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ARTIFICIAL INTELLIGENCE IN MANUFACTURING – SYSTEMATIC LITERATURE REVIEW

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Purpose: The purpose of this paper is to explore the current state of research on artificial intelligence in manufacturing. The paper aims to identify key trends, leading authors, institutions and research topics, as well as to identify the main areas of scientific interest in this field.
Design/methodology/approach: The research objectives were achieved by using a systematic literature review and bibliometric analysis. The study used Web of Science and Scopus databases, where searches were conducted according to specific keywords and inclusion criteria, such as document type, language and publication time range (2015-2024). The collected data was then analyzed for the distribution of documents by type, year of publication, country, institution, author, and co-occurrence of keywords, which made it possible to extract major thematic clusters and research trends.
Findings: The analysis revealed five thematic clusters representing key research areas, alongside a rapid growth in publications from 2019, particularly in countries such as China, the United States, and India. These findings highlight an increasing global focus on AI's application in manufacturing.
Originality/value: This article offers a comprehensive and up-to-date analysis of research on artificial intelligence in manufacturing, covering publications up to 2024. By identifying five key thematic clusters, it provides unique insights that will benefit researchers, industry practitioners, and decision-makers aiming to integrate AI into manufacturing processes. The study provides a better understanding of research trends and developments in the field, making it a valuable resource for researchers, industrial practitioners and decision makers interested in integrating AI into manufacturing processes.
Keywords: artificial intelligence, manufacturing, systematic literature review.
Category of the paper: literature review.

1. Introduction

The modern world is witnessing a continuous technological transformation, with the technology available on the market evolving at an unprecedented pace. Advances in areas such as big data, the Internet of Things (IoT) and artificial intelligence are not just the domain of the world's largest industrial centers, but are transforming the market on a global scale (Rymarczyk, 2020). Businesses are facing challenges that were unimaginable a dozen years ago. These include globalization, increasing customer requirements and the need to make decisions quickly in a dynamic environment (Lina, 2022).

In response to these challenges, artificial intelligence could become a key tool (Patalas-Maliszewska et al., 2020), enabling manufacturing companies not only to manage resources efficiently, but also to respond more quickly to changing trends and deliver more personalized services (Huang, Rust, 2018). With its ability to analyze vast amounts of data, AI is speeding up decision-making processes while opening the door to new business models (Patalas-Maliszewska, 2020).

AI encompasses a broad spectrum of technologies, including machine learning, neural networks, and expert systems, which collectively enable machines to perform tasks that traditionally required human intelligence. These technologies are instrumental in addressing contemporary manufacturing challenges, such as optimizing resource utilization, reducing downtime through predictive maintenance, and enhancing product quality through automated defect detection. The application of AI extends beyond operational efficiency, offering transformative potential in areas such as product personalization and sustainable energy management.

Despite the growing interest in the application of artificial intelligence (AI) in the manufacturing sector, there is a significant gap in the literature regarding a comprehensive understanding of where research on the use of AI in manufacturing sector stands. Additionally, many studies are based on case studies or a specific technology, which limits their generality and universality. Therefore, there is a need for a broad literature review that not only identifies and summarizes existing research, but also highlights untapped opportunities and future research directions. This study aims to provide a comprehensive analysis of the current state of research on AI applications in manufacturing, identifying key trends, thematic clusters, and emerging opportunities. By leveraging bibliometric analysis and a systematic literature review, the study not only highlights the progress achieved in this domain but also identifies gaps and areas for future exploration. The findings serve as a valuable resource for researchers, practitioners, and policymakers, offering insights into the strategic deployment of AI to drive industrial innovation and sustainability.

2. Literature review

One of the most straightforward definitions of artificial intelligence (AI) is that it is a field of study concerned with the development of systems that are capable of performing tasks that would typically require human intelligence (Boden, 2016). Some researchers, on the other hand, point to the fact that AI does not just match the capabilities of the human mind, but sometimes surpasses them (Angelov et al., 2021), this may be due to the fact that this field of science is so broad (Arinez et al., 2020).

The sub-areas of artificial intelligence include, but are not limited to, expert systems, neural networks and machine learning. It should also be noted that these fields are not inseparable. Very often they overlap to form complex structures (Arias, 2022).

The development of expert systems can be traced back to the second half of the twentieth century. Subsequently, a system was developed for use in the field of chemistry. The success of this system led to the initiation of scientific research, which in turn resulted in the development of numerous other systems that were subsequently applied in the field of medicine (Grabarek, Stasiak-Cieślak, 2019). Expert systems are limited to a specific discipline. In this way, they are regarded as a form of traditional artificial intelligence, although they do not learn by constructing comprehensive models; instead, they draw on a database that has been encoded by humans (Arias, 2022). Expert systems represent one of the earliest tools to be employed in practice. By design, this system is intended to replace the expert in solving more complex tasks and problems. By recording the knowledge of experts in a specific field, the system can access and apply it repeatedly (Wyskwarski, 2015).

An artificial neural network (ANN) can be defined as a biologically inspired computational model comprising processing elements (referred to as neurons) and connections with coefficients. These connections constitute the neuronal structure to which the learning and recall algorithms are attached. In simple terms, artificial neural networks are a collection of mathematical techniques used for signal processing, prediction and clustering (Shanmuganathan, 2016). Their structure is modelled on the human brain, and their approach to problem solving and structure itself resembles the operation of the nervous system (Wyskwarski, 2015). However, the human brain is much more complex and many of its cognitive functions remain to be discovered (Shanmuganathan, 2016).

Another part of artificial intelligence, considered a subset of it, is machine learning. It consists of teaching machines the given rules according to which they should act, and then using them to solve a problem. The model that is prepared is intended to enable a decision to be made or a phenomenon to be predicted based on the analysis of data that was previously provided in the learning phase. This data is called training data and is fundamental to the final creation of the model. It is also crucial to select an appropriate algorithm responsible for carrying out the learning process (Młodzianowski, Rostowski, 2021). There are three variants of machine learning based on the method of learning - supervised, unsupervised and reinforcement learning (Morales, Escalante, 2022).

A review of the literature indicates that artificial intelligence is being implemented in the manufacturing sector at multiple levels, including optimization of the production process, collaboration between humans and robots, and resolution of maintenance issues (Arinez et al., 2020).

One example of the application of artificial intelligence is the machine learning model presented by researchers Hrnjica and Softic, which is used in the field of predictive maintenance. Machine learning was used to develop a model for predicting the failure of production machine components/parts. The model created in the study achieved high prediction accuracy (99% in test data), suggesting that AI can make a significant contribution to reducing the costs associated with unplanned downtime, failures and precent the occurrence of machine errors (Hrnjica, Softic, 2022).

Another area of industrial application for artificial intelligence is quality assurance. Today, there are a number of solutions for achieving high product quality through the use of highly automated production machines (Arora, Gupta, 2022). In the context of quality assurance in manufacturing, process automation is becoming a crucial component of industrial strategies. The utilization of artificial intelligence, particularly machine learning algorithms, not only facilitates the expeditious and precise identification of defects, but also the implementation of real-time monitoring systems. The utilization of models such as convolutional neural networks (CNNs) enables the automatic identification of undesirable phenomena, thereby markedly enhancing the quality of the final product. The implementation of such solutions facilitates an immediate response to detected irregularities, which can result in time and resource savings, as well as increased production efficiency (Patel et al., 2019; Schreiber et al., 2019).

In the field of manufacturing, collaborative robots (cobots) are also being deployed. Over the past decade, research into human-machine relationships has concentrated on the intricacies of collaboration, in which cobots must not only avoid collisions but also respond adaptively to circumstances and communicate in a manner that is analogous to that of humans (Faccio, Cohen, 2024). Cobots are being applied in a diverse range of industries, reflecting their versatility and high level of accuracy. Their ability to perform tasks requiring precision and to handle hazardous substances without risk to human operators makes them an attractive option in many workplaces. The potential benefits of cobots, particularly in terms of enhanced safety, flexibility and improved efficiency, are frequently highlighted (Javaid et al., 2022).

Furthermore, artificial intelligence can be employed not only in the operational activities of manufacturing businesses but also in planning and strategic decision-making. In particular, it can be utilized in forecasting consumer demand (Aktepe et al., 2021). In general, a multitude of demand forecasting techniques are based on artificial intelligence (Mediavilla, Dietrich, Palm, 2022), in certain cases, these techniques are combined with additional approaches that extend the conventional boundaries of artificial intelligence. For instance, examples include hybrids of AI and metaheuristic algorithms (Goli et al., 2018). The use of artificial intelligence algorithms makes it possible to analyze huge amounts of data, leading to more accurate demand forecasts. These models can identify hidden patterns and changes in consumer behavior that traditional statistical methods may miss. This can lead to increased operational efficiency and reduced costs associated with running the business (Kondapaka, 2021). In addition to the previously mentioned applications, artificial intelligence can also be utilized to develop innovations that may prove to be of considerable importance in the field of manufacturing (Szymańska, Berbel Pineda, 2024).

The integration of artificial intelligence (AI) into manufacturing represents a comprehensive strategy for advancing product efficiency, operational effectiveness, and safety standards. Through the optimization of production processes, the efficient allocation of resources, and the implementation of sophisticated quality assurance methodologies, AI enables substantial improvements in overall operational performance. Within the domain of skills analysis related to manufacturing processes, the adoption of AI assumes a critical role. This technology facilitates a proactive framework for workforce development by systematically analyzing historical data, identifying recurring patterns, and forecasting future skill demands. Consequently, it ensures the identification and cultivation of essential competencies necessary for sustaining industry advancements (Doanh et al., 2023).

3. Methodology

The methodology used in this study was based on a systematic review of the literature. This approach has been described in a number of papers (Okoli, 2015; Xiao, Watson, 2019). A large number of scientific papers based on a systematic review of the literature have shown that this is a method that gives satisfactory results (Halicka, 2017; Szum, 2021; Kozłowska, 2022; Szpilko et al., 2023). The study carried out for this publication was divided into five phases. The whole, and the order in which it was carried out, is shown in Figure 1.

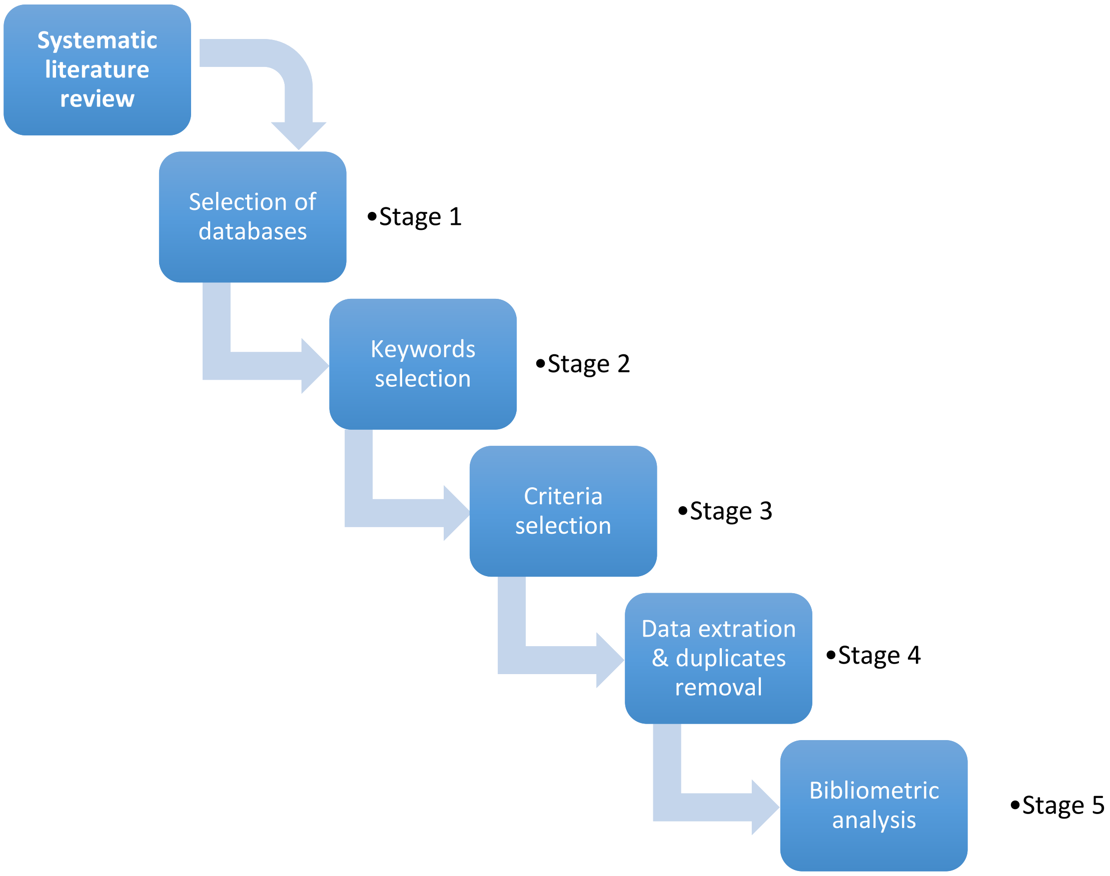

Figure 1. Methodology of the literature review carried out.

Source: author's own elaboration.

The initial stage of the process entailed the identification of pertinent scientific databases that align with the subject matter of the study. This involved the critical assessment of sources that exhibited a high degree of quality and relevance. The databases ultimately selected for the study were Web of Science and Scopus. In the second step, however, a set of keywords was developed to enable literature searches. The keywords were chosen to reflect the theme of the study as closely as possible. The next step was to establish inclusion criteria. It was determined which publications would be included in the analysis. In this study, items published from the beginning of 2015 to the end of October 2024 were included. In addition, the language of publication - English - was a factor in the criteria. For document types, the following were considered: articles, conference papers, book chapters, reviews, editorial materials, books and short surveys. At this stage, papers that did not meet the specified conditions were excluded. Once the results were collected, a data extraction process was carried out, which involved extracting key information from the publications (e.g. authors, titles, citations). Duplicates were then removed to ensure the data set was unique. The criteria used to identify duplicate papers were document characteristics such as DOI, titles and authors. The final stage involved conducting a bibliometric analysis that identified research trends, the most cited papers, key countries and authors and other relevant aspects of the literature. This analysis provided valuable information on the structure of the study area.

Table 1.
Research results

Step	Databases	
	Web Of Science	**Scopus**
	First search	
Research query #1	(TS=(ai) OR TS=(artificial intelligence)) AND (TS=(manufacturing) OR TS=(production))	TITLE-ABS-KEY ("ai" OR "artificial intelligence") AND TITLE-ABS-KEY ("manufacturing" OR "production")
Number of results without inclusion criteria	19,744	41,800
Number of results with inclusion criteria	15,107	29,414
	Second search	
Research query #2	(TI=(ai) OR TI=(artificial intelligence)) AND (TI=(manufacturing) OR TI=(production))	TITLE ("ai" OR "artificial intelligence") AND TITLE ("manufacturing" OR "production")
Number of results without inclusion criteria	1,038	1,790
Number of results with inclusion criteria	770	1,370
Unique items	1,451	

Source: author's own elaboration.

The initial search was conducted using the document's title, abstract, and keywords as search terms. However, as the first search yielded several thousand results and the inclusion criteria were applied, only the title was considered in the second search. Documents containing the terms "AI" or "artificial intelligence" and "manufacturing" or "production" in the title were subjected to examination. This yielded 1,038 results from the Web of Science database and 1,790 from the Scopus database prior to the application of the inclusion criteria. Following the application of the inclusion criteria, 770 and 1,370 documents were obtained, respectively. After the removal of duplicate items, the final result was 1,451 items.

4. Results

Based on the unique results extracted from both databases (1451 positions), a summary showing the breakdown of items by document type was developed. The results are presented in Figure 2.

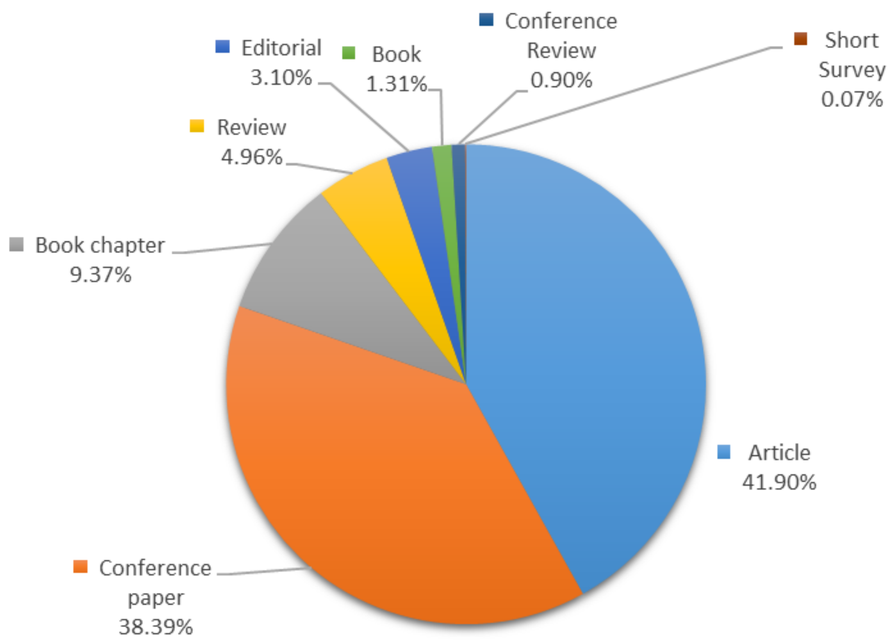

Figure 2. Documents by type.

Source: author's own elaboration.

The two most numerous categories account for more than 80% of all results. The most frequently occurring type of work was the article, while the second most common was the conference paper. Book chapters accounted for almost 10% of all results, while the remaining items reached values of 5% or less. This means that, in the field under study, the publication of results in the form of articles and conference papers is the most popular way of scientific communication. Book publications and niche forms (e.g. conference reviews and short surveys) are of secondary importance, indicating the dynamic nature of knowledge and the preference for quick sharing of research results in the form of scientific articles. Additionally, the results highlight the importance of conferences in the field of artificial intelligence.

The following stage in the bibliometric analysis was to provide a summary of the distribution of papers in terms of the years in which they were published. The results are presented in Figure 3.

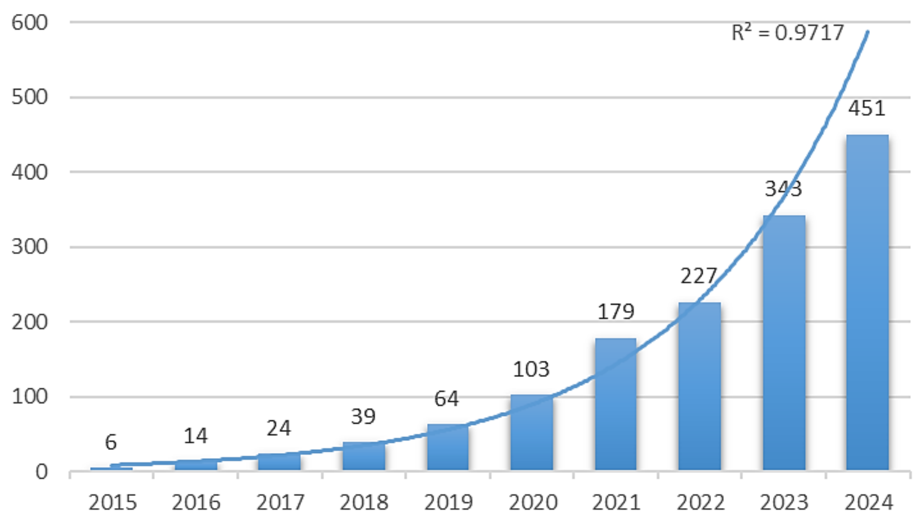

Figure 3. Documents by publication year.

Source: author's own elaboration.

As illustrated in the figure, the number of publications is increasing in a dynamic manner. It is important to note that the data for 2024 represents a period from January to the end of October. This indicates that the total number of publications is likely to increase by the end of the year. The figure uses an exponential trend line, for which an R^2 value equal 0.9717 was calculated. The high degree of coefficient of determination confirms that the number of publications is growing exponentially. The rate of growth accelerated significantly following 2019. From 2015 to 2019, the number of publications increased from 6 to 64. In contrast, the number of publications increased from 64 to 451 between 2020 and 2024. This represents a significant expansion in the volume of published work, particularly when viewed in the context of the exponential rate that became more apparent after 2020. The increase in the number of publications reflects the intensification of research activities and the growing importance of the field in the scientific community.

The third element of the study was to summarize the data collected in terms of the most productive countries, organizations and authors. The results are presented in Table 2.

Table 2.
Research results in terms of most productive countries, organizations and authors

No.	Item	NP	%	Average citation count
	Most productive countries			
1	China	262	18.06	8.45
2	United States	242	16.68	11.70
3	India	194	13.37	3.97
4	Germany	161	11.10	5.27
5	United Kingdom	95	6.55	11.12
6	Italy	73	5.03	6.40
7	Spain	42	2.89	2.83
8	South Korea	40	2.76	4.83
9	France	39	2.69	14.10
10	Canada	35	2.41	2.63

Cont. table 2.

Most productive organizations				
1	Fraunhofer Gesellschaft	17	1.17	7.06
2	Polytechnic University of Milan	17	1.17	2.65
3	University of Johannesburg	15	1.03	28.67
4	University of Patras	13	0.90	15.46
5	RWTH Aachen University	12	0.83	11.92
6	Technical University of Munich	11	0.76	2.00
7	Indian Institute of Technology System	10	0.69	40.90
8	Helmholtz Association	10	0.69	6.90
9	University System of Ohio	9	0.62	32.22
10	University System of Georgia	9	0.62	4.33
Most productive authors				
1	Alexopoulos K	7	0.48	20.57
2	Wang Y	6	0.41	5.33
3	Chryssolouris G	5	0.34	28.20
4	Qian F	5	0.34	21.40
5	Kumar A	5	0.34	18.60
6	Wagner J	5	0.34	16.00
6	Burggräf P	5	0.34	16.00
8	Arkouli Z	5	0.34	11.00
9	Lee J	4	0.28	136.50
10	Liu J	4	0.28	68.00

Note. NP – number of publications; % - percentage share of the data set (1451 results); the sorting in the ranking was adopted according to the following criteria: (1) number of publications, (2) average number of citations

Source: author's own elaboration.

The two countries with the highest number of publications are China (262) and the United States (242). In terms of the average number of citations, the US is the favorite of the two, as it has 11.70 citations per publication, while China has 8.45. This may indicate the greater scientific influence of the US compared to China. India ranked third with a high number of citations (194), but a relatively low average number of citations per publication (3.97).

In examining the most productive organizations, it is notable that the first two positions are occupied by European centers with an identical number of publications, 17. However, the average number of citations for the Fraunhofer Gesellschaft is higher, at 7.06. For the Polytechnic University of Milan, the ratio is 2.65 citations per publication. In third place is the University of Johannesburg with 15 publications and an average number of citations of 28.67.

In terms of authors with the highest number of citations, Alexopoulos K is in the leading position with 7 publications and a citation average index for these publications of 20.57. The next most cited author is Wang Y with 6 publications and a citation average of 5.33. The third most cited author is Chryssolouris G with 5 publications and a citation average of 28.20.

This compilation provides an overview of the global dynamics of research and its impact, organized by country, institution and academia, as well as by author. China and the United States lead in terms of the number of publications, but publications from the United States, the United Kingdom, and France are more influential, which may indicate that they represent higher quality research. While India and certain European countries (e.g., Italy, Spain) make notable quantitative contributions, the average number of citations suggests a more limited scope of influence. It is evident that developing countries (e.g., India) and less well-known institutions have the potential to enhance the impact of their research. One strategy may be to establish global networks.

The next stage in bibliometric analysis was performance of keywords co-occurrence in given dataset. A thesaurus file was also created to guarantee correctness and relevance of analyzed keywords dataset. This was done in order to exclude terms that were not related to the study (such as article, case study) or duplicate terms with similar meanings (such as artificial intelligence and AI). Keyword analysis and an examination of the publication collection served as the foundation for the creation of this file. The analysis's findings made it possible to identify thematic clusters that reflect the primary and new areas of investigation. The results are presented in Figure 4.

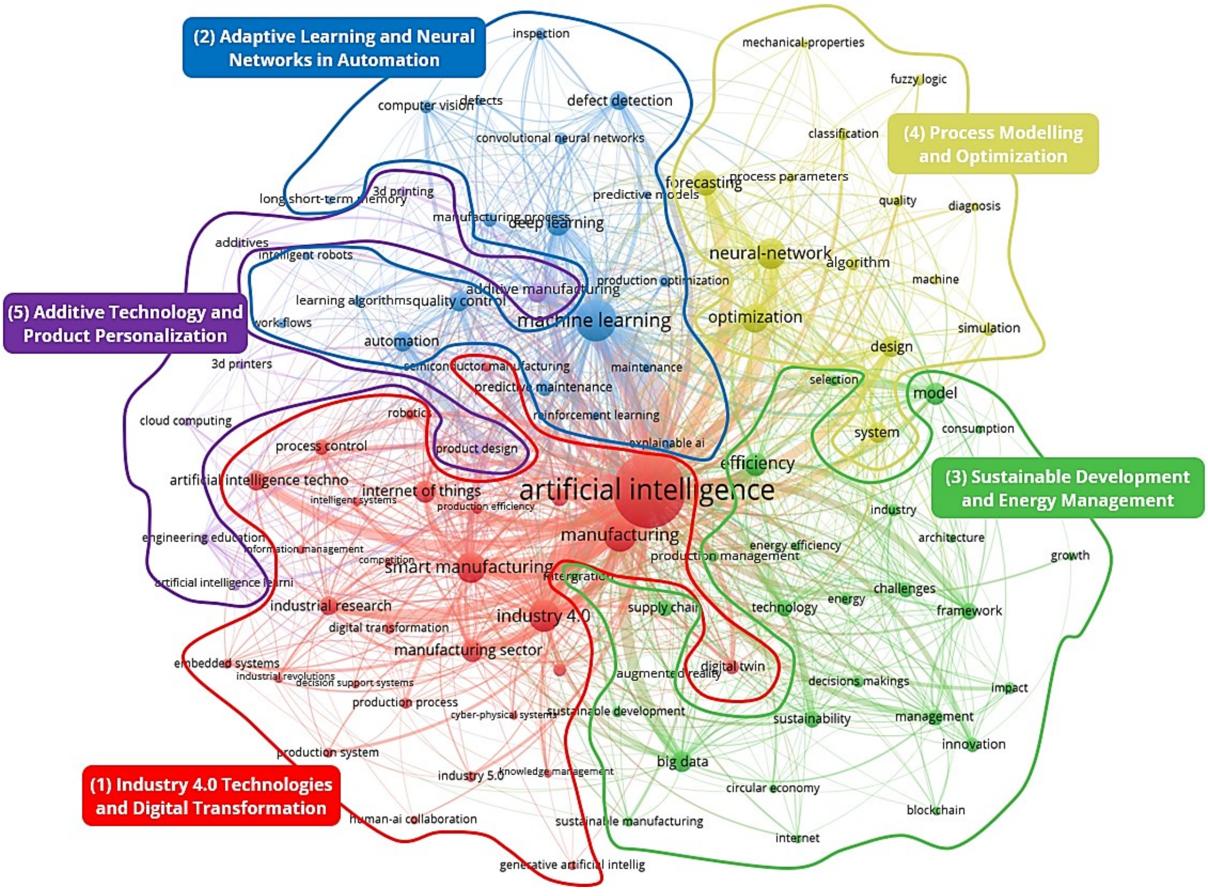

Figure 4. Keywords co-occurrence for artificial intelligence in manufacturing divided into thematic clusters.

Source: author’s own elaboration using VOSviewer software.

5. Discussion

First cluster, the biggest one, entitled “Industry 4.0 Technologies and Digital Transformation”, concentrates on the function of Industry 4.0 in the digital transformation of the manufacturing sector. The central node is the concept of “artificial intelligence” (730 occurrences) which encompasses a vast array of applications. Additionally, pivotal topics such as “manufacturing” (157), “smart manufacturing” (128) and “internet of things” (65) are of significance in this cluster. These concepts underscore the advanced interconnectivity between devices and systems, resulting in enhanced manufacturing processes and efficiency. The concept of “Industry 4.0” (131) represents a significant aspect of this cluster, reflecting a general tendency towards the integration of intelligent technologies in industrial processes. This includes the utilization of advanced concepts such as “digital twin” (30) and “cyber-physical systems” (10). Additionally, terms like “decision making” (43) and “data analytics” (26) highlight the growing importance of data-driven decision-making and analytics based on advanced algorithms.

The second cluster, which is entitled “Adaptive Learning and Neural Networks in Automation”, is concerned with the deployment of innovative artificial intelligence approaches in the context of industrial process automation. At the core of this cluster are technologies such as “machine learning” (234) and its subset “deep learning” (86), which facilitate adaptive and intelligent decision-making in high-complexity industrial settings. One of the central themes of this cluster is the concept of “automation” (53) and the related processes of “defect detection” (48) and “quality control” (60). Additionally, the cluster demonstrates an interest in areas such as “computer vision” (25) and “predictive maintenance” (33), which have the potential to enhance the operational profitability of companies. The use of terms such as “reinforcement learning” (15) and “learning algorithms” (16) indicates that these systems are becoming increasingly autonomous and capable of learning from experience, leading to further optimization and automation.

Cluster three, designated as “Sustainable Development and Energy Management”, is concerned with matters related to energy efficiency, resource management, and the implementation of sustainable strategies in industry. In addition to concepts such as “model” (62), “big data” (59), and “supply chain” (39), issues such as “sustainability” (35), “energy” (20), and the more narrowly defined “sustainable manufacturing” (17) were included. The theme of “efficiency” (20) is a key focus of the cluster, indicating that the objective is to achieve the highest possible operational efficiency while reducing energy and resource consumption. However, the phrase “challenges” (32) suggests an attempt to address the sustainability challenges of modern industry under the broader concept of “sustainable development” (17) through the use of diverse technological solutions, which are outlined under the theme “technology” (37).

The fourth cluster, named “Process Modelling and Optimization”, focuses on the modelling of industrial processes, their optimization and the application of advanced analytical techniques and technologies, such as neural networks, to improve the quality, efficiency and precision of production. An analysis of the keyword weights in this cluster makes it possible to distinguish dominant themes such as “optimization” (106), “simulation” (25), “system” (53) and “process parameters” (13). This indicates that the main objective of the cluster is to improve industrial processes through detailed modelling and optimization. On the purely technical side, keywords such as “neural-network” (125) and “algorithm” (23) pointed out, highlighting the use of neural networks for prediction and analysis of process data. This is supported by technologies related to “forecasting” (87), which enables the prediction of future problems and risk management, which is invaluable in production planning. Topic “design” (60), on the other hand, indicates the design of optimized production systems.

The final cluster, “Additive Technology and Product Personalization”, is the least significant in terms of importance and focuses on the utilization of additive technologies and product customization, reflecting the most recent trends in industrial personalized manufacturing. The cluster is defined by two key terms: "additive manufacturing" (52) and “additives” (25). These indicate the dominance of "3D printing" (15) technology and methods related to the creation of layer-by-layer structures. These technologies facilitate the production of highly complex shapes while reducing the amount of waste and materials needed for production. It was therefore unsurprising that the term “3D printers” featured prominently. The concept of “product design” (24) is also pivotal in this process, facilitating the creation of customized solutions that align with the specific requirements of the end user. The importance of “engineering education” (18) in equipping professionals with the requisite knowledge and expertise to utilize these technologies on a large scale is also highlighted.

The co-occurrence analysis made it possible to identify five thematic clusters that constituted research subareas in the context of AI in manufacturing. In Table main research subareas and main research issues of each cluster are presented.

Table 3.
Research subareas and main research issues in AI in manufacturing

No.	Cluster name	Research subareas	Main research issues
1.	Industry 4.0 Technologies and Digital Transformation	cyber physical systems, IoT, digital twins	- Integration of IoT technology and cyber-physical systems with AI (Ahmmed, Isanaka, Liou, 2024; Moosavi et al., 2024; Trakadas et al., 2020) - Development of digital twins for industrial process modeling and monitoring using AI (Pracucci, 2024; Urgo, Terkaj, Simonetti, 2024; Vyskočil et al., 2023) - Decision-making based on advanced artificial intelligence algorithms (Castañé et al., 2023; Patalas-Maliszewska, Pająk, Skrzeszewska, 2020; Franke, Franke, Riedel, 2022)

Cont. table 3.

2.	Adaptive Learning and Neural Networks in Automation	process automation, quality control, predictive maintenance	- Implementing machine learning algorithms for defect detection and process optimization (Chauhan, 2023; Leberruyer et al., 2023; Getachew et al., 2024, Rezaei et al., 2023) - Using neural networks to predict process behavior (Obaidullah, 2023; Rathore et al., 2023; Baskar et al., 2024) - Predictive maintenance of machinery and equipment using AI (Netisopakul, Phumee, 2022; Rossini et al., 2021; Liu et al., 2022, Hrnjica, Softic, 2020)
3.	Sustainable Development and Energy Management	energy efficiency, sustainable manufacturing strategies	- Optimize industrial energy and resource consumption with AI (Shi et al., 2023; Akinadewo et al., 2024; Lamsaf et al., 2024) - Implementing sustainability strategies in manufacturing based on AI technologies (Rojek et al., 2024; Wang, Wen, Long, 2024; Agrawal et al., 2023) - Life cycle analysis of products in the context of AI-supported sustainable manufacturing (Andres et al., 2023; Mirzaei et al., 2023; Kaab et al., 2019)
4.	Process Modelling and Optimization	process modeling, forecasting, systems projecting	- Simulation and optimization of production processes using AI (Baskar et al., 2024; Stavropoulos, Papacharalampopoulos, Christopoulos, 2023; Jadhav et al., 2024; Rentsch, Heinzel, Brinksmeier, 2015) - Development of prediction algorithms for better risk management in industrial processes (Mmbando, 2024; Umer, Belay, Gouveia, 2024; Radanliev, De Roure, 2023; Massaro et al., 2021)
5.	Additive Technology and Product Personalization	3D printing, product design, additive technologies	- Optimization of 3D printing parameters using AI algorithms to reduce defects and increase quality (Abbili, 2024; Ulkir, Bayrakilar, Kuncan, 2024; Amini, Chang, Rao, 2019) - Product design using AI (Wan et al., 2020; Singh, Singh, Soni, 2024; Liu, Tian, Kan, 2022; Aphirakmethawong, Yang, Mehnen, 2022)

Source: author's own elaboration.

The analysis of Table 3 in the context of artificial intelligence (AI) applications in manufacturing reveals an intricate interplay between thematic research clusters, key technological advancements, and emerging trends. Five thematic clusters were identified, each highlighting distinct aspects of AI's role in transforming manufacturing processes and strategies. These clusters—Industry 4.0 Technologies and Digital Transformation, Adaptive Learning and Neural Networks in Automation, Sustainable Development and Energy Management, Process Modelling and Optimization, and Additive Technology and Product Personalization—serve as focal points for understanding the multifaceted impact of AI in manufacturing.

Industry 4.0 Technologies and Digital Transformation is the most prominent cluster, underscoring the critical role of integrating IoT, digital twins, and cyber-physical systems with AI to enhance decision-making and operational efficiency. Research within this cluster highlights the sophistication of AI-driven data analytics and the centrality of real-time process monitoring. The development of digital twins, as evidenced by the literature, has enabled predictive analytics and proactive decision-making, emphasizing AI's transformative potential in achieving seamless digitalization.

The Adaptive Learning and Neural Networks in Automation cluster focuses on AI's capability to automate quality control, optimize defect detection, and predict maintenance requirements. With technologies like machine learning and deep learning, AI applications have shifted from reactive to predictive, ensuring operational efficiency and minimizing downtime. This cluster illustrates the increasing autonomy of AI systems and their ability to learn from data for continuous process improvement.

Sustainable Development and Energy Management has emerged as a pivotal area, addressing the dual challenge of efficiency and sustainability in manufacturing. AI's integration with energy management systems demonstrates its ability to dynamically optimize resource use and reduce carbon footprints. Research here also highlights AI's contribution to life cycle analysis and the adoption of sustainable practices in manufacturing strategies, aligning with global sustainability goals.

The Process Modelling and Optimization cluster demonstrates AI's role in refining manufacturing processes through simulation, forecasting, and risk management. The use of neural networks and optimization algorithms has proven effective in identifying inefficiencies and proactively addressing production challenges. This thematic area underscores the importance of precise modeling for achieving operational excellence.

Finally, Additive Technology and Product Personalization represents the cutting-edge of manufacturing innovation. AI's application in 3D printing and product customization signifies a paradigm shift towards individualized manufacturing solutions. By leveraging advanced machine learning algorithms, manufacturers can design products tailored to specific consumer needs while maintaining high quality and efficiency. This cluster also highlights the educational implications of equipping professionals with the knowledge to harness these emerging technologies.

The identified clusters collectively illustrate the breadth of AI applications in manufacturing and its potential to redefine industrial paradigms. However, challenges remain, such as the need for seamless technology integration, addressing ethical considerations, and bridging the gap between theoretical research and practical implementation.

The research conducted enabled quantitative analysis of the results obtained, which allowed a detailed examination of trends in the literature and the main directions of ongoing research. As a result of the analysis, five thematic clusters were identified, which reflect the key areas of scientific interest in the field. At the same time, the overall popularity of each cluster was shown, which allows a better understanding of the distribution of research priorities in the overall literature on artificial intelligence in manufacturing.

To answer the question of how artificial intelligence affects Industry 4.0, one must first explore the field of "industrial artificial intelligence". The field of industrial AI is concerned with the application of AI in industrial contexts, including manufacturing, logistics, and supply chain management. The objective is to optimize industrial processes, enhance operational efficiency, and improve product quality (Lee et al., 2018). While this concept has been discussed in the literature, it is important to consider the role of "traditional" AI in industry. This issue is addressed by the present work.

In the context of adaptive learning in their work, authors Kumar, Dimitrakopoulos, and Maulen, approach the topic of production planning in an innovative way, combining various digital techniques and machine learning algorithms. Their work emphasizes the importance of integrating sensor-generated data with traditional sources of information, and points to the need to constantly update production decisions in response to changing operational conditions (Kumar, Dimitrakopoulos, Maulen, 2020).

Analysis of the results indicates that sustainability and energy management have become key topics in research on the application of artificial intelligence in industry. A separate thematic cluster highlights how technologies such as artificial neural networks, optimization systems, and predictive algorithms are being used to efficiently manage resources, reduce energy consumption, and minimize the environmental impact of manufacturing operations. Contemporary research often emphasizes the integration of AI with energy management systems to dynamically adjust production processes to the availability of energy from renewable sources, while reducing greenhouse gas emissions (Vinuesa et al., 2020).

The application of modelling processes to improve existing processes is not a recently observed trend. These processes continue to play a pivotal role in modern manufacturing, enabling the increase in efficiency, reduction in costs, and improvement in product quality. As evidenced in the literature, applications of this nature include the prediction of system behavior based on input variables, thereby facilitating the expedient identification of potential issues and the subsequent pursuit of solutions. In particular, techniques such as simulations based on machine learning algorithms allow for the testing of multiple scenarios in a virtual environment before implementation in the physical world. Successful AI implementations in industry have been shown to result in significant operational improvements and cost savings. Case studies illustrate the effectiveness of AI technology in real-world manufacturing scenarios, which provide valuable guidance for other manufacturers looking to begin implementing AI in production optimization (Kasaraneni, 2021).

The research has identified a significant role for additive technologies and product personalization in modern industry, as evidenced by a separate thematic cluster. The personalization of products, supported by advanced machine learning algorithms and neural networks, plays a particularly important role in sectors that require a high degree of product customization in order to meet specific customer requirements. The literature indicates that artificial intelligence makes it possible to analyze consumers' preferences in order to dynamically design products tailored to their expectations. Furthermore, artificial intelligence is used in three key stages of product development: design, manufacturing, and evaluation (Liu, Tian, Kan, 2022).

6. Conclusions

The research conducted, based on a systematic literature review, provided a comprehensive picture of the rapidly growing field of artificial intelligence (AI) application in the manufacturing industry. Bibliometric analysis showed a significant increase in the number of publications in recent years, especially after 2019, reflecting the intensification of scientific interest and the growing importance of AI in the context of industrial transformation.

The most productive countries in this field are China and the United States, which dominate in terms of the number of publications. However, the higher average number of citations of US publications indicates their greater scientific influence. The analysis of leading authors and institutions showed considerable diversity in terms of their influence on the development of the study area. The results indicate that both prestigious research institutions and individual scientists play an important role in building knowledge and shaping global trends in this rapidly developing field.

The findings of this study also highlight the transformative role of artificial intelligence (AI) in the manufacturing sector, driven by rapid advancements in technology and a growing demand for innovation.

AI's impact is reflected across five key thematic clusters, showcasing its diverse applications. From enabling digital transformation through Industry 4.0 technologies to advancing process optimization and sustainable energy management, AI has proven indispensable in addressing contemporary challenges. Notably, the adoption of adaptive learning systems and additive manufacturing underscores AI's ability to enhance both operational efficiency and product customization.

The study underscores the importance of sustainability as a focal point, with AI-driven strategies significantly contributing to energy efficiency and reduced environmental impact. These findings align with global priorities for sustainable industrial practices and highlight the potential of AI to shape an environmentally conscious future for manufacturing.

However, significant challenges persist, including barriers to widespread implementation, economic feasibility, and technological readiness. Bridging the gap between academic research and industrial applications requires targeted efforts to overcome these obstacles. Collaborative research initiatives, policy support, and investment in workforce education will be critical to maximizing the benefits of AI in manufacturing.

In conclusion, AI represents a cornerstone of modern manufacturing innovation. Its ability to drive efficiency, foster sustainability, and deliver personalized solutions positions it as a transformative force in the industry. Continued exploration of its potential and proactive measures to address existing challenges will ensure that AI fulfills its promise as a catalyst for the next industrial revolution.

Future research can focus on analyzing the extent to which scientific findings presented in the literature are reflected in practical implementations in actual manufacturing processes. For example, while additive manufacturing technologies and optimization algorithms are widely explored in scientific publications, it is necessary to investigate whether and to what extent their theoretical potential translates into successful applications in industrial practice. Such research will allow the identification of technological, organizational or economic barriers to the implementation of innovative solutions, as well as the development of strategies to accelerate the transfer of knowledge from the field of research to actual production.

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