages, it is well necessary to meet the increased needs of productivity, while respecting a continuous reduction of costs, and strong flexibility with enhanced efficiency. In addition, the SM offers permanent good performance. In addition, the real-time responsiveness in SM systems makes it easy to increase customer touch rates, customize products and services, and create innovative SM solutions.

Finally, the P3 dimension of the SM frameworks obtained, by far the highest attention [44], [53], [54], [55], [62], [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [79], [80], [82], [83], [84], [85], [86], [87], [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], [102], [103], [104], [105], [106], [107], [108], [109], [110], [111], [112], [113], [114], [115], [116], [117], [118], [119], [120], [121], [122], [123], [124], [125], [126], [127], [130],

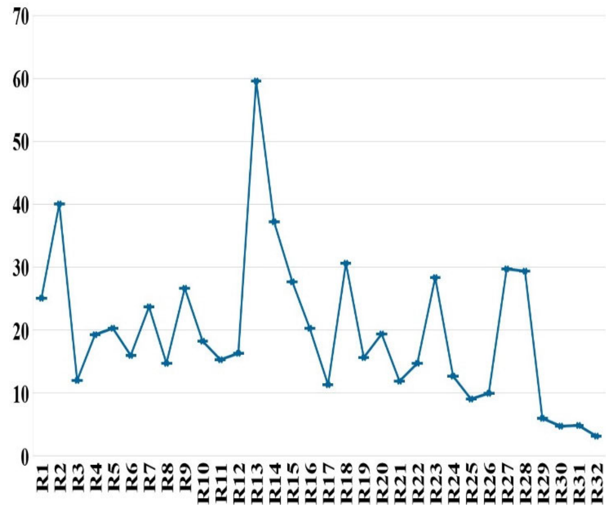

FIGURE 5. The rates of studied publication according to SM requirements.

[131], [132], [133], [134], [135], [136]. But, for the manufacturing sector, it is also crucial to focus on different topics such as how decentralization can influence SM activities and how it can be included in present SM processes. The benefits of decentralization were more regularly discussed, which may attract progressing attention to overcome the related obstacles unsolved. Beyond the adoption of new technologies, decentralization raises the issue of management. The continuous multiplication of data and the intermittency of new forms of consumption require an agile, responsive, and distributed infrastructure.

Innovative technologies are becoming strategically important in emerging SM solutions. The SM principles play a central role as necessary support for the deployment of SM environments. The content of the six papers, which all dealt with SM principles, emphasized constructive cooperation [91], [96], [104], [114], [131], [135].

Figure 5 contains an analysis of these works concerning the requirements of SM systems. It is obvious that the most attention in the literature was accorded to IoT, and AI, offering core processes as services, standard communication, standard infrastructure, and reinforcement learning tools (R13, R2, R18, R27, R28, R23, and R15).

Contemporary scientific research is more often oriented toward the new digital era. This scientific evolution is based on economic, social, technological, and political factors, which have shaped the environment in which contemporary scientific research develops. However, in the analysis of this evolution, several factors make it possible to observe that the publication interested in the SM systems tends to dissolve with the profit of the higher granularity of the works. These contents are based on SM platforms, where the definition of the publication no longer depends solely on the model of the journal based on the materiality of the papers.

V. ADVANCED TECHNOLOGIES AND SM

In SM environments, it is crucial to transfer the produced data to the storage systems through the internet. Establishing

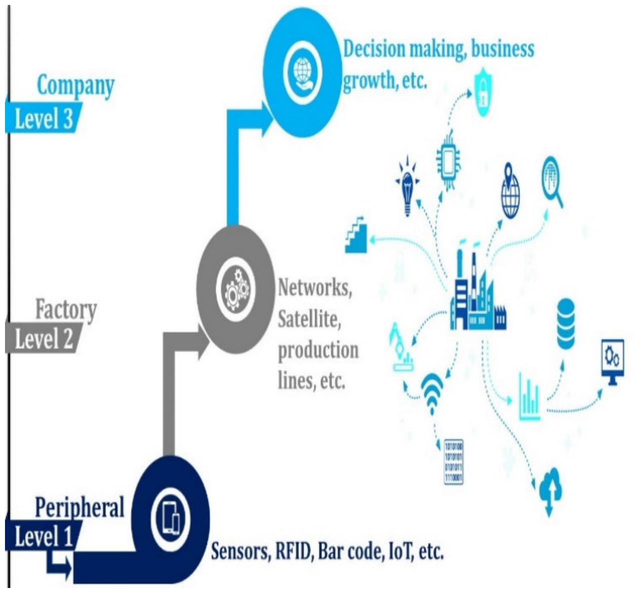

FIGURE 6. The three levels of SM architecture mapping.

effective reporting and connectivity is a tremendous task for SM systems. For that, it is required to properly introduce new technologies either for data sensing, communication, collection, or processing. Currently, numerous businesses, especially the industrial sector, are actively concerned about expanding their work process by implementing SM systems. However, the infrastructure improvement and the optimization cost remain fundamental pillars for SM emerging technologies.

A. SM ARCHITECTURE MAPPING

Undeniably, SM has become a major economic standpoint, which entails integrating new technology trends to address cost and service issues. SM offers are based on the new generations of technologies (IoT for connectivity in real-time, Big Data for huge volumes of data, AI for complex problem solving and enhanced knowledge, etc.) for better decision making [137]. Practically, it is a complicated task to outline all the technologies that shape the potential of SM environments surrounding us. For that, it is interesting to divide these technologies into three fundamental classes (as illustrated in figure 6):

- Peripheral level, which consists of physical devices, for data collection, i.e.: RFID, GPS, cameras, etc. The part of the SM environment, where product-related activities take place.
- Factory level characterizes the protocol and communication tools. It is at this level that SM local activities or processes are orchestrated and connected.
- Company level where the evaluation of all SM information levels is carried out, and where the storage of information for further visualization and analytical purposes takes place.

1) PERIPHERAL LEVEL

Whereas in the past manufacturing industrial units were manufactured in series and in advance, today the consumer is driving the agenda: this makes planning more complicated and requires greater flexibility in manufacturing processes. SM achieves these goals through customized mass manufacturing, which is the basis for intelligent and connected processes.

The peripheral level includes the physical part of the SM systems [138]. These elements act as the facilitator between real perceived data and the digital world. Since the hardware level is a vital part of SM systems, it includes a large scale of devices i.e.: sensors, servers, remote dashboards, control devices, etc. This level enables the management of the SM's key tasks, roles, as well as processes [139]. Furthermore, as smart devices are essential in SM systems to collect data and screen real-time parameters, they are employed in everything from system design, equipment installation, buildings, production processes, etc. Currently, all SM systems use machines, where numerous sensors and microchips are plotted to make them smarter. However, the high cost of these level components is an important issue that may be met in the future [140], [141]. Also, the compatibility of the used SM devices with the freshly developed ones may be reduced over time [142], [143].

The SM network should be well managed to provide the SM elements with connectivity to the Internet to acquire the feedback of information [144]. Selecting the most fitting communication network depends on the coverage, the communication distance, the battery life of the objects, the service cost, etc. The network level offers a clear transmission path for the newly used smart devices. Since the network is mandatory in SM systems, it can rely on both hardware and software systems [135]. The SM network should connect highly distributed physical devices to gather and exchange data for the best monitoring, management, and decision-making [136]. For that, the SM network level outlines the communication infrastructure and its protocols, the adopted technologies, cloud platforms, etc. Most SM systems adopt the following categories:

- Long-range and low-power networks (LPWAN), such as Sigfox, LoRa, or cellular technologies (GSM, 2G, 3G, 4G, 5G) can transmit data from one device to another over vast distances. They are used by companies that want to connect kilometers of infrastructure to the Internet or in smart cities projects for example.
- Short-range networks such as Wi-Fi, Z-Wave, ZigBee, or Bluetooth Low Energy, allow data to be transferred over short distances. They are used a lot in home automation or the consumer wearable market.

2) FACTORY LEVEL

Each piece is individually manufactured, and each consumer expects perfect quality. Furthermore, the traceability of each part must be ensured at every stage of the process. Intelligent software and processing technology make the zero-defect approach a success. These technologies are inspired by the perfection of human intelligence. They can avoid errors or detect and correct them quickly. Saving time and money.

The factory level is based on technologies, that screen and monitor data exchanges to provide real-time information to workstations and applications so that they can be converted and presented as truthful information, to fulfill manufacturing activities [137]. Smart tools or software are the main power of SM systems [138]. In addition to the flow of goods, data flows must now be coordinated efficiently: because every component or product must have the right information at every stage of the process. Therefore, fully integrated solutions are the brain of smart manufacturing.

3) COMPANY-LEVEL

As SM is one of the newest industrial paradigms for the coming decade, it implies an unprecedented fusion of the physical and digital worlds. For example, the emergence of commercially viable IoT devices; 5G connectivity, sophisticated cloud computing applications, and Bigdata analytics; combined with new technologies such as AR/VR, indeed, the adoption of smart factory initiatives; can help the manufacturing sector to triple the manufacturing labor productivity rate in the 2030 timeframe [139].

Implementing technologies and resolutions to operate the SM data allows manufacturers to develop new customized products and services. Beyond expanding their business, SM is the basis of a new economic model relying on the selling of additional services. With the decrease in sensor prices as well as the growth of networks connecting industrial objects, all manufactories can deploy an SM strategy.

In the SM architecture, intelligent components help the plant improve its performance potential. The plant management team (managers, engineers, maintenance supervisors, process engineers, quality engineers, etc.) can acquire relevant, prescriptive, and predictive information, which enables them to achieve plant and corporate goals.

B. TOWARDS SM: TECHNOLOGICAL STAGES

Previous industrial revolutions have always aimed at increasing productivity and the profitability of manufacturing systems [94]. However, the fourth industrial revolution aims to improve both manufacturing and management systems. In the industrial domain, the combination of IoT-generated data and analytics promoted the emergence of new functionalities, including predictive maintenance and quality. Based on smart manufacturing, these new functionalities are changing business methods, ensuring new solutions to predict breakdowns or product quality issues before they occur [40].

To properly manage and accelerate these activities, SM systems rely on industrial solutions such as IoT and AI. For industrial companies, this allows them to measure their level of coverage to verify the use cases to implement.

The needs analysis must also be addressed in the first step to defining the development plan, as early as possible [119]. This analysis is crucial because it strengthens the decision process related to the various deployment scenarios among the periphery, factories, and business levels. After the first evaluation has been implemented and executed, the basics of the core SM architecture (i.e., scalability and management assessment) are expected to be in place. Key architectural decisions should be validated and documented. From the SM solution perspective, it must be able to:

- Obtain good quality manufacturing data from output devices.
- Have robust sensors and state-of-the-art performance capabilities.
- Expose a minimum initial set of standardized interfaces between edge, factory activities, and central computing.
- Ensure that flow and function ideally through a model-based executable approach to speed development.

Most classical factories include operational technological resources, such as those that are not always connected. The current SM trend is based principally on the use of more IT to save time and money, costs, maintenance, and service. With the convergence of technologies, the AI and IoT emerging platforms remain a novel and innovative concept of SM [98]. To meet the needs of autonomy, of different types of professionals, and self-sufficiency of each manufacturing site, it is essential to establish a kind of load balance of the peripheries (physical part, where manufacturing activities take place), the factory (where activities are orchestrated and connected), and the company (where the analysis of all levels of information is performed (as explained in figure 7).

SM offers management solutions that primarily enable cost savings and improve operational efficiency throughout the manufacturing chain. In an SM environment, the solution portfolio analyzes various information from different workflows to enhance operations, promote quality, and facilitate decision-making. These SM solutions aim to advance intelligent manufacturing by properly managing the following steps:

- Data collection: Collecting data that already exists allows equipment and resources to be well-instrumented for better data collection in real-time.
- Trend identification: visualizing data in clear dashboards will allow us to distinguish trends.
- Analytics and digitization: Extracting knowledge from data will facilitate the creation of SL models to predict recommendations that will add value to the work and above all streamline business processes.
- Cognitive injection: the use of cognitive machine learning will refine the SL models with other cognitive functions to improve engagement

SM solutions provide a flexible, fast, and resilient manufacturing ecosystem. This creates value, using data collection to optimize performance and increase agility in both short and long manufacturing cycles.

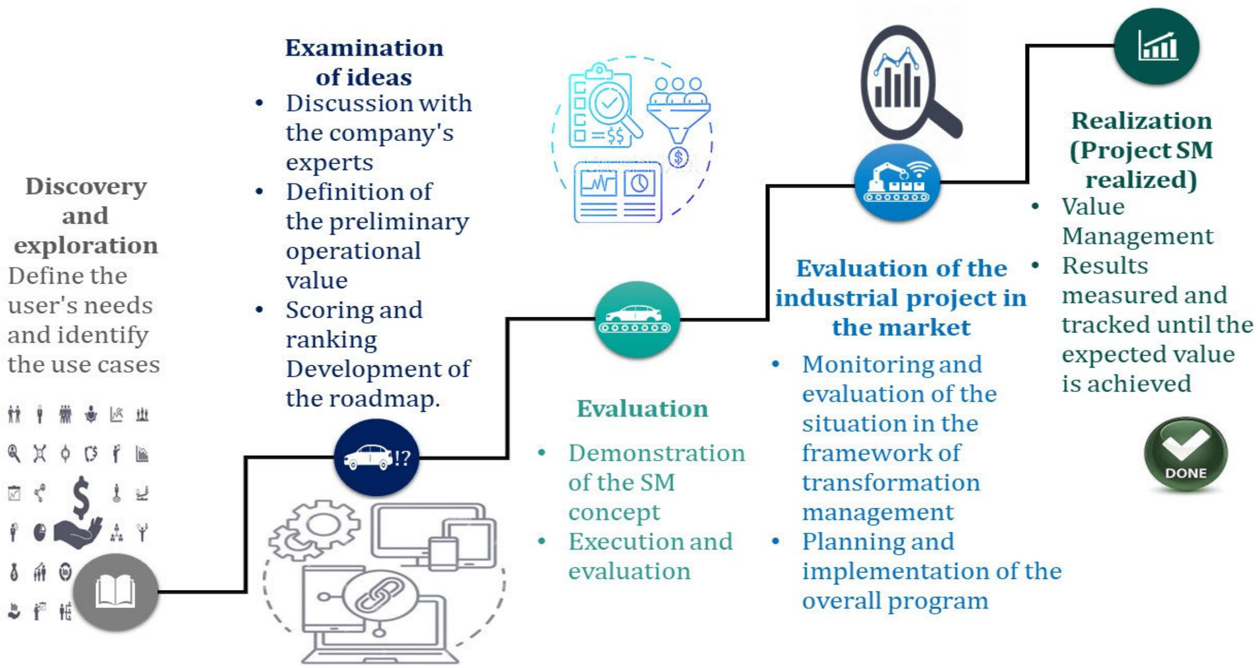

FIGURE 7. Technological SM stages.

C. THE STATUS OF SM

As the world stands on the cusp of a new era of smart manufacturing, the demand for precision motion management systems in the industry is reaching unprecedented levels. The study further explores and evaluates the existing landscape of the evolving business sector and the current and impending effects on the SM market. The comprehensive study demonstrates the growth of SM adoption as well as its effectiveness in the market. Furthermore, the statistical analysis of the studied work highlights that the focus is on costs, product requirements, capacity, market players, and marketing channels, as shown in figure 8.

The SM segmentation, described in figure 9, helps in understanding aspects such as products/services, available technologies, and applications of the global SM Platform industry. To describe the years of growth and the path that will follow in the years to come, the market segmentation is written. The SM market is segmented by type (device and connectivity management, application enablement), by application (performance, optimization, asset, and condition management), by end-use industry (oil and gas, chemicals, energy and power, food and beverage, pharmaceuticals, metals, and mining, electrical, and electronics). The research analysis also provides useful insights into emerging patterns that may describe the development of these segments over the next few years.

Quick technological advances in manufacturing - and the increased gains they promised - were already forcing companies to invest in digital infrastructure. These promising results illustrate the value of digital ecosystems and tools and prove that transformation is more necessary than ever. SM is a specific application of the IIoT. Its deployment involves integrating sensors into manufacturing machines to collect data on their operating status and performance [77].

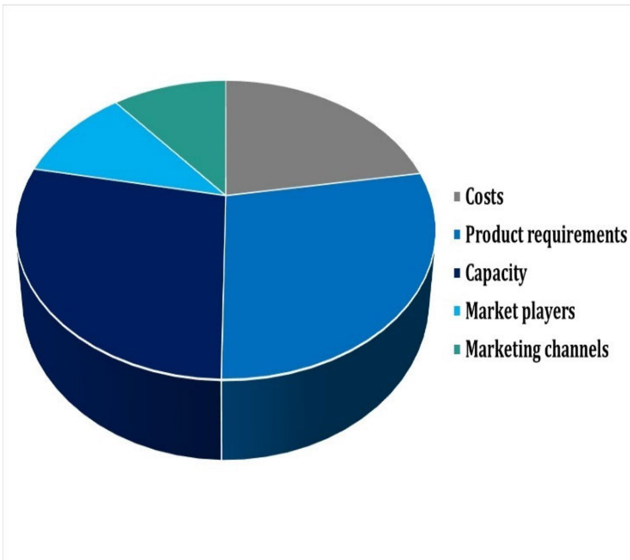

FIGURE 8. The main focus of the studied papers.

While the SM equipment market continues to experience strong growth, competition remains fierce. Manufacturers must differentiate themselves in a saturated market to advance. In a saturated market, efforts to minimize production costs are essential [112].

As SM becomes more popular and the number of connected machines increases, machine-to-machine communication will improve increasingly, leading to more [110]. For

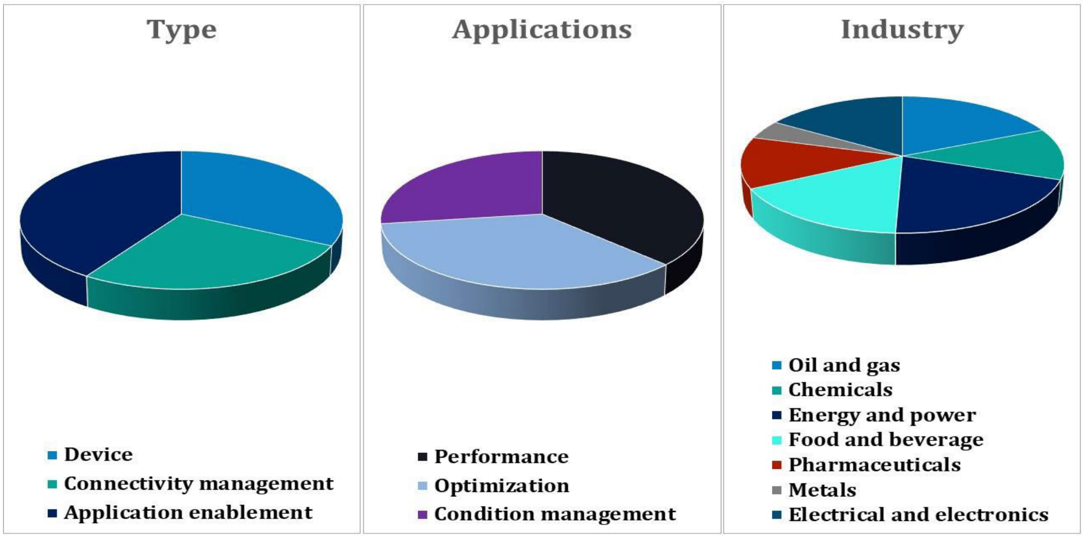

FIGURE 9. SM segmentation.

example, SM systems could automatically order raw materials when inventory drops, assign other machines to manufacture to fulfill orders and prepare distribution channels when orders are ready. Indeed, the adoption of SM technologies is based on three main forces:

- Sensing and computing resources: computing, sensing, and data analytics have progressed to a point where they can promote separate consumers, not just businesses.
- Consumer awareness: consumers are becoming more tech-understanding and their opportunities have grown.
- End-to-end automation and effectiveness: IoT helps, usually, to decrease operating costs while guaranteeing continuous accessibility of the devices concerned.

Many factors are creating strong pressure on the industry: the demand for ever-lower costs, the need to save resources, the desire to protect the environment, and the desire to use more and more products tailored to needs. Industrial companies are faced with real and sometimes complex challenges. The intelligent factory provides the solution. Manufacturing is optimized and self-organizing. This makes it possible to manufacture products more efficiently, even in small quantities. In the future, companies will be able to succeed and compete in their markets.

Considering the processes of conception, implementation, and manufacturing modes, it is quite important to identify and characterize the applications, objects, or devices, which carry and concentrate information as a consubstantial element. The industrial transformation of the modern world integrates advanced techniques associated with augmented reality, virtual reality, mega data, the IoT, or new methods of additive manufacturing and robotics [132], [133].

Industrial robotics, which takes up several major challenges, ensures the transition from repetitive tasks to more complex operations requiring coordination and interaction with the physical world, which implies the use of sensitive sensors and control algorithms capable of acting in real-time.

The flexibility, adaptability, and re-programmability of these technical systems are also vital to facilitate the reorganization of SM environments. Moreover, the use of autonomous robotic systems, which adapt interactively to production conditions, allows the integration of physical realities in an interactive way, or cooperation functionalities with humans. These are needs that mobilize digital technologies to stimulate and accompany creative design, through original exploration, going beyond the simple automation of predetermined tasks. The renewed use of a traditional process or tool is made possible by the integration of know-how within a new technical system mobilizing various robotized machines [134], [135].

In the context of intelligent technologies, the use and development of instrumented materials represent another characteristic of the transformations at work for SM activities. Smart robots refer to a new generation of products that can perform various functions previously reserved for the living [136], [137]. Consequently, robots have become a real design parameter as a modulable and adaptable attribute. The degrees of intelligence can correspond to functionalities such as capturing, collecting, processing, self-organizing, self-repair, or continuous learning [132], [133], [134], [135].

The architectural form of SM environments, as dynamic systems, requires the integration and adaptability of materials to SM conditions [139], [140]. The hybridization activities of production and informational functionalities, concerning the development of IoT, accentuate the development of cyber-physical devices.

SM is made up of cyber-physical systems. These systems allow machines, resources, and people to communicate together on the Internet of Things [140], [141], [142], [143], [144], [145]. Information is exchanged via the cloud, the intranet, or directly via RFID circuits [94], [140], [141],

[142]. For example, manufacturing lines are equipped with diagnostic systems: when a check is required, it is reported to the machine itself in good time. This results in a significant reduction in downtime and an increase in the life of the machine. In the smart factory, not only the machines communicate but also the objects themselves: RFID circuits allow them to share important information with the manufacturing systems. The smart factory controls itself and makes manufacturing much more efficient.

These processes of cyberization lead to an ethnicization of social, cognitive, and physical environments. A general SM environment, which allows us to reconsider the relationship between nature and technique, as well as the couplings between human and non-human agents, emerges from the hybridization of physical and digital realities [131]. In this context, systems and cyber-physical devices integrate the notion of information in a consubstantial way. The data and their encodings constitute informational flows inscribed in digital continuums [132], [133].

In the manufacturing field, robots can learn by reinforcement [136]. They can perform tasks that are dangerous for humans, and often more efficiently [130]. Now, data centers are completely controlled by AI without the need for human intervention. The system takes data snapshots from the data centers every five minutes and feeds data into neural networks. Intelligent agents enrich SM systems by offering interaction possibilities [129]. These objects integrate the notions of situation, service, information, and relationship. Inert objects have given way to systems, devices, relational objects, interface objects, information, and communication objects.

Behaviors, conditions, and interactions between humans and non-humans produce information and knowledge that are constituted as data streams [128]. The physical device acquires a capacity for self-adaptation to SM environmental conditions and social activities. This adaptive architecture is interested in the interactions between matter, environment, logical control, information, and human activity. It opens the way to new forms of architecture, no longer thought of as an object but rather as a system, a system in interaction with its extended environment.

The permanent exchange of data in the smart factory facilitates the organization and autonomy of supply chains. The smart factory controls the manufacturing processes and, if necessary, adapts them to new requirements: if, for example, a machine stops working, another available system automatically takes its place. This makes manufacturing much more flexible and cost-effective, even when small quantities are produced.

VI. SM CHALLENGES

SM implies the need to handle a large amount of specific data from several devices: the rise of Big Data analytics, which is mainly suitable for these types of data, has also facilitated the evolution of SM. Like most evolving technologies, SM has some challenges to overcome as summarized in Figure 10.

A. INTEROPERABILITY IN SM

One of the crucial concepts of SM is interoperability [44], which represents the ability to communicate and cooperate between two different systems despite their heterogeneity and the little knowledge they have of each other. The considered SM systems can include specific manufacturing sensors, machines, products, or information systems [1], [34], [108], [153]. For that, each company must pick technologies according to its own needs and systems to implement its interoperability framework and develop its SM strategy.

Interoperability is a key concept in SM and is the subject of academic studies and projects to define structures and implementation methods. Different structures and standards have been introduced to understand, analyze, and guide the implementation of an interoperability framework [154]. Interoperability can be segmented into three levels:

- Organizational interoperability concerns the interactions between business groups, business processes, and people across the SM ecosystem. It represents the ability of each unit to provide, receive and use services to ensure the overall functioning of the enterprise.
- Semantic interoperability ensures that information and service sharing preserve the semantic flow. The objective is to ensure that all the exchanged information is understandable by all the applications, even if they were not developed for this purpose. Each SM system, even if heterogeneous, must be able to discover data, represent it and give it a context to interpret the shared data coherently.
- Technical interoperability covers all SM technical issues. Its goal is to facilitate communications by using protocols that allow data and message exchanges between SM system applications. This type of interoperability is associated with the physical, computer, and network components that enable intermachine communication.

These three levels of interoperability are the most recurrent in the literature, address different aspects of the system, and are necessary for the integration of an interoperability framework.

B. LARGE AMOUNTS OF SM DATA

IoT devices connected through a smart factory are constantly collecting data about the production process [151]. The lack of appropriate analysis tools makes this data useless. The number of interconnected devices needed to collect data can lead to security issues, as more devices lead to more entry points into the network. Therefore, it is essential to choose the right software platform for industrial automation [92].

Before talking about data issues, it is important to know that today's manufacturing industries put product quality at the heart of any manufacturing process. This is for productivity and cost reduction. They rely on new digital technologies such as the Internet of Things, robotics, augmented reality, 3D printing, and AI. Intelligent, interconnected automation requires machines to collect and share information. And it's

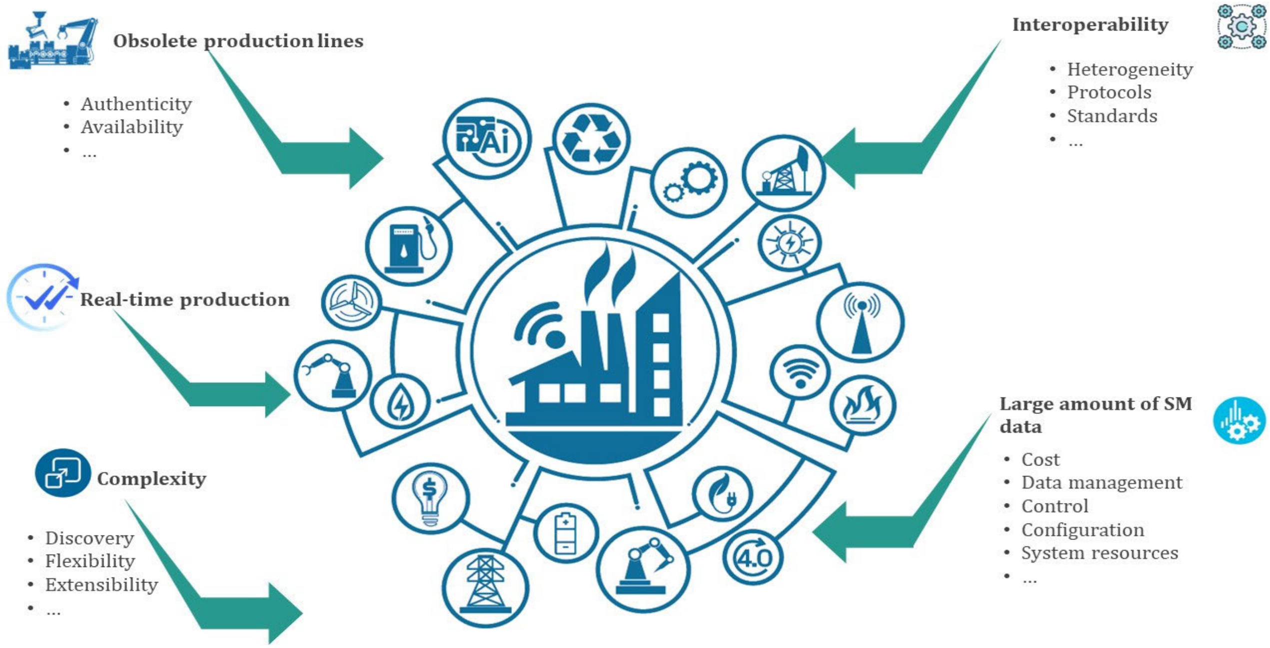

FIGURE 10. Challenges of SM.

the way these machines and the factory communicate via networks that characterizes what is known as Industry 4.0. Seamless connectivity of all sensors and actuators in the plant, even those in remote locations, is possible using Big Data. Through the dematerialization of activities and the widespread interconnection of objects, machines, and people, access is opened to the collection and analysis of massive data in manufacturing units [5], [25], [43], [155].

This correlated data, coupled with predictive analysis, enables manufacturers to supervise, control and monitor their facilities. But also, to anticipate malfunctions and reduce production tool downtime. By integrating MES (Manufacturing Execution System) and lean industrial solutions, manufacturers are guaranteed to reduce costs, increase productivity, ensure process reliability, and improve quality.

C. OBSOLETE SM PRODUCTION LINES

Complex machines are expensive and rarely replaced. It may be necessary for a company to phase out old equipment before being able to purchase machines compatible with smart factory technology. With hardware-independent smart factory software, retrofitting becomes a more viable option [149]. This means using the right technology to create smart production line configurations. Studies have shown that more than 70% of manufacturers believe that smart technologies such as the Internet of Things; Big data analytics; machine learning and augmented reality are integral to their future. Indeed, according to McKinsey, Industry, 4.0 could yield \$3.7 trillion in value for manufacturers and suppliers by 2025, but only 30% of companies are currently benefiting from Industry 4.0 solutions at scale [156].

As a result, companies that are already making the most of the initiative are adopting these technologies; adapting their work models, and introducing interconnected machines to streamline their operations more beneficially [89], [108], [120]. Approximately 79% of manufacturers consider increasing profitability and margins as their top priority; which means it's reasonable to assume they are adopting smart systems; primarily to push their growth boundaries. Most companies that leverage technology for growth aim to improve the following:

- Agility: anticipate changes within their facilities and across broader markets more quickly; also, being able to react quickly to any changes.
- Faster delivery: move products more quickly from ideation and modeling processes to markets.
- Productivity: increase the quality and quantity of products and services delivered by each agent on the production line.
- Mass customization: quickly deliver products specifically tailored to the needs of specific audiences, without compromising efficiency.

D. SM SYSTEM COMPLEXITY

Interconnectivity increases the complexity of the SM system. Each component must be integrated with the others and work as intended. Making sure all the little sensors are working properly can take a lot of time and resources [34], [99]. SM has paved the way for ever-increasing market demands for innovation, safety, reliability, smart functionality, increased quality, ergonomics, and product aesthetics. As a result, product development has become increasingly complex. Increasing product complexity also increases the risk that execution and manufacturing issues will disrupt programs and inflate budgets. Adopting a simulation-based approach to the product development process can alleviate the challenges associated with complex products. It can validate designs early to avoid surprises, delays, and cost overruns [47], [80], [94], [154].

E. REAL-TIME PRODUCTION

High-quality production planning admits many growing challenges for manufacturing companies. Inefficiencies at this level cause significant costs with difficulty in meeting market demands, which have serious effects on the capacity of manufacturers to generate continuously growing profits.

The maximization of SM productivity requires the optimal use of resources and the synchronization of operations according to specific SM constraints. In this context a specific interest must be given to the problems related to the management of the production in real-time:

- Loss of control due to rapid growth in demand: Production often faces the challenge of keeping up with the pace of demand when the company is growing at a high rate. The more orders that accumulate, the more production capacity will be exceeded and therefore lead times will increase. This will cause penalties and a lot of management problems.
- The complexity of planning and scheduling: Planners must consider the different tasks and SM activities, as well as constraints, which complicate the optimal and feasible approach to a production plan. Scheduling multiple DM activities generates billions of possible sequences. Therefore, the analysis of all scenario combinations must consider all the constraints of the global market.
- Production bottlenecks: Bottlenecks impact the smooth running of SM operations, so managing them is an ongoing challenge for manufacturing companies. The production schedule must be optimized to minimize waiting and machine set-up times. This results in less wasted time, which frees up additional production capacity and improves the production flow.
- The difficulty to deliver on time: Just-in-time delivery is essential to ensure good competitiveness in the market and to satisfy a large and increasingly demanding clientele. Therefore, it is essential to optimize the operations according to the delivery times and the various constraints by taking into consideration the reality on the floor to easily adjust the plan according to the unforeseen.
- Labor shortage: small staff numbers make it difficult to deliver on time and even cause orders to be lost to the competition. It is therefore advisable to optimize the use of personnel not only according to availability but also according to skills.
- The inability to evaluate various scenarios: It is often difficult to evaluate the real impact of a decision or an unforeseen event. Therefore, the ability to measure the repercussions of a scenario on the whole production through a simulation becomes necessary. Thanks to innovative technologies, it is possible to vary the availability of resources, modify efficiencies, or simulate an equipment shutdown.

VII. DISCUSSION AND OPEN ISSUES

This section discusses the research questions to provide a better vision of SM improvement.

A. SM CHARACTERISTICS

Technically, SM is an extension of traditional industrial systems and reveals a merging of manufacturing processes with digital technologies. In this research, we were able to cross-literature SM-related approaches to specify the benefits and the drawbacks [141], [142].

1) SM-ADVANTAGES

SM represents a technological move that enables automation for:

- Improving the manufacturing system's effectiveness by making quicker, more accurate, and more knowledgeable decisions.
- Decreasing the maintenance charges by replacing redundant maintenance with more cost-effective and personalized predictive maintenance.
- Improving the SM processes with enhanced communication networks and remote monitoring of manufacturing tasks to recognize risks and potential waste sources.
- Predicting the maintenance interferences on the SM production lines significantly diminishes the risks of sudden interruptions.
- Monitoring the productivity and efficiency of the manufacturing equipment.

2) DIFFICULTIES IN USING SM

While customers appreciate the simple interactions made possible by automated digital tools, they need to be able to contact a human advisor at any time. Therefore, relying solely on robotization for customer service is not yet possible and, in any case, would be a big mistake. It must be part of the tools, but it only serves to complete the existing toolbox. Relying on robotization to do all the work is not what you should expect, but unleashing the available intelligence to serve the customer even better, regardless of their touchpoint. However other obstacles may affect SM evolution such as:

- People consider SM frameworks still a complex environment concerning the organization, plans, and maintenance, to be used and adopted in wide industrial innovation scopes.
- Many people are anxious to find themselves in opposed or closed systems.

- The fulfillment of SM must meet global regulations and standards.

B. DISCUSSION

Digitizing the manufacturing processes, and adopting more advanced technologies, is a strategy to effectively address fundamental supply chain activities complexity, which is an evolving topic, and a crucial key for the industrial area. Manufacturing processes are derived and guided toward their objectives. Yet in growing manufacturing systems, acting with little or no clear insights on the one hand may lead these systems to respond with inertia, which in economic terms, means unwanted costs. For that, a decent level of flexibility in production and logistics structures can transform the manufacturing environment in a more promising position to adjust according to market variations when seeking objectives, to make them more flexible.

The importance of optimally altering classical manufacturing systems lies in the technological area. Studying the speed and changes with which smart technologies are introduced are vital factors. Since they manage SM systems in such a way that inertial outcomes and their possible negative effects are reduced. During the SM process, speed, efficiency, and anticipation of the result are more important. Intelligent technological adoption must be oriented to the improvement of all factors forming the main SM challenges. This potential is shown by the growing interest demonstrated by the industrial and scientific community in the last decades, which has been ascending since 2015 and covers more than half of all the literature since 2020. The reasons behind this growing interest in SM could be the maturity that smart technologies, the diverse and potential application of these emerging technologies, and the renewed interest of both industry and academia in SM environments management.

The reviewed literature offers a wide spectrum of opportunities for studying and developing SM approaches. Undeniably, it is not only essential to consider SM's advantages, but it is also important to be aware of SM's limitations. The main findings of this paper and research gaps of SM trends in this regard are discussed below.

1) STEP 3: PROVIDING SM SYSTEM WITH INTELLIGENT CAPABILITIES

Addressing SM alignment axes, it is obvious that the SM system's capacity to take the right action in real time enables an enhanced interaction within the SM environment without extra delays, other than the normal delays of the manufacturing environment itself. In turn, within an SM process automation, enabling an SM with the capacity to act in real-time, provides decent decision-making, even if many actions are running synchronously. For that, AI technologies avoid awaits periods for a decision to be made. AI allows for generating issues solving solutions, as well as predictive models that can absorb disruptions without affecting the manufacturing process. Such approaches are essential in SM systems for resilient behavior with zero machine failures, zero loss, zero defective products, zero accidents, etc.

The study revealed that sensors use is usually associated with planning or prediction needs; however, when integrating new technologies into production cells, that involves the adoption of some AI models to favor better SM functioning. To overcome the lack of the IoT, and its related technologies, in classical manufacturing environments containing numerous, Big Data technologies are gradually making inroads in SM environments. It is necessary to build an awareness of the users while ensuring the availability of data to exceed the standard manufacturing efficiency and productivity threshold. Additionally, collecting and managing SM knowledge allow better data exploitation for semantic interoperability conditions.

2) STEP 2: EMPLOYING MORE ENABLING DIGITAL TECHNOLOGIES

Assisting SM systems by employing enabling digital technologies (i.e.: simulation, virtualization, etc.), is a concept very present in the reviewed papers [41], [74], [77], [80], [82], [83], [88], [89], [91], [94], [96], [98], [99], [101], [104], [105], [107], [108], [111], [112], [114], [116], [118], [120], [131], [132], [133], [135]. These intelligent solutions provide the manufacturing system with intelligent capabilities through IoT and AI-based models for real-time processing. It is worth mentioning that using only one enabling digital technology remains a limited solution by the absence of heuristics approaches specifically devoted to fitting small and/or medium-sized enterprises (SMEs) specific requirements and the partial incorporation and interconnection of the manufacturing elements.

However, it may be helpful to integrate several technological areas into a single SM system. In contrast to this integration lies the fact that these models do not operate through a single cloud platform, which is an essential restriction. In addition, data security tools and strategies are less discussed in SM systems. Additionally, the validation of a real complete SM environment, outside the laboratory, is still pending. Furthermore, other research areas are still less explored, such as SM modeling methodologies, SM implementation guidelines, SM simulation or evaluation tools, etc. The second SM alignment axis is the adoption of IoT sensors, which is the most reported technology in the reviewed literature. The IoT provides a huge shop floor, which contributes to increasing SM situational awareness to ensure more visibility of SM systems to reduce defects and increase the robustness of SM decision-making processes.

3) STEP 1: APPLYING THE TECHNOLOGIES AND/OR THE SM SYSTEMS

The first SM methodological step is applying new technologies. Thus, the SM alignment position was studied, which includes the essence of scientific works. Various papers warned about the value of the flexibility of real-time actions in SM contexts [22], [106], [117], [121], [132], as well as the convenience of reducing manufacturing failures to avoid interrupting manufacturing, logistics operations, and purchasing.

Preventing real-time SM actions capability, flexibility and interruption remain the pivot around which SM environments rotate. Hence this vision is relevant as it is based on the combined use of emerging technologies for better SM process performance. The limitation of this study arises from the restricted examples, in the literature, of scientific papers that outline and explain the partial scopes that deal with the SM subject. One important aspect of applying intelligent technologies, which is critical for SM, and its relation to flexibility and interoperability, is widely addressed.

C. SM OPEN ISSUES

In the latest decade, industrials and scientists have been showing a growing interest in addressing SM challenges. However, some concerns still need to be studied in future works.

1) SYSTEM DESIGN

Significant SM systems, have particular features i.e.: decentralized strategies, continuous development, conflicting needs, wide-ranging agreements, extreme interactions among heterogeneous components or systems, etc. Each SM system may be built employing diverse software design policies, without exact knowledge of other SM systems' specificities. Since the design of these SM systems is made independently for specific purposes, various designs would be introduced. Therefore, different implementation ways and maintenance rules are adopted. Moreover, the SM sub-systems may be monitored by separated structures and policies.

2) A COMPREHENSIVE EVALUATION OF SM REQUIREMENTS

The increasing SM popularity improved the development of new manufacturing systems with distinctive requirements and characteristics. Alternatively, controlling each requirement may affect the whole system. Therefore, proper cooperative methods must be considered for SM designing to warrant better functionalities. Therefore, interoperability issues require the help of industry experts for a complete analysis that distinguishes and arrange SM system requirements.

3) FLEXIBLE AND GENERAL-PURPOSE APPROACHES

The fast progress of SM environments, lead to significant concerns considering the configuration of SM systems and involve flexible approaches for numerous scenarios. Accordingly, for more robust manufacturing management, regarding industrial changes, and general objectives. Therefore, additional studies are required to ensure conventional approaches that may be flexible to industrial changes and utilized in various scenarios.

D. STUDY LIMITATIONS

The qualitative nature of systematic literature surveys remains the primary limitation of the current study. Even, though this paper was conducted considering the uppermost methodological standards, where data extraction stages were performed by three authors autonomously, to decrease the bias of the study, while measuring the data efficiency, the critical assessment of study contents remains uncertain degree. Furthermore, not all papers that could be of interest were integrated despite the organized selection process, this is due to the vast related research and the increasing publications number. Retrieving papers from further scientific databases might theoretically lead to the addition of additional pertinent papers.

More significantly, more inclusion criteria as well as quality constraints may potentially enrich the literature regarding the quantity. Moreover, manufacturing reports and articles published on internet forums, interviews and webpages could provide an essential source of information specified in a fast-growing and pioneering field such as SM. Further, SM can be categorized as a multidisciplinary sector term of the various incorporated fields. Different SM approaches are built at different velocities and could also potentially impact the SM in different ways. This is a characteristic that has not been reported in this study.

VIII. CONCLUSION

This study has examined the SM literature papers and presented a detailed outline of the current state of SM papers involving various aspects. As an evolving industrial trend, SM is expected to be largely implemented soon. This paper discussed the technical advanced, as well as SM challenges, and provides a strong basis for SM-related future studies. In this study, we defined our research methodology and chose well-known scientific databases for analyzing SM's current advances. Furthermore, in this study, SM challenges are classified into four main groups: interoperability, large amounts of data, obsolete SM production lines, and SM systems complexity, with much more attention on interoperability issues. This study offers many advantages for both industrials and researchers. Also, it shapes a strong information foundation by illuminating the state of the art of an evolutive research field.

From a quantitative point of view, further statistical proof and longitudinal research are needed, and the presented study only examines the SM environment regarding smart technologies used, to offer a strong basis for researchers to build new smart mechanisms to solve the current issues and overcome the discussed challenges. The use of AI and IoT is widely stated in the relevant literature, even if authors' growth approaches rationally differ, according to context or needs.

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