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Review

Integrating Large Language Models into Digital Manufacturing: A Systematic Review and Research Agenda

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Abstract

Industries 4.0 and 5.0 are based on technological advances, notably large language models (LLMs), which are making a significant contribution to the transition to smart factories. Although considerable research has explored this phenomenon, the literature remains fragmented and lacks an integrative framework that highlights the multifaceted implications of using LLMs in the context of digital manufacturing. To address this limitation, we conducted a systematic literature review, analyzing 53 papers selected according to predefined inclusion and exclusion criteria. Our descriptive and thematic analyses, respectively, mapped new trends and identified emerging themes, classified into three axes: (1) manufacturing process optimization, (2) data structuring and innovation, and (3) human–machine interaction and ethical challenges. Our results revealed that LLMs can enhance operational performance and foster innovation while redistributing human roles. Our research offers an in-depth understanding of the implications of LLMs. Finally, we propose a future research agenda to guide future studies.

Keywords: large language models; artificial intelligence; digital manufacturing; Industry 4.0; Industry 5.0

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1. Introduction

The fourth industrial revolution transformed manufacturing systems by integrating advanced technologies into the value chain lifecycle [1], thereby making organizations increasingly intelligent thanks to technological advances. The shift toward Industry 4.0 and 5.0 has transformed the global manufacturing sector. Since 2019, the adoption of I4.0 has increased by 80% [2]. The size of the digital transformation market in this sector reached USD 427.68 billion in 2024 [3] and is expected to grow from USD 467.72 billion in 2025 to USD 1046.61 billion by 2034 [3]. Hebert Simon envisioned this evolution by declaring that "machines will be capable, within twenty years, of doing any work that a man can do" [4] (p. 38). Indeed, Industry 4.0 (I4.0) as well as Industry 5.0 (I5.0) have changed manufacturing and management methods as well as industrial operations, automating industrial systems through technology solutions, including artificial intelligence (AI), blockchain, the Internet of Things (IoT), and large language models (LLMs) [5]. To improve productivity and reduce costs, companies have adopted several advanced technologies [2], specifically IoT, AI, and machine learning, which are among the most widely used [3]. This strategy has helped these companies overcome the challenges of skilled employee shortages [2].

Among all technologies, large language models (LLMs) represent a significant advancement in the field of AI, comprising deep neural networks that process and understand human language [6]. They bring innovative perspectives to the digital transformation of industries, motivating the implementation of technology-based strategies [7]. Today, LLMs are considered among the dominant technologies. For example, ChatGPT surpassed one million users in just five days after its launch, and OpenAI expects to reach one billion users by the end of 2025 [8]. This highlights the significance of LLMs for informed decision-making in industrial settings. Several research studies have paid particular attention to LLMs, notably through the introduction of LLAMA [9] and ChatGPT [10,11]. These systems significantly contribute to the development of the manufacturing sector, facilitating the design, optimization, and automation of manufacturing processes [12] while reducing costs and improving productivity [7]. This technology also enables human language understanding [6] and real-time functional reasoning to better understand human needs [13], reduce errors [14], and efficiently leverage data [15].

Despite these advances, research on the use of LLMs is still fragmented [16]. In other words, applications of this technology are often presented in isolation in the literature [17]. The systematic literature reviews conducted focused primarily on presenting an overview of the progress made and the challenges involved in integrating artificial intelligence technologies into the industrial context. For example, the study of Zhang et al. [18] explored and analyzed the literature on the integration of LLMs into next-generation manufacturing, highlighting the technological limitations. Fan et al. [19] examined the contributions of LLM-based agents in several scenarios, including improving autonomy and industrial robotics. Wan et al. [20] examined the application of knowledge graphs in smart factories. Other systematic literature reviews have been conducted on related topics, including the use of AI technology in the context of Industry 4.0 [21], human-oriented AI in I4.0 [22], and the joint integration of this technology with DTs [23]. Nevertheless, although some systematic analyses have examined the phenomenon of LLMs in industry (e.g., Li et al. [24] and Zhang et al. [18]), they are limited to particular situations. Furthermore, they do not provide a comprehensive and unified theoretical framework for understanding the potential of integrating LLMs to address the challenges of digital manufacturing [22,23], which highlights the relationship between the functional and technical tasks of LLMs, distributed power, and the ethical issues related to their use [25,26]. To our knowledge, only the analysis by Chen et al. [27] has presented a framework for the integration of LLMs into digital twins under I5.0. However, it remains limited. Furthermore, there is no operational and targeted future research agenda to guide future research effectively.

In light of these findings, it is relevant to fill this gap by conducting a systematic and integrative analysis of existing knowledge to rethink various use cases, including system automation, process optimization, supply chain management, big data, and cybersecurity.

This analysis will enable us to propose three contributions: (1) the identification of emerging themes related to the integration of LLMs in the digital manufacturing sector, (2) the development of an integrative framework synthesizing the key areas of LLM use, and (3) the presentation of a structured research agenda to guide future investigations. Our research stands out for its detailed and systematic analysis of the literature on the implications of LLMs in the context of digital manufacturing, an innovative topic that is relevant to the evolution of Industry 4.0 and 5.0 and lies at the intersection of technology, strategy, and organization.

We therefore seek to answer the following research question (RQ):

(RQ) What are the multifaceted implications of LLMs in the context of digital manufacturing?

Our article is structured around five key points. First, we explain the methodological approach followed. The next two sections present, respectively, the results of the descriptive analysis, obtained using VOSviewer 1.6.20.0, and the thematic analysis carried out to explore the various themes identified. Proposals for future research are then presented to guide subsequent studies. Finally, we conclude with a summary of the main findings of our research.

2. Methodology

Our objective is to examine the impact of LLMs on digital manufacturing. To this end, we employed the PRISMA methodology to conduct a systematic review of the literature. Indeed, this systematic review is considered "a fundamental scientific activity" [28] that quantifies the dispersed scientific evidence relating to the topic under consideration, via a rigorous and reproducible process [29]. This approach facilitates a synthesis of studies from the literature to inform future research. Although we have adopted the PRISMA method, we have selected articles that are not limited to systematic literature reviews. The sample articles also include experimental studies, industrial cases, and exploratory studies, among other types of research.

2.1. Selection Database

To identify and select relevant articles for our systematic literature review, we used a multi-database approach. This approach aimed to reduce the risk of omitting relevant and essential findings. We chose Scopus, ABI/Inform, EBSCO and Springer. These sources present different perspectives and references pertinent to our study, maximizing access to open-access articles and reinforcing the representativeness of the existing literature.

2.2. Search String

At this stage, we used a comprehensive and relevant query, using Boolean logic, that covers several relevant aspects, such as techniques (AI, LLM, GPT and BERT), industrial domains to reflect digital manufacturing and the supply chain, and the objectives of these technologies, including optimization, efficiency, automation and resilience. This facilitates literature retrieval. The search terms were as follows:

("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "large language model" OR "LLM" OR "transformer model" OR "GPT"* (A pre-trained language for text generation, natural language analysis and response to various queries) *OR "BERT" (Bidirectional Encoder representations from transformers* is a pre-trained language model)) *AND ("digital manufacturing" OR "smart manufacturing" OR "intelligent manufacturing" OR "Industry 4.0" OR "cyber-physical systems") AND ("supply chain" OR "supply chain management" OR "SCM" OR "Operations and Supply Chain Management" OR "OSCM" OR "logistics" OR "operations management" OR "production planning" OR "inventory optimization" OR "resource planning") AND ("optimization" OR "efficiency" OR "resilience" OR "automation" OR "real-time decision-making")*

- The first block covers classic and advanced AI techniques. AI, machine learning and deep learning for AI in general, and language models (LLM, GPT, BERT) link up with technological advances in natural language processing.

("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "large language model" OR "LLM" OR "transformer model" OR "GPT" OR "BERT")*

- The second block defines the overall context, i.e., digital manufacturing and the supply chain. Digital manufacturing, smart manufacturing, intelligent manufacturing, Industry 4.0, and cyber–physical systems are all linked to the industry of the future.

("digital manufacturing" OR "smart manufacturing" OR "intelligent manufacturing" OR "Industry 4.0" OR "cyber-physical systems")

- The third block presents industrial functions, including operations management, supply chain management, and logistics.

("supply chain" OR "supply chain management" OR "SCM" OR "Operations and Supply Chain Management" OR "OSCM" OR "logistics" OR "operations management" OR "production planning" OR "inventory optimization" OR "resource planning")

- The fourth block presents the objectives of technology use (e.g., efficiency, optimization, automation).

("optimization" OR "efficiency" OR "resilience" OR "automation" OR "real-time decision-making")

2.3. Data Filtering (Inclusion and Exclusion Criteria)

To refine our corpus, we used inclusion and exclusion criteria. These criteria enable us to sort the publications from various databases during our initial search and subsequently select those that are relevant and rigorous to our research.

For this selection process, we considered publications published between 1 January 2015 and 30 April 2025, to include the latest trends and emerging challenges in the field addressed. Indeed, 2015 was marked by the emergence of AI technologies, particularly deep learning, which laid the essential foundations for the future evolution of intelligent systems [30]. In addition, the introduction of residual networks (ResNet) by He et al. [31] has enabled the proposal of more sophisticated models, including large language models (LLMs) [31]. Thus, the chosen time frame encompasses the development of learning techniques that integrate LLMs in various sectors, including digital manufacturing. Next, we selected two types of documents, which are papers presented at international academic conferences and publications published in peer-reviewed journals. This enables us to choose research work that follows a rigorous scientific approach and has been validated by peers, which is important to ensure a more accurate comparison of the conclusions drawn. It should be noted that only papers written in English and French were considered, as English dominates the international scientific literature while French, although not dominating at the international level, has regional and disciplinary importance. This guarantees the absence of interpretation bias in our analysis. Our final inclusion criterion concerns the presence of at least one keyword in the title, abstract or keyword section.

To ensure a finer selection of relevant articles exploring the enhancement of digital manufacturing by large language models (LLMs), we removed publications that explored artificial intelligence in contexts other than digital manufacturing, as well as those that focused on digital manufacturing without explicitly mentioning artificial intelligence or LLMs. This exclusion criterion enables the selection of only those articles that are at the intersection of digital manufacturing and LLMs. We also excluded book chapters, books, professional reports, doctoral theses, research dissertations and press articles, so as not to compromise the intellectual and scientific rigour essential for a systematic literature review.

Table 1 summarizes the inclusion and exclusion criteria used in this research to establish a relevant corpus for reinforcing our thematic analysis.

Table 1. Inclusion and exclusion criteria (Authors).

Inclusion criteria	- Articles published between 1 January 2015 and 30 April 2025; - Papers presented at academic conferences; - Scientific articles published in peer-reviewed journals; - Papers written in French and English; - The presence of at least one topical keyword in the title, abstract or keyword section.
Exclusion criteria	- Off-topic publications; - Book chapters, books, professional reports, doctoral dissertations, research papers and press articles.

2.4. Data Collection Process

In our research, we adopted the PRISMA model, which is based on factual elements that facilitate the systematic presentation of the stages in a literature review [32]. The process of creating our corpus was followed rigorously and methodically to select relevant publications linked to our theme.

The initial search yielded 413 publications from the selected databases for this research. They are distributed as follows: 114 publications from Scopus, 95 publications from ABI/Inform, 122 publications from Springer and 82 publications from EBSCO. Then, to avoid over-representation of specific research, we removed duplicates (49 publications). The next step was to read and analyze the abstracts of the remaining 364 publications to check their thematic relevance to our study. This careful analysis resulted in the deletion of 180 articles, as they did not adequately address the role of LLMs in digital manufacturing. Finally, 184 papers were read in their entirety to confirm the relevance of their contributions to our research and to create a coherent, manageable corpus for our systematic literature review. This exhaustive analysis refined our corpus, and approximately 12.8% of the initially selected articles were retained, resulting in 53 publications.

The following diagram illustrates the selection process (Figure 1).

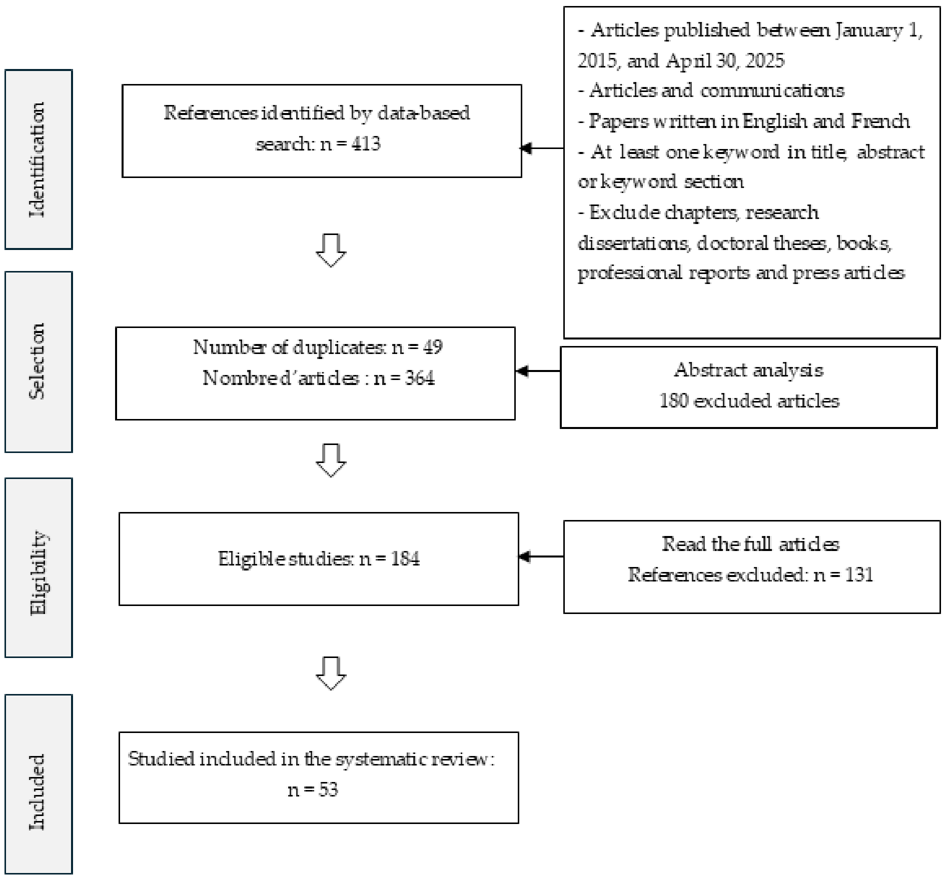

Figure 1. PRISMA flowchart (authors).

3. Bibliometric Analysis

In this section, we present a visual mapping, based on citation analysis, co-occurrence analysis of key concepts and bibliographic coupling. These are visual representations that illustrate the relationships between selected articles, authors, journals, countries, and other entities [33]. This bibliometric analysis was conducted using VOSviewer software to elucidate research trends.

It is worth noting that there are other useful software programs for systematic literature analysis, such as *Bibliometrix* (via *R*), which generates bibliometric maps in a scripted environment, and *CiteSpace*, which focuses on trends over time. In our case, we chose VOSviewer because, unlike the other two tools, it is easy to use and capable of processing a large dataset to generate clear and interactive visualizations immediately. Therefore, it is the most suitable tool for our exploratory objectives.

3.1. Keyword Analysis

We performed a keyword co-occurrence analysis, using authors' keywords as a unit of study, to obtain a precise and faithful mapping of the themes covered by the authors. This method also minimizes the semantic noise generated by automatically indexed keywords. This method enables us to provide more targeted results and structure our analysis, as it examines the keywords that are central and considered most representative by the authors.

Figure 2 shows the co-occurrence map of the keywords proposed by the authors belonging to our corpus (Figure 2). It is composed of 19 clusters of different sizes to indicate the frequency of occurrence of each key concept. This map illustrates a multi-cluster structure, displaying 588 relationships between the various keywords in our corpus (Table 2). In other words, the concepts are associated with several thematic groups, indicating that studies on LLMs and digital manufacturing are multidisciplinary (e.g., artificial intelligence, optimization, industries 4.0 and 5.0). Thus, the total link strength index, which equals 618 (Table 2), indicates a strong connection between certain concepts in the literature. By deduction, our network is robust and coherent between the various themes.

This analysis identified 19 clusters presented in Table 2, which we have classified into five key thematic axes to improve the clarity of our results. The first axis groups clusters 1, 3, 10, 11, 15 and 19, which concern advanced automation through intelligent systems. Indeed, these clusters focus on the use of autonomous and interconnected systems ("cyber-physical systems (CPSs)", "simulation", "real-time sensor data", "smart factory", "fault detection", "digital shadow"). The second axis focuses on human–machine interaction (clusters 2, 6, 8, 9 and 18), highlighting the intermediary role of LLMs between employees and production systems ("chatbot", "natural language processing", "human–robot collaboration (HRC)", "ChatGPT", "human–computer interaction"). The third axis includes clusters 3, 7, 12, and 14, which focus on the use of LLMs to optimize operations and solve planning problems, such as "fuzzy topsis," "engineering design," "additive manufacturing," and "scheduling." The next axis, which brings together clusters 4, 5, 13 and 17, focuses on the contribution of LLMs to improving data processing and structuring, as well as compliance with digital regulations ("ontology", "business processes", "compliance checks", "failure mode and effect analysis (FMEA)"). Finally, the fifth axis (clusters 5 and 16) is associated with the human and social impacts of the transition to a smart industry, as well as sustainability through a reduction in the environmental effects ("workforce impact", "circular economy").

However, the co-occurrence analysis method based on key concepts chosen by the authors risks ignoring relevant aspects of the field in question. That is why we have decided to broaden our perspective by conducting a co-occurrence analysis of keywords based on all keywords ("all keywords"). This approach enables a more comprehensive exploration of cross-cutting and emerging concepts, providing a broader view of the lexical field.

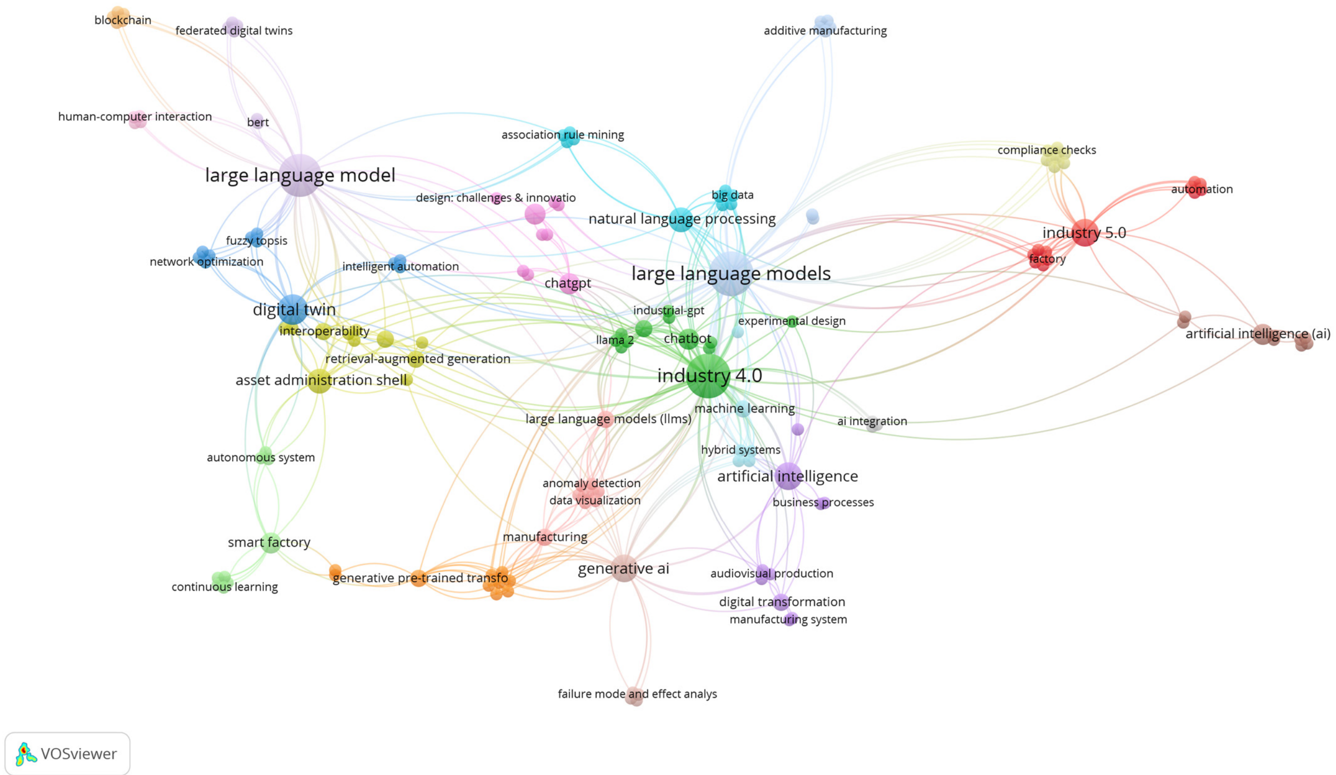

Figure 2. Analysis of keyword occurrence frequencies—authors' keywords (authors).

Table 2. The structure of keyword clusters—authors' keywords (authors).

Clusters	Keyword	Occurrences	Total Link Strength
Cluster 1	Automation	1	5
	Benchmarking	1	7
	Cobot	1	5
	Cyber–physical system (CPS)	1	5
	Digital twins (DTS)	1	5
	Explainable artificial intelligence (EXAI)	1	5
	Factory	1	7
	Industrial settings	1	7
	Industry 5.0	5	29
	Information retrieval	1	7
	Knowledge sharing	1	7
	Natural language interface	1	7
Cluster 2	Adaptive automation	1	3
	Chatbot	3	15
	Cybersecurity	1	3
	Experimental design	1	5
	Industrial-gpt	1	4
	Industry 4.0	13	73
	Langchain	2	11
	Llama 2	1	7
	OpenAI	1	4
	PCB manufacturing	1	7
	Retrieval-augmented generation (rag)	1	7
	User-centric evaluation	1	7

Table 2. *Cont.*

Clusters	Keyword	Occurrences	Total Link Strength
Cluster 3	Digital twin	6	29
	Fuzzy topsis	1	4
	Intelligent automation	1	4
	Intelligent management	1	5
	Morphological matrix	1	4
	Multi-agent system	1	4
	Multi-objective optimization	1	5
	Network optimization	1	5
	Real-time optimization	1	5
	S4 framework	1	4
	Simulation	1	4
Cluster 4	Asset administration shell	4	23
	Entity matching	1	5
	Information modeling	1	7
	Interoperability	2	12
	Knowledge representation	1	5
	Knowledge-based systems	1	4
	Ontology	1	7
	Quality control	2	11
	Retrieval-augmented generation	2	10
	Semantic interoperability	1	6
	Zero defect manufacturing	1	7
Cluster 5	Artificial intelligence	5	27
	Audiovisual production	1	6
	Business processes	1	4
	Communication	1	6
	Decision-making	1	2
	Digital transformation	2	8
	Human-in-the-loop	1	3
	Manufacturing system	1	2
	Society 5.0	1	6
	Workforce impact	1	4
Cluster 6	Association rule mining	1	5
	Big data	1	7
	Chat-bot	1	7
	Embeddings	1	7
	Human–computer interaction	1	7
	Industrial applications	1	5
	IoT	1	7
	Maintenance work order	1	5
	Natural language processing	4	21
	Text mining	1	5
Cluster 7	Creativity	1	10
	Deep learning	1	3
	Engineering design	1	10
	Generative pre-trained transformer	2	13
	Intelligent digital twins	1	10
	Intelligent maintenance	1	10
	Mechanical engineering	1	10
	Mechanics	1	10
	Pre-trained language models	1	10
	Process optimization	1	3

Table 2. *Cont.*

Clusters	Keyword	Occurrences	Total Link Strength
Cluster 8	5G networks	1	5
	Artificial intelligence (AI)	3	13
	Conversational artificial intelligence	1	4
	Edge computing	1	5
	Generative pre-trained transformer (GPT)	1	4
	Human–robot collaboration (HRC)	1	4
	Human–robot interaction (HRI)	1	4
	Industrial chatbot	1	4
	Large language models (LLMs)	1	4
Cluster 9	Bottleneck mining	1	3
	ChatGPT	3	15
	Design: challenges and innovation	1	2
	Digital supply chain	1	3
	Knowledge graph	3	8
	Lean Six Sigma	1	5
	Manufacturing service discovery	1	3
	Ship manufacturing process	1	3
	Text mining and analysis	1	5
Cluster 10	Anomaly detection	1	9
	Data visualization	1	9
	Data-driven decision-making	1	9
	Large language models (LLMs)	2	16
	Manufacturing	2	19
	Natural language queries	1	9
	Production process optimization	1	9
	Real-time sensor data	1	9
	Shop floor analytics	1	9
Cluster 11	Autonomous system	1	5
	Continuous learning	1	5
	GPT	1	5
	Intelligent agent	1	5
	Knowledge integration	1	5
	Real-time data processing	1	5
	Retrieval-augmented generation-large language Model architecture	1	5
	Smart factory	3	13
	System performance modeling	1	5
Cluster 12	Additive manufacturing	1	5
	Domain knowledge management	1	5
	Fused deposition modeling	1	5
	Human–robot collaboration	1	2
	Large language models	13	70
	Manufacturing systems	1	2
	Named entity recognition	1	5
	Retrieval augmented generation	1	5
Cluster 13	Compliance checks	1	8
	Eworks	1	8
	Internet of Things	1	8
	Regulatory science	1	8
	Regulatory technologies	1	8
	Tool calling	1	8
	Web services	1	8

Table 2. *Cont.*

Clusters	Keyword	Occurrences	Total Link Strength
Cluster 14	Bert	1	3
	Federated digital twins	1	5
	Flexible job-shop	1	5
	Large language model	12	56
	Scheduling	1	5
	Supply chain management	1	3
	The software-defined factory	1	5
Cluster 15	Fault detection	1	9
	Fault diagnosis	1	9
	Hybrid systems	1	9
	Machine learning	2	13
	Real-time systems	1	9
	Smes	1	4
Cluster 16	Blockchain	1	5
	Circular economy	1	5
	Distributed manufacturing	1	5
	Energy-efficient scheduling	1	5
	Multi-agent	1	5
Cluster 17	Failure mode and effect analysis (FMEA)	1	4
	Generative AI	5	35
	Knowledge management	1	4
	Large language model (LLM)	1	4
	Product quality	1	4
Cluster 18	Human–computer interaction	1	4
	Interactive manufacturing execution system	1	4
	LLM-agent	1	4
	Text2sql	1	4
Cluster 19	AI integration	1	4
	Digital shadow	1	4
	Manufacturing data model	1	4
		Total clusters	19
		Links	588
		Total link strength	618

The co-occurrence analysis of all key concepts from our corpus revealed 24 clusters (Figure 3). This reflects the homogeneity of the terms used in the articles selected for our systematic literature review, as well as the approaches adopted in the field of study. Consequently, several areas address the relationship between digital manufacturing and LLMs. We also note that the map displays fragmented clusters with technical keywords, such as “digital twin” and “knowledge graph,” as well as general keywords, including “artificial intelligence,” “manufacturing,” and “Industry 5.0.” The diversity of concepts indicates the richness and lexical coverage of the automatically indexed concepts.

Compared to the co-occurrence analysis of key concepts (all keywords), thematic consistency is higher in the study of keywords deliberately chosen by authors to refer to the core of the phenomenon being addressed. In other words, the examination of targeted keywords provided 19 structured and relevant clusters for research on the use of LLMs in digital manufacturing.

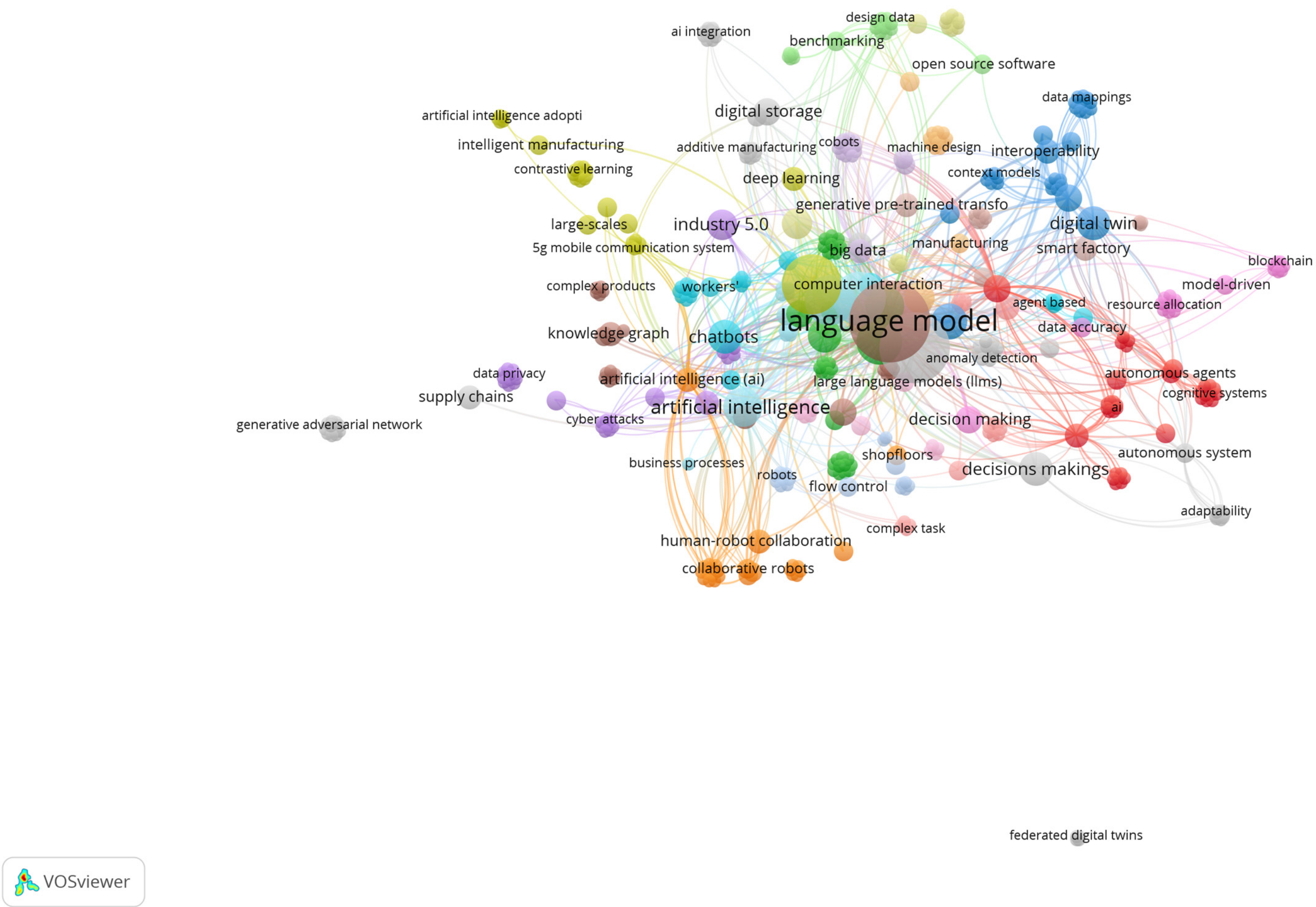

Figure 3. Analysis of keyword occurrence frequencies—all keywords (authors).

In addition, the keywords “ChatGPT” and “retrieval-augmented generation” are presented in the map of the co-occurrence analysis of the authors’ key concepts (Figure 2). By deduction, there is a clear trend toward the use of LLMs in industrial systems, for example, through conversational agents. The same applies to the concept of “Smart factory,” which shows the transition to intelligent, interconnected systems powered by LLMs in the field of digital manufacturing.

3.2. Co-Citation Analysis: Cited Authors

To identify the most connected and influential authors, we applied a scientometric method using VOSviewer.

The author Wang X. has the highest number of citations (48 citations), indicating his key role in the literature on advanced technologies, particularly LLMs, in the field of digital manufacturing. Furthermore, this researcher has not only been cited by 110 different authors in our corpus (Links = 110) but has also been co-cited extensively with other key authors (total link strength = 3154). This demonstrates cross-disciplinary visibility and significant influence in the literature. On the other hand, Wang X. occupies a strategic position in the scientific network, even a central position in the green clusters in this network. Consequently, his work is considered a relevant reference for studies exploring the application of LLMs to optimize and automate manufacturing processes.

Author Li, J., also plays a central role in the field due to his high citation rate (36 citations). Although this author is cited less frequently than Wang X., he is highly connected (Links = 111) and co-cited by other researchers in the network (total link strength = 2209). By deduction, Li, J. plays a structuring role, combining various research and approaches adopted in the literature.

Finally, the results revealed that Zhang, J., is also well integrated into the network. He has been cited 33 times and is strongly linked to other scientific communities (with 109 links). In addition, Zhang, J., influences several different research projects in the field of digital manufacturing (total link strength = 1950).

The co-citation map provided highlights five clusters (Figure 4) that bring together authors exploring similar or closely related issues within the same thematic area.

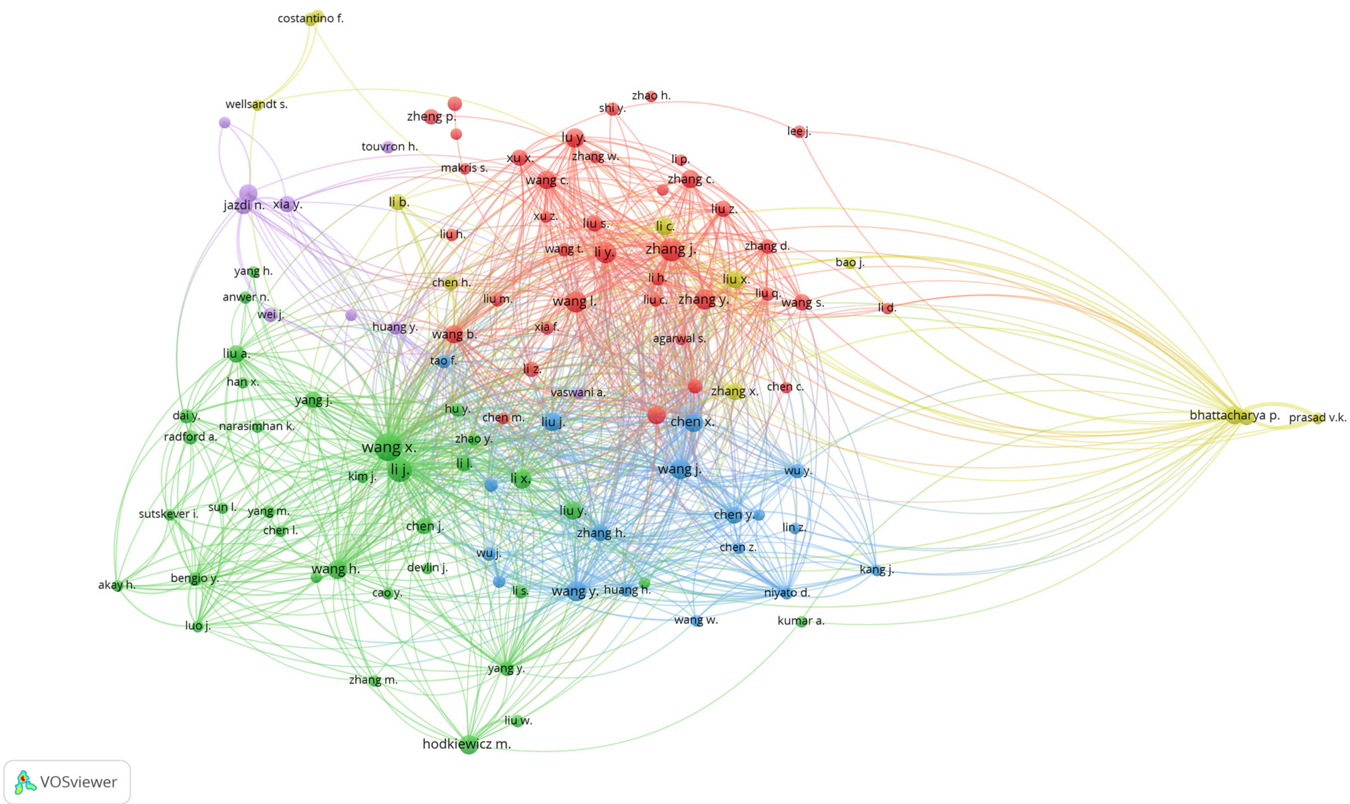

Figure 4. The authors' co-citation map (authors).

Cluster 1 focuses on digital engineering and intelligent manufacturing systems. For example, Makris, S., Li, H., Li, Y., Wang, C., Liu, C., and Wang, Z., addressed the field of digital engineering, process automation and control, and intelligent manufacturing systems. All these fields share the idea of adopting technologies in the context of digital manufacturing.

Cluster 2 brings together authors who have provided a comprehensive overview of the use of artificial intelligence in learning, including language models and deep learning.

Cluster 3 focuses on several areas, such as sustainability and the automation of production processes through advanced technologies, including artificial intelligence and the IoT. This cluster, therefore, comprises researchers whose work focuses on energy optimization and sustainability in industrial processes through the application of advanced technologies.

Cluster 4 presents authors who have examined sustainability and supply chain management to improve organizational performance.

Finally, Cluster 5 includes nine researchers who have highlighted the importance of security in digital manufacturing. They explained how to combat cyber threats, for example, through the use of cyber–physical systems and automation.

We present the thematic classification of clusters in Table 3.

Table 3. Thematic classification of clusters (authors).

Clusters	Authors	Theme Cluster
Cluster 1	Agarwal S., Chen, C., Chen, M., Lee, J., Li, D., Li, H., Li, P., Li, Y., Li, Z., Liu, C., Liu, H., Liu, M., Liu, Q., Liu, S., Liu, Z., Lu, Y., Makris, S., Shi, Y., Vogel-Heuser, B., Wang, B., Wang, C., Wang, I., Wang, S., Wang, T., Wang, Z., Wuest, T., Xia, F., Xu, X., Xu, Z., Zhang, C., Zhang, D., Zhang, J., Zhang, I., Zhang, S., Zhang, W., Zhang Y., Zhao, H., Zheng, P.	Digital engineering and smart manufacturing systems
Cluster 2	Akay, H., Anwer, N., Bengio, Y., Cao, Y., Chen, J., Chen, I., Dai, Y., Devlin, J., Han, X., Hodkiewicz, M., Hu, X., Hu, Y., Kim, J., Kumar, A., Li, J., Li, I., Li, S., Li, X., Liu, A., Liu, W., Liu, Y., Luo, J., Narasimahan, K., Radford, A., Sun, I., Sutskever, I., Wang, H., Wang X., Yang, H., Yang, J., Yang, M., Yang, Y., Zhang, M., Zhao, M., Zhao, Y., Zhou, Y.	Artificial intelligence and learning
Cluster 3	Chen X., Chen Y., Chen Z., Huang H., Kang, J., Lin, Z., Liu, J., Niyato, D., Tao, F., Wang, J., Wang, W., Wang, Y., Wu, H., Wu, J., Wu, Y., Zhang H., Zhang, Z., Zhou, H.	Energy optimization and sustainability in industrial processes
Cluster 4	Bao, J., Bhattacharya, P., Chen, H., Colabianchi, S., Costantino, F., Li, B., Li, C., Liu, X., Prasad, V.K., Tanwar, S., Wellsandt, S., Zhang, X.	Sustainability and supply chain management to improve organizational performance
Cluster 5	Diedrich, C., Huang, Y., Jazdi, N., Touvron, H., Vaswani, A., Wei, J., Weyrich, M., Xia, Y., Zhao, W.X.	Cybersecurity of industrial systems

3.3. Bibliographic Coupling

Given that our corpus is recent, i.e., the selected publications are not sufficiently cited, we performed a bibliographic coupling analysis. This method relies on common bibliographic databases to show the relationship between the selected articles, as shown in Figure 5. For example, the nodes of the articles by Liu et al. [34], Colabianchi et al. [35], and Srivastava et al. [36] are close to each other. Although these articles address different topics, including intelligent assistants, supply chains, and industrial information processing, they share specific bibliographical references on the use of LLMs in an industrial context. The similarity between these articles reflects the development of a theoretical framework on the adoption of LLMs in digital manufacturing. Similarly, the articles by Xia et al. [37] and Kernan Freire et al. [38] explore two different topics, but they share the idea of using LLMs in manufacturing to increase organizational performance. By deduction, these two articles share common references and present a new research direction that focuses on digital technology powered by LLMs.

In addition, the bibliographic coupling method classifies the selected publications into clusters based on shared elements, such as theoretical frameworks and methodological anchors, to better understand the structure of the field in question (Table 4).

Cluster 1 consists of eight articles, three of which are highly cited: the article by Xia, Xiao et al. [39] (17 citations), Kernan Freire et al. [38] (14 citations), and Chang et al. [9] (12 citations). These articles, therefore, enjoy a certain degree of visibility. Although these articles are set in the context of Industry 4.0/5.0 and explore the integration of LLMs into industrial processes, the researchers have adopted different techniques (e.g., fine-tuning LLMs, benchmarking LLMs) depending on the field of applications, such as chip design, knowledge management, and the development of digital twins. Bibliographic coupling is represented by the sharing of specific references related to the integration of LLMs.

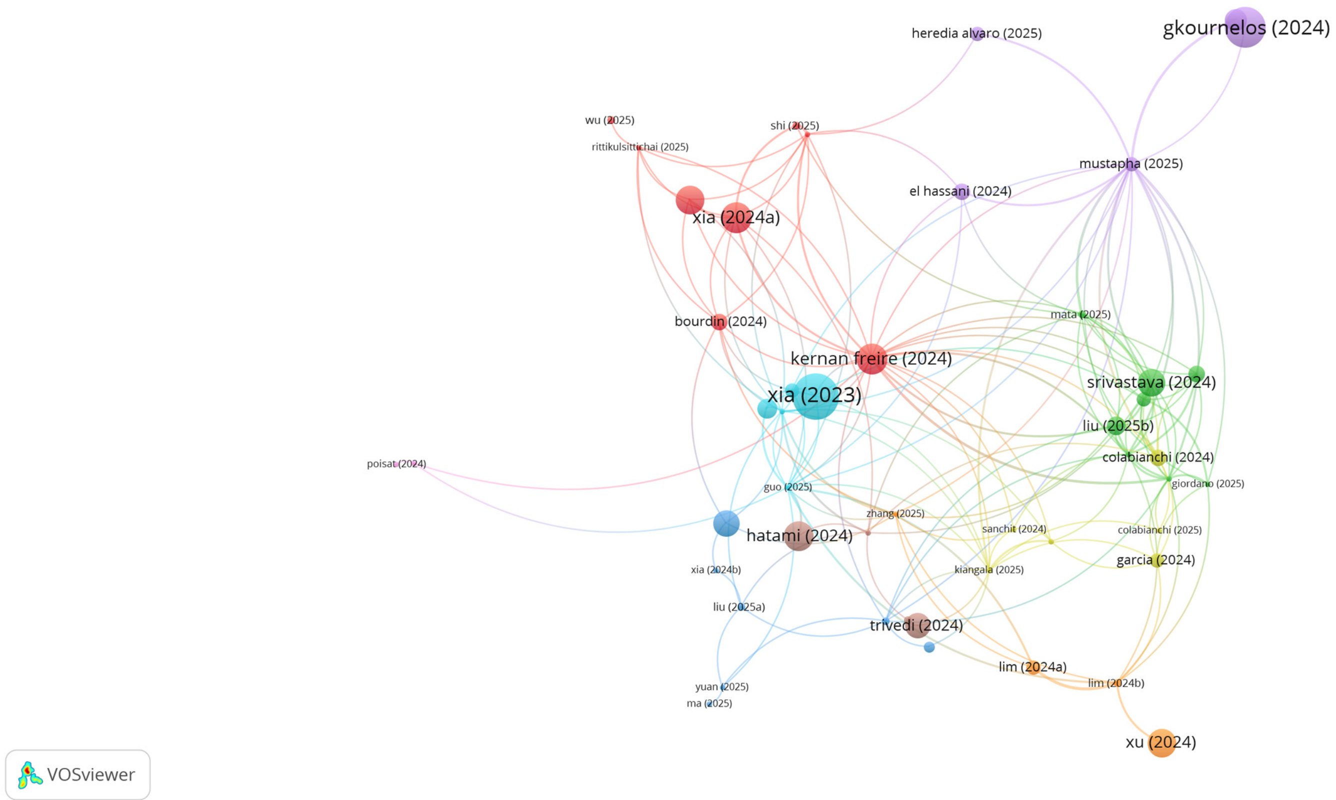

Figure 5. The publications' bibliographic coupling map (authors).

In Cluster 2, the article by Srivastava et al. [36] has the highest number of citations (11 citations). This article highlighted the contribution of LLMs, particularly BERT, in improving supply chain management.

The articles grouped in Cluster 3 have low to moderate citation counts. The most cited article is that of Acharya et al. [40] (10 citations), which explored the phenomenon of Agentic AI, a form of artificial intelligence that enables automated control of industrial systems.

Cluster 4 is characterized by a low number of citations for the articles it comprises (ranging from 0 to 4 citations), due to the topicality of the articles, which date from 2024 to 2025, as well as the new themes they address. For example, Colabianchi et al. [35] examined the effect of virtual assistants in an industrial context, and Garcia et al. [6] discussed the role of intelligent assistants in the development of human–machine relationships.

Cluster 5 indicates that the article by Xia et al. [37] is the most cited (31 citations). This article addresses the transition to a smart industry through the integration of digital twins, LLMs, and automation systems.

Cluster 6 features a single article that is highly cited compared to the other articles in this cluster. This article by Gkournelos et al. [41] (23 citations) analyzes two industrial cases to gain a deeper understanding of how LLMs facilitate collaboration between humans and robots in the context of smart manufacturing.

In Cluster 7, the article by Xu et al. [42] is the most cited (12 citations). This article highlights the concept of intelligent and collaborative assistants developed using LLMs and 6G networks.

In Cluster 8, the article by Hatami et al. [43] received the most citations (13). It examines the synergistic application of digital twins, artificial intelligence, and connectivity in the context of digital manufacturing, aiming to enhance data processing efficiency.

Finally, Cluster 9 comprises two articles that explore the contribution of humans to smart industries. The lack of citations for these articles could be justified by the emergence of a new research topic, namely, the importance of the human aspect in the transition to Industry 5.0.

The low-citation articles in each cluster reflect the innovative nature and ongoing development of research on the use of LLMs in the field of digital manufacturing. However, these low citations did not call into question the relationship between the articles in our corpus, as they share specific themes and bibliographic references, as explained in this section.

Table 4. Bibliographic coupling analysis of selected articles (authors).

Clusters	Authors	Articles	Citations
Cluster 1	[44]	NLP in SMEs for Industry 4.0: Opportunities and challenges	4
	[9]	Data is all you need: Finetuning LLMs for Chip Design via an Automated design-data augmentation framework	12
	[38]	Knowledge sharing in manufacturing using LLM-powered tools: user study and model benchmarking	14
	[45]	An Intelligent Chatbot Assistant for Comprehensive Troubleshooting Guidelines and Knowledge Repository in Printed Circuit Board Production	0
	[46]	Interoperable information modelling leveraging asset administration shell and a large language model for quality control toward zero defect manufacturing	0
	[47]	Dual data mapping with fine-tuned large language models and asset administration shells toward interoperable knowledge representation	1
	[48]	The impact of artificial intelligence adoption on Chinese manufacturing enterprises' innovativeness: new insights from a labor structure perspective	1
	[39]	Generation of Asset Administration Shell With Large Language Model Agents: Toward Semantic Interoperability in Digital Twins in the Context of Industry 4.0	17
Cluster 2	[49]	Decomposing maintenance actions into sub-tasks using natural language processing: A case study in an Italian automotive company	0
	[50]	LLM-Enhanced Human–Machine Interaction for Adaptive Decision-Making in Dynamic Manufacturing Process Environments	0
	[51]	A survey of LLM-augmented knowledge graph construction and application in complex product design	4
	[34]	Knowledge extraction for additive manufacturing process via named entity recognition with LLMs	5
	[10]	Evaluating the Performance of ChatGPT in the Automation of Maintenance Recommendations for Prognostics and Health Management	3
	[52]	Towards a GPT-Based Lean Manufacturing Consultant for Manufacturing Optimization	0
	[53]	Digital twin designs with generative AI: crafting a comprehensive framework for manufacturing systems	1
	[36]	Exploring the Potential of Large Language Models in Supply Chain Management: A Study Using Big Data	11
Cluster 3	[40]	Agentic AI: Autonomous Intelligence for Complex Goals—A Comprehensive Survey	10
	[54]	Multimodal Large Language Model-Based Fault Detection and Diagnosis in Context of Industry 4.0	2
	[55]	Accelerating Industry 4.0 and 5.0: The Potential of Generative Artificial Intelligence	1
	[56]	A blockchain-based LLM-driven energy-efficient scheduling system towards distributed multi-agent manufacturing scenario of new energy vehicles within the circular economy	2
	[57]	Enhancing Bottleneck Analysis in Ship Manufacturing with Knowledge Graphs and Large Language Models	0
	[58]	LLM experiments with simulation: Large Language Model Multi-Agent System for Simulation Model Parametrization in Digital Twins	0
	[59]	Chat with MES: LLM-driven user interface for manipulating garment manufacturing system through natural language	0

Table 4. *Cont.*

Clusters	Authors	Articles	Citations
Cluster 4	[60]	A Conceptual Framework for a Latest Information-Maintaining Method Using Retrieval-Augmented Generation and a Large Language Model in Smart Manufacturing: Theoretical Approach and Performance Analysis	0
	[35]	Assessment of a large language model based digital intelligent assistant in assembly manufacturing	4
	[61]	Application of a digital intelligent assistant to support industrial processes: The case of adaptive allocation in the face of cyber attacks	0
	[6]	Framework for LLM applications in manufacturing	3
	[62]	A generative pre-trained transformer industrial bot to improve operators' working experience in a small Industry 5.0 factory	0
	[63]	Deriving inferences through natural language from structured datasets for asset lifecycle management	0
Cluster 5	[64]	A Survey on Applications of Large Language Model-Driven Digital Twins for Intelligent Network Optimization	0
	[65]	Digitization of the enterprise—prospects for process automation with using RPA and GPT integration	3
	[66]	Large Language Models in Human–Robot Collaboration with Cognitive Validation Against Context-induced Hallucinations	0
	[67]	A novel approach to voice of customer extraction using GPT-3.5 Turbo: linking advanced NLP and Lean Six Sigma 4.0	6
	[37]	Towards autonomous system: Flexible modular production system enhanced with large language model agents	31
Cluster 6	[13]	Push-pull digital thread for digital transformation of manufacturing systems	7
	[14]	Integrating large language models for improved failure mode and effects analysis (FMEA): a framework and case study	4
	[41]	An LLM-based approach for enabling seamless Human–Robot collaboration in assembly	23
	[68]	An advanced retrieval-augmented generation system for manufacturing quality control	3
	[69]	A survey of emerging applications of large language models for problems in mechanics, product design, and manufacturing	3
Cluster 7	[70]	Enhancing Human–Robot Collaborative Assembly in Manufacturing Systems Using Large Language Models	3
	[71]	Large Language Model-Enabled Multi-Agent Manufacturing Systems	1
	[42]	When Large Language Model Agents Meet 6G Networks: Perception, Grounding, and Alignment	12
	[72]	Large-scale foundation models for intelligent manufacturing applications: a survey	0
Cluster 8	[7]	Literacy Deep Reinforcement Learning-Based Federated Digital Twin Scheduling for the Software-Defined Factory	0
	[43]	A Survey of the Real-Time Metaverse: Challenges and Opportunities	13
	[73]	Applying Large Language Model Analysis and Backend Web Services in Regulatory Technologies for Continuous Compliance Checks	1
	[74]	Explainable AI for Industry 5.0: Vision, Architecture, and Potential Directions	9
Cluster 9	[75]	SAMBA: A reference framework for Human-in-the-Loop in adaptive Smart Manufacturing	0
	[76]	Human resource managers' perceptions on the impact of AI on the South African workforce	0

4. Thematic Analysis

Analysis of the articles in our corpus has identified several emerging themes in the use of LLMs in digital manufacturing.

Theme 1: Automation and optimization of industrial operations

Some research has highlighted the ability of LLMs to automate manufacturing processes, including planning and digital model creation [14,52,57,67]. This contributes not only to improving performance and efficiency by reducing human error in the industrial context, but also to managing complex manufacturing processes. El Hassani et al. [14] have proposed a framework that presents a process model and an information system for automatically and accurately processing data to enhance failure mode analysis (FMEA). On the other hand, in the context of ChatGPT's use, Shahin et al. [67] and Magnus and Venschott [52] discussed the use of GPT-3.5 and ChatGPT-4, respectively. Shahin et al. [67] focus on a customer-oriented approach, stating that GPT-3.5 Turbo captures the voice of the customer (VoC) to analyze their recommendations and feedback. This helps guide and align industrial processes with customer needs, thereby optimizing industrial operations. As for Magnus and Venschott [52], they demonstrated that although this technology optimizes Lean Manufacturing processes, the presence of human expertise remains crucial to verify ChatGPT4's suggestions due to its limitations, notably hallucination. The contributions of LLMs have also been examined by Ma et al. [57]. These researchers employed the SPKG method to assess the models' ability to identify bottlenecks in the shipbuilding context effectively. They found that, in this case, the method guaranteed a high success rate of 65%, reflecting the fact that LLMs enhance the interpretability and traceability of industrial analyses.

LLMs are also utilized in supply chain management and production planning [36]. Their role is to model different scenarios based on processed quantitative (e.g., cost) and qualitative (e.g., customer opinions) data. This enables the more precise specification of industrial operations, such as supply chain management, flow management, and coordination of manufacturing stages. For example, LLMs can be used in logistics chain management, based on the transportation problem formulated below (Equation (1)), to plan logistics efficiently.

$$\min \sum_{i=1}^{m} \sum_{j=1}^{n} C_{ij} x_{ij} \tag{1}$$

With:
i: warehouse (sources)
j: clients (destinations)
C_{ij}: Unit cost of transport between i and j
x_{ij}: Quantity of products transported from i to j
$x_{ij} \geq 0$ (the quantity transported cannot be negative)

In conclusion, through this mathematical model, which reduces transportation costs, LLMs can participate in this process by adapting this model from natural language. The adaptation enables informed decisions to be made regarding dynamic supply chain management. As a result, industries make well-founded decisions to improve their efficiency and sustainability.

To summarize, the literature has mobilized several important issues for understanding the contribution of LLMs in automating and optimizing industrial operations, including improving the accuracy of risk/failure analysis [14], the decisions and track records associated with the use of LLMs in the supply chain [36], how far LLMs can go beyond human expertise [52], and the indirect involvement of customers to improve industrial processes [67]. The literature has also highlighted conceptual frameworks used by researchers to optimize industrial tasks, such as the Lean Manufacturing process [52], the framework that merges LLMs and blockchain to provide a planning system [56] and the use of LLMs in the context of FMEA [14].

Theme 2: The adaptability of manufacturing systems

This theme is central in the context of digital manufacturing, as the use of LLMs facilitates the adaptation of systems to rapid changes in industries by efficiently planning the tasks required for production [6,41]. Indeed, LLMs can generate texts and analyze all types of information and situations to ensure planning that is adapted to the changes that occur over time. The literature supports this assertion. For example, Choi and Jeong [60] have combined LLMs with retrieval-augmented generation (RAG) to provide a layered architectural framework (data analysis, continuous incorporation of new knowledge, continuous learning) relevant to industries. This framework supports the regular updating and real-time management of data based on robust mathematical estimates, such as a throughput of 1000 transactions per second (processing up to 1000 data items in one second), average latency of 50 ms (the time required to complete all stages (data collection and processing, response proposals)) and availability of over 99.9% [60]. By deduction, the decision-making process has become faster, more reliable, and easier in smart factories, thanks to the use of LLMs, which can process and understand natural language to adapt the systems used. The phenomenon of system adaptability has also been addressed in the context of human–robot collaboration [41]. These researchers have demonstrated that LLMs facilitate more effective programming, planning, and reconfiguration of industrial operations. Thus, merging these models with digital twins facilitates coordination between employees and robots, thereby improving the efficiency of the systems used. However, some models cannot include learning [60].

Theme 3: Human–machine collaboration and its impact on employees

The transition to digital manufacturing necessitates collaboration between humans and machines. The use of LLMs in this context offers several innovative approaches for processing and understanding human queries, thereby enhancing and ensuring optimal human–machine collaboration on multiple levels [35]. So, while LLMs have automated and empowered the manufacturing process, some researchers are focusing on their effects on humans. In fact, the use of LLMs in manufacturing not only contributes to improving industrial operational processes but also transforms the role of employees in industries. LLMs can offer relevant advice and train employees while minimizing cognitive load, thereby redefining the human–machine relationship [38].

Colabianchi et al. [35] have highlighted the role of intelligent digital assistants (IDAs) in the assembly process. According to these researchers, IDAs based on LLMs help minimize errors and cognitive load, thereby improving the quality of the finished product and enhancing the experience of employees involved in the manufacturing process in industries. This has led to a favorable perception on the part of employees. Furthermore, as the integration of advanced technologies characterizes Industry 4.0, without neglecting the important role of operators, Industry 5.0 places more emphasis on several human-related aspects. IDAs align with the principles of both industries [35]. In a similar vein, Colabianchi [61] proposed a human-centered approach to examine the impact of LLMs on digital intelligent agents (IDAs) and their employees. This researcher has found that this approach significantly improves the fluidity of human–machine communication. In fact, responsive, natural, and intuitive interactions with IDAs help employees better manage attack reports, reducing anxiety and stress, and boosting operators' confidence in digital agents. The same applies to GPT-4, which provides employees with relevant information and suggestions tailored to the problems encountered [38].

Further, Ranasinghe et al. [66] examined collaborative robotic systems powered by LLMs to exploit human–robot collaboration (HRC). These systems not only reduce errors, as with IDAs, but also hallucinations [66]. The researchers also reported that collaborative systems powered by LLMs perform better, with a task completion rate of 69.6%, than conventional systems (40%). This reflects the efficiency and reliability of human–robot interactions. Yuan et al. [59] concur with this statement, indicating that, compared with graphical interfaces, conversational interfaces powered by LLMs improve the accuracy level with which operations are carried out. These interfaces also reduce training costs and simplify employee interaction with the technology [59].

Moreover, compared to traditional systems, LLMs can process a large amount of information, whether simple or complex, from various databases to propose relevant solutions and predictions tailored to queries provided in human language [50]. Integrating LLMs into the industrial world provides clear visualizations that illustrate processed data, enabling the identification of deviations in the manufacturing process [50]. This integration helps employees to interact with models effectively and make informed decisions. Another framework facilitating human–machine interaction has been proposed by Bianchini et al. [75], namely the service-augmented manufacturing-based approach, SAMBA. This framework utilizes LLMs to process data related to the procedures of various industrial operations and communicate them to employees in a clear, structured manner [75].

Theme 4: Interoperability of digital systems in industry

At the end of the literature review, LLMs are shown to contribute to improving information management in complex digital systems, thereby reinforcing the transition to an intelligent, connected industry, as explained by several researchers [39,77]. By inference, LLMs provide innovative solutions to address the challenges of data fragmentation.

Xia et al. [39] have demonstrated that the use of LLMs enables the consistently successful automation of Asset Administration Shell (AAS) instances, with a success rate of up to 79%, and consequently leads to better management of heterogeneous and unstructured data. Shi et al. [46] also combined LLMs and AAS to improve interoperability in industrial operations. This facilitates the exchange of information between different tools and software, ensuring semantic interoperability in digital twins with minimal manual effort, and reduces defects [39,46]. Finally, Li and Starly [77] proposed another approach, incorporating knowledge graphs (KGs) and ChatGPT, to facilitate connections between manufacturing SMEs. This approach is based on processing unstructured data from various sources, combined with machine learning, to propose a Manufacturing Service Knowledge Graph (MSKG). This provides digital support for employees by processing complex queries and optimizing production processes.

Theme 5: Quality control by LLMs

Quality control is a crucial task in ensuring the relevance and reliability of the products and services offered. Today, this task is carried out more efficiently thanks to LLMs, which automate quality control and detect errors. LLMs are distinguished by their ability to meticulously and efficiently process data (e.g., reports, photos, texts) using artificial intelligence and retrieval-augmented generation (RAG), enabling them to identify defects, problems, and errors during digital manufacturing [10,49].

Several conceptual frameworks have been mobilized to address the phenomenon of quality control by LLMs. Firstly, retrieval-augmented generation (RAG) techniques and the Langchain framework are utilized for this purpose [45]. These models enhance the chatbot's ability to offer precise, tailored responses. More specifically, Rittikulsittichai and Siriborvornratanakul [45] used chatbots to improve troubleshooting and data management in printed circuit board manufacturing. The researchers confirmed that these models are reliable, contributing to the acceleration of knowledge exchange, rapid problem-solving, and quality control in the industrial context. Secondly, natural language processing (NLP) techniques were exploited by Giordano and Fantoni [49] to prioritize efficiently and link repair-related knowledge to suitable failure situations. This approach helps to automate maintenance and establish standard norms. Within the same maintenance framework, the literature highlights another framework, namely the concepts of equipment health management (PHM) and Technical Language Processing [10]. These researchers have explored the ability of LLMs, in particular ChatGPT, to provide reliable maintenance suggestions, while emphasizing the importance of capturing industry knowledge to avoid inappropriate recommendations.

Theme 6: Knowledge extraction and structuring

This theme has been reported by various publications belonging to our corpus due to its importance. Indeed, emphasis has been placed on the ability of LLMs to enhance efficiency and the degree of adaptability to industrial environments. These models enable the extraction of knowledge from multiple sources, including databases, technical manuals, and maintenance reports [38,68]. By inference, LLMs have changed knowledge extraction practices in smart factories, notably by combining them with other technologies, such as:

- Knowledge graphs (KGs): used to facilitate the design of complex assets. Indeed, combining LLMs with KGs enhances the structuring of heterogeneous data, optimizes operational design tasks, and enables reliable decision-making [51].
- RAGs: this combination (LLMs + RAGs) facilitates the detection of errors and failures during product manufacturing by processing not only internal, but also external knowledge [68]. This enables the overcoming of limitations inherent in conventional approaches while enhancing the recommendations provided [68].
- GPT-4, to interact with conversational interfaces and access any type of reliable information relevant to problem-solving in the industrial sector [38].

To sum up, LLMs make data actionable by structuring it and utilizing it to create knowledge graphs that provide linked and clear information, offering relevant insights tailored to the manufacturing process. This helps engineers to make informed, operational decisions.

Theme 7: Innovation produced by LLMs

Another interesting avenue explored in our corpus was the innovation generated by LLMs [9]. These models stimulate creativity by analyzing various digital designs and customer feedback (e.g., interactions, comments) to propose new, original, and innovative ideas. Thus, LLMs could generate 3D prototypes based on textual data provided by engineers, significantly reducing the time and effort required. By deduction, industries can quickly manufacture customized and innovative goods thanks to the automation of tasks by LLMs.

Several key results have been highlighted in the literature. Firstly, Chang et al. [9] reported that data automation contributes to improving the performance of LLMs, particularly in the areas of Verilog code repair and EDA scripting. Additionally, training these models with aligned data enhances their performance in handling complex operations, thereby accelerating innovation in hardware design [9]. Next, Wu et al. [48] point out that artificial intelligence, including LLMs, enhances industries' capacity for innovation, thanks to the automation and optimization of industrial processes, improved collaboration and knowledge processing. However, it should be noted that this innovation produced by LLMs also depends on the expertise of employees, given their essential role in LLMs development [48]. The importance of the relationship between operators and machines in enhancing innovation is also confirmed in the context of digital twin design, as it facilitates the management and design of complex systems [57]. Similarly, in the context of mechanical engineering, LLMs contribute to the improvement of several aspects, including digital twin integration, asset design, and better process planning [69]. As a result, all these LLM-assisted approaches promote innovation in the industrial sector.

Theme 8: Ethical challenges related to the use of LLMs

Although the use of LLMs is transforming operational tasks within industries, notably by enhancing the efficiency and performance of digital manufacturing in the context of Industry 5.0, various ethical challenges must be considered [65,74]. For example, the ethical, technical, and legal risks involved in automating robotic processes (RPA) using LLMs [65] are mitigated by the combination of these two elements, which simplifies the handling of complex and demanding organizational tasks. Firstly, ethical risks, such as transparency, are a concern, as it is difficult to understand precisely how LLMs make decisions, which limits the auditing and verification of answers generated by this technology. Besides, fully automated processes do not allow for error detection in the event of misinterpretation by LLMs [65]. Great importance must also be attached to the data used to train LLMs [65]. Secondly, technical risks, such as the resources required to maintain these models, pose sustainability challenges [65]. Finally, legal risks include data protection challenges when using ChatGPT [65]. Other issues related to the use of LLMs in Industry 5.0 have been highlighted by Trivedi et al. [74]. These researchers emphasized the importance of validating and reinforcing the transparency of the results provided by LLMs to avoid damaging user trust. Trivedi et al. [74] also addressed the ethical challenges of social impact. Indeed, today, LLMs are replacing certain jobs, or at least require well-trained employees to use and supervise them effectively, and to adapt to the new orientations of the manufacturing market.

5. Integrative Framework

To classify the themes identified in our thematic analysis, we employed an inductive approach, which involves ranking them according to their complementarity and conceptual proximity [78,79]. More specifically, the study of the different themes (Section 4) allowed us to group them into broader areas that reflect the phenomena addressed, and to develop an integrative framework that summarizes the results obtained and structures the integration of LLMs in digital manufacturing (Figure 6). This framework highlights the relationship between the identified themes and classifies them into three major areas:

- *Axis 1—Optimization of Manufacturing Processes:* This focus area addresses the contribution of LLMs to improving operational efficiency in smart factories. In other words, it encompasses several functions of LLMs, including the automation of industrial operations, adaptability, interoperability, and quality control. This functional basis of LLMs enables innovation and knowledge structuring. Hence, the second axis is presented below.
- *Axis 2—Data structuring and innovation:* This second axis focuses on the ability of LLMs to innovate while structuring the knowledge needed to make informed decisions. The first two areas, exploring technical and cognitive advantages, respectively, transform the role of employees. Hence, the third area involves the ethical challenges associated with integrating LLMs and human–machine interaction.
- *Axis 3—Human–machine interaction and ethical challenges:* This axis highlights the role of employees in digital manufacturing processes and the challenges associated with the use of LLMs.

To summarize, in contrast to the current literature, which focuses on isolated cases, our research presents a function illustrating the functional representation of the overall impact of LLMs based on three interdependent axes, derived from our thematic analysis (Equation (2)) and an integrative framework relevant to the field of LLM-powered digital manufacturing, encompassing the key axes of LLM integration.

$$F_{LLM} = f(A_1, A_2, A_3) \tag{2}$$

With F_{LLM}: global impact function of LLMs in digital manufacturing

A_1: optimization of manufacturing processes
A_2: data structuring and innovation
A_3: human–machine interaction and ethical challenges

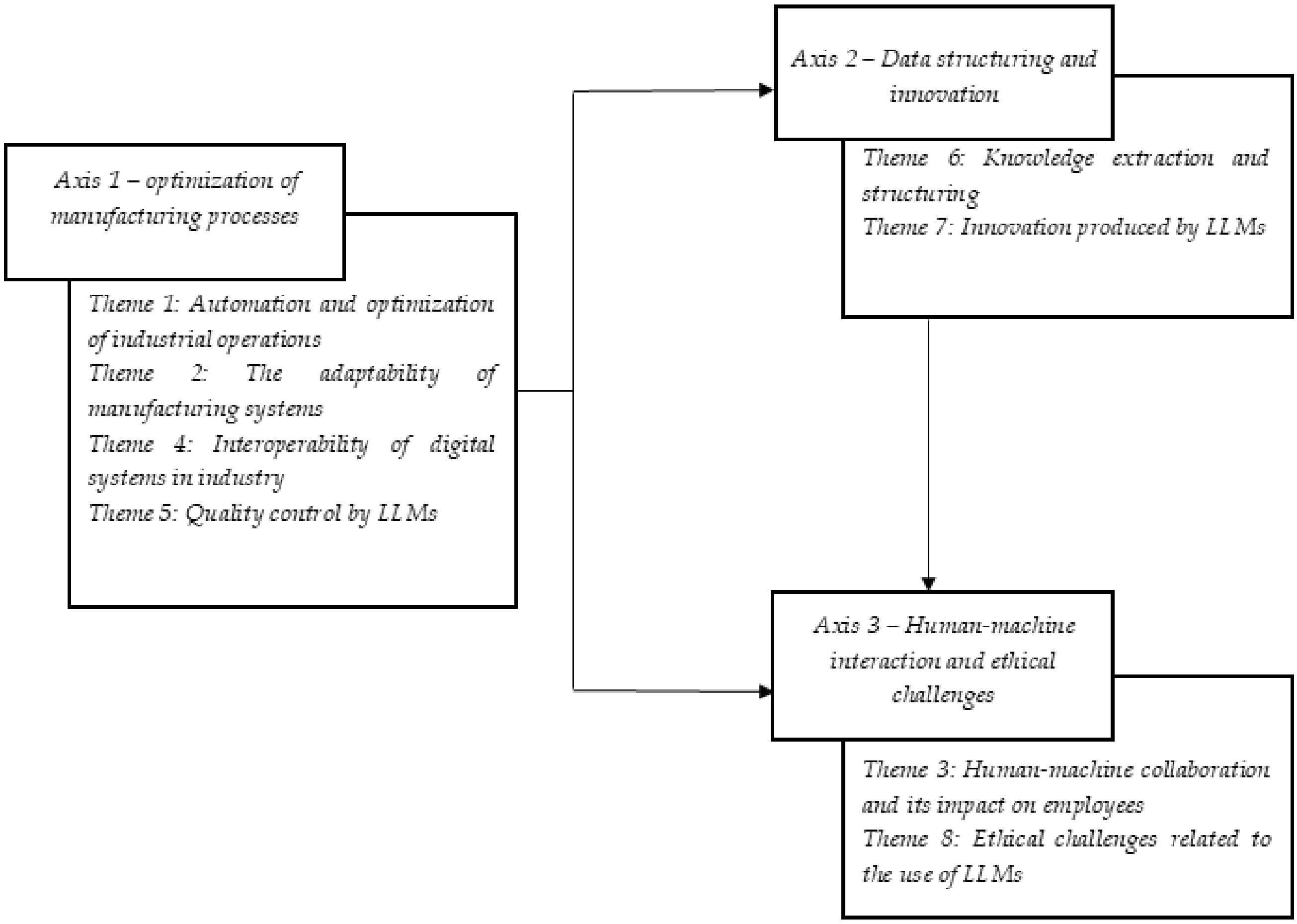

Figure 6. An integrative framework for the use of LLMs in the context of digital manufacturing (Authors).

6. Agenda for Future Research

The literature has highlighted the role of LLMs in facilitating the transition to digital manufacturing, enabling the automation of industrial operations and the adaptation of production systems. However, several avenues are emerging for future research.

Axis 1: Optimization of manufacturing processes

Theme 1: Automation and optimization of industrial operations

LLMs have revolutionized the way industrial operations are conducted. For example, they can better manage the supply chain by making informed decisions based on the processing of both unstructured data (such as news articles and text) and structured data (such as databases and registers) [36,56]. These models also enable the examination of failures (FMEA) to optimize the manufacturing process [14].

However, most of the research conducted is limited to case studies or simulated environments [57]. Furthermore, there is no comprehensive and robust framework examining the use of LLMs in complex industrial systems [14]. Magnus and Venschott [52] also indicated that some of the conclusions presented are not reproducible. Therefore, it will be relevant to develop a comprehensive conceptual framework to explore the use of LLMs in complex industrial contexts and analyze the impact of automated decisions on the manufacturing chain. Thus, future research may examine the fusion of LLMs with multi-agent systems [71] to improve the scalability and resilience of complex systems. In other words, analyze the impact of this fusion on distributed coordination to ensure adequate collective progress that converges toward a common goal.

RP1: Develop a comprehensive conceptual framework for modeling the incorporation of LLMs into complex systems.

RP2: Analyze the effect of automated decisions on the manufacturing chain.

RP3: Analyze the effects of merging LLMs and multi-agent systems to strengthen coordination between employees.

RP4: Conduct studies in a real manufacturing context to explore the benefits of integrating LLMs into industries.

Theme 2: The adaptability of manufacturing systems

As explained in the previous section, LLMs enable flexible planning to manage risks and unforeseen events while optimizing the manufacturing process [41]. However, this planning is called into question because it depends mainly on prompts. That is, LLMs will offer planning tailored to the requests received. An ambiguous request reduces the quality of planning and vice versa. It would therefore be relevant to analyze the adaptability of AI-powered systems [55]. More specifically, future investigations should focus on the impact of prompt types on the adaptability of manufacturing systems by LLMs. Studies often use limited test environments, which could affect the generalizability of the results.

RP5: Study the effect of prompts on the effectiveness of planning provided by LLMs.

RP6: Conduct a comparative study between simulated and real environments to better understand the performance of LLMs in the context of digital manufacturing.

Theme 4: Interoperability of digital systems in industry

LLMs ensure better information management between various tools and facilitate the implementation of complex systems, including Asset Administration Shells [47], IoT captures and LLMs. However, the inclusion of technologies requires an organized architecture and strategy to reduce enterprise fragmentation [75].

RP7: Develop an interoperability framework for the implementation of complex systems.

RP8: Examine the effect of interoperability on the proactivity of LLMs in decision-making.

RP9: Analyze the effect of LLM scalability in smart factories.

Theme 5: Quality control through LLMs

LLMs play a crucial role in quality control thanks to their ability to identify errors in the production process through several methods, such as retrieval-augmented generation (RAG) [49]. Nevertheless, it is important to consider the development of industrial process performance in complex situations [71], as the effectiveness of LLMs depends on the type of data or its specialization (specialized or generalist LLM). It will then be relevant to compare specialized and generalist LLMs in the context of digital manufacturing, in order to understand their ability to detect anomalies [71]. It is also interesting to explore the hybrid approach to quality control, i.e., the contribution of collaboration between humans and LLMs in detecting possible errors.

RP10: Carry out a comparative benchmark between specialized and generalist LLMs to analyze their ability to control the production process and make well-founded decisions effectively.

RP11: Analyze the relationship between humans and LLMs to optimize the distribution of control tasks.

Axis 2: Data structuring and innovation

Theme 6: Knowledge extraction and structuring

LLMs are capable of extracting and processing knowledge [38,51,68] to make it usable. However, LLMs are not yet capable of linking the various elements of the manufacturing process due to the difficulty of analyzing technical data [34] and the rapid evolution of data [60].

RP12: Develop more sophisticated learning methods capable of adapting in real time to the evolution of knowledge.

RP13: Design and evaluate the role of a hybrid system (e.g., LLMs and semantic graphs) in automatic data updating.

Theme 7: Innovation produced by LLMs

The literature suggests that LLMs facilitate innovation in various industries [9,53]. However, some aspects require further study. For example, does the imposed innovation of LLMs affect the functioning and strategy of the manufacturing sector [48]? Indeed, sophisticated technologies sometimes compel industries to innovate in order to maintain their market positions. It is therefore interesting to analyze their ability to adapt to this innovation. If so, how do LLMs influence innovation in production processes, such as planning and design [69]? On the other hand, are there effective solutions for SMEs with limited resources to effectively leverage LLMs [44]?

RP14: Analyze the ability of industries to resist the innovation imposed by LLMs.

RP15: To what extent does innovation imposed by LLMs influence production process stages?

RP16: What is the impact of using shared LLMs among SMEs with limited resources?

Axis 3: Human–machine interaction and ethical challenges

Theme 3: Human–machine collaboration and its impact on employees

The ability of LLMs to understand natural language significantly facilitates human–machine interaction [50,75], particularly through chatbots and virtual assistants. However, the literature does not address the phenomenon of decision-making role sharing between humans and LLMs. Furthermore, little research has analyzed the impact of collaboration between these two actors on performance, trust, and decision-making power in an industrial context. Finally, researchers can model the incorporation of LLMs into a real interactive environment to ensure interoperability [75].

On the other hand, LLMs significantly contribute to the improvement of industrial operations by acting as a guide that not only processes and simplifies complex information but also generates appropriate solutions and explanations, and provides training support [59]. As a result, these models improve and facilitate the employee experience [35]. However, several issues related to the effects of LLM use on cognitive and social dimensions have not been addressed [38]. For example, what impact will the integration of LLMs have on human interaction? Will LLMs replace humans in digital industries? Will employees' expertise be called into question by intelligent assistants? Can engineers trust LLMs' proposals? Another aspect to be explored is the psychological effect of frequent human–machine collaboration.

RP17: Analyze the effect of human–machine collaboration on trust and decision-making power in an industrial context.

RP18: Develop a comprehensive conceptual framework for modeling the integration of LLMs into a human–machine interaction environment.

RP19: Analyze the impact of LLM use on employees' cognitive capacity.

RP20: Analyze the impact of LLM use on employee well-being and satisfaction.

RP21: Analyze the psychological effect of man-machine collaboration on employees.

Theme 8: Ethical challenges associated with the use of LLMs

Although the ethical issues surrounding the use of LLMs are highlighted in the literature [74,80], they are relatively underexplored during the implementation and development of these systems. In fact, it is essential to examine the ethical challenges, security, and data confidentiality when using LLMs in an industrial context [55]. In addition, it would be relevant to propose a governance and ethical framework for Agentic AI to verify whether systems based on LLMs are developed ethically and responsibly [40]. In other words, we need to confirm whether these systems align with human values and assess their impact on society. Transparency in decision-making is also less explored in the industrial context [72].

RP22: Develop a governance and ethical framework for the use of LLM-based systems.

RP23: Propose methods/indices to explain decisions generated by LLMs to ensure transparency.

RP24: Develop an ethical audit tool to analyze the compliance of LLM practices.

7. Conclusions

The use of LLMs is a notable asset in the context of digital manufacturing, due to the multifaceted implications of this technology. Indeed, our analysis has shown that it is a crucial catalyst for a more effective transition to smart factories.

The systematic literature review conducted provided an overview of the research that has explored this phenomenon, proposing a comprehensive framework that sheds light on the relationship between LLMs' functional and technical tasks, human–machine interaction, and ethical challenges. More specifically, we explained the role of LLMs in the optimization and automation of industrial operations (e.g., planning, supply chain management, coordination) [36,56] through text generation and the ability to adapt manufacturing systems [6,41]. Our results also focused on human–machine interaction, redefining the role of employees in the manufacturing process [35,66]. Finally, we shed light on the ethical issues involved in using LLMs [74]. These include transparency, decision-making bias, and privacy. These issues call for a governance framework to ensure the responsible use of LLMs. Our analysis has also highlighted the importance of cybersecurity, particularly concerning secure data processing and the integration of LLMs in various industries.

In summary, our research has provided a structured analysis of the contributions of LLMs in the context of digital manufacturing, consolidating scattered information and offering clear recommendations for future research in the field of industrial innovation.

Furthermore, compared to other systematic literature reviews, such as those by Zhang et al. [72], Wan et al. [20], and Gabsi [21], our analysis provided a more integrative perspective. Indeed, this research presents a rigorous bibliometric analysis, as well as a thematic analysis. Through this, we identified three main functional areas of LLMs: the optimization of manufacturing processes, data structuring and innovation, and human–machine interaction and ethical challenges. In addition, 24 operational and specific research proposals were offered. Consequently, our approach facilitates an understanding of the role of LLMs in the context of digital manufacturing on both technical and human levels while proposing avenues for future investigations. These contributions reflect the originality of our research.

Nevertheless, our study has methodological limitations. Firstly, our results are based on a selection of articles. Therefore, relevant information from non-accessible documents has not been considered. Secondly, although we selected articles published between 1 January 2015 and 30 April 2025, further advances may have been published after the data collection period, given the rapid evolution of this field. Therefore, future research should conduct further examinations to assess the actual impact of LLMs on the performance of digital manufacturing processes. From a managerial perspective, engineers should consider metrics before implementing LLM-based solutions. In other words, it would be beneficial to include performance indicators from the very first phase of implementing these solutions, ensuring continuous real-time evaluation and a seamless transition to tomorrow's industry.

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