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Review

Challenges and Opportunities in the Implementation of AI in Manufacturing: A Bibliometric Analysis

Lorena Espina-Romero [1,*], Humberto Gutiérrez Hurtado [1], Doile Ríos Parra [2], Rafael Alberto Vilchez Pirela [3], Rosa Talavera-Aguirre [1] and Angélica Ochoa-Díaz [4]

[1] Escuela de Posgrado, Universidad San Ignacio de Loyola, Lima 15024, Peru; humberto.gutierrez@epg.usil.pe (H.G.H.); rtalavera@usil.edu.pe (R.T.-A.)
[2] Centro de Investigaciones Sociales y Económicas, Universidad Popular del Cesar, Valledupar 200002, Colombia; doilerios@unicesar.edu.co
[3] Departamento de Ciencias Sociales, Universidad de Córdoba, Montería 230027, Colombia; rafaelvilchezp@correo.unicordoba.edu.co
[4] Facultad de Derecho, Universidad del Sinú "Elías Bechara Zainúm", Montería 230001, Colombia; angelica.ochoa@unisinu.edu.co
* Correspondence: lespina@usil.edu.pe

Abstract: This study explores the evolution and impact of research on the challenges and opportunities in the implementation of artificial intelligence (AI) in manufacturing between 2019 and August 2024. By addressing the growing integration of AI technologies in the manufacturing sector, the research seeks to provide a comprehensive view of how AI applications are transforming production processes, improving efficiency, and opening new business opportunities. A bibliometric analysis was conducted, examining global scientific production, influential authors, key sources, and thematic trends. Data were collected from Scopus, and a detailed review of key publications was carried out to identify knowledge gaps and unresolved research questions. The results reveal a steady increase in research related to AI in manufacturing, with a strong focus on automation, predictive maintenance, and supply chain optimization. The study also highlights the dominance of certain institutions and key authors driving this field of research. Despite the progress, significant challenges remain, particularly regarding the scalability of AI solutions and ethical considerations. The findings suggest that while AI holds considerable potential for the manufacturing industry, more interdisciplinary research is needed to address existing gaps and maximize its benefits.

Keywords: artificial intelligence; smart manufacturing; Industry 4.0; process optimization; predictive maintenance; industrial automation; operational efficiency; AI-based business models

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1. Introduction

The implementation of artificial intelligence (AI) in manufacturing has taken on a central role within Industry 4.0, where advanced automation, data analysis, and system interconnectivity have profoundly transformed industrial processes [1–3]. This field of study has attracted the attention of researchers and professionals due to the opportunities it offers for improving efficiency [4], process optimization [5], product customization [6], and reducing operational costs [7]. However, it also presents a series of challenges, such as technological complexity [8], the lack of specialized skills [9], and organizational barriers [10], which hinder its widespread adoption. The scientific literature reflects this balance between opportunities and obstacles, providing a solid foundation for understanding the evolution of AI in manufacturing.

AI in manufacturing is associated with a wide range of applications, including predictive maintenance [11,12], supply chain optimization [13], and the design of personalized products [6]. According to Diez-Olivan et al. [14], the concept of "smartization" in manufacturing industries, a fundamental component of Industry 4.0, enables more efficient knowledge extraction through data fusion and intelligent monitoring strategies. However, one of the main challenges faced by the adoption of AI is the lack of technological infrastructure and limited real-time data processing capabilities, highlighting the need for more detailed research on the effective integration of these technologies into existing manufacturing systems.

At the academic level, authors such as Carletti et al. [15] and Antosz et al. [16] have pointed out the lack of interpretability of machine learning methods as a significant obstacle to their implementation. The ability to interpret and understand the results generated by AI models is crucial for decision-makers to trust the technology and adopt it in complex industrial environments. Additionally, recent studies like that of Williams et al. [17] highlight the need for significant organizational adaptation, which involves not only technological changes but also cultural transformations and skill development within the workforce.

Despite these advances, there is a clear gap in the literature related to the ability of companies to implement commercially viable AI models. Cassoli et al. [18] point out that although AI offers opportunities to prevent equipment failures and improve operational efficiency, few manufacturers have managed to integrate these technologies into products or services that generate sustainable economic returns. This gap highlights the need to explore how companies can overcome challenges related to costs, infrastructure, and skills to effectively integrate AI into their operations.

In this context, a bibliometric analysis is justified as the appropriate method to address these questions [19], as it allows for the examination of the evolution of AI research applied to manufacturing, the identification of key trends, authors, and sources, and the highlighting of emerging topics and areas of opportunity. Bibliometric analysis not only provides an overview of the existing literature but also helps map collaborations between institutions and countries, which is crucial for understanding how this field of knowledge is developing. According to Donthu et al. [20], bibliometric studies are an essential tool for identifying patterns in scientific production and assessing the impact of research on a global level. This study focuses on answering the following research questions:

- RQ1. What are the underlying factors that explain the evolution in scientific production and the impact of research on the implementation of AI in manufacturing between 2019 and August 2024?
- RQ2. What factors explain the variation in impact and productivity of the main scientific sources in AI research applied to manufacturing?
- RQ3. What determinants explain the collaboration structure and academic impact of the most influential authors in AI research applied to manufacturing?
- RQ4. What are the determinants that influence the challenges and opportunities identified in the most cited documents on AI application in manufacturing?
- RQ5. How are the leading global institutions distributed in AI research applied to manufacturing, and what challenges and opportunities arise from their collaboration networks and scientific impact?
- RQ6. What are the most used methods and study approaches in AI research applied to manufacturing, and what challenges and opportunities arise from their application?
- RQ7. How is global scientific production on AI in manufacturing distributed, and what are the implications?
- RQ8. How are the topics developed within the conceptual structure of AI applied to manufacturing, and what challenges and opportunities do they present for its integration and development in the industrial sector?

These questions align with the central objective of the study, which is to analyze trends, identify key contributions, and assess the challenges and opportunities in the adoption of AI in manufacturing between 2019 and August 2024 in Scopus. The contribution of this study lies in providing a structured view of how research on AI in manufacturing has evolved, highlighting not only technological advancements but also the practical challenges that must be overcome for successful implementation. This analysis will allow for the identification of opportunities for future research and industrial applications and will offer a detailed map of the main collaborations and influential sources in the field.

The content of the document will be structured as follows: First, a comprehensive literature review will be offered, where the main studies on AI in manufacturing will be analyzed, highlighting their advances and limitations. Then, the bibliometric methodology employed will be detailed, explaining the data collection and analysis methods, as well as the tools used. Next, the results of the analysis will be presented, including the evolution of scientific production, the most influential sources, prominent authors, and the most cited documents. Finally, the implications of the findings will be discussed in terms of opportunities and challenges for the adoption of AI in manufacturing, concluding with recommendations for future research.

2. Literature Review

The implementation of AI in manufacturing, framed within the Fourth Industrial Revolution or Industry 4.0, has been a topic of growing interest in the recent academic literature. This interest arises because AI presents both significant challenges and opportunities for manufacturing industries, making it a key area for this bibliometric study. To better understand this emerging field, it is essential to examine the major studies that have addressed this topic from different perspectives.

First, Diez-Olivan et al. [14] introduce the concept of the "smartization" of manufacturing industries as a fundamental component of Industry 4.0. According to the authors, this process, driven by the maturity of Information and Communication Technologies (ICTs), enables the extraction of relevant knowledge through intelligent monitoring strategies and data fusion. However, they face significant challenges, such as the effective prediction of anomalous behaviors in industrial machinery and the anticipation of critical events. These challenges highlight the importance of developing data-driven prognosis techniques, suggesting a fertile field for future research in smart manufacturing.

In line with this thinking, Carletti et al. [15] delve into one of the most critical challenges: the lack of interpretability of machine learning methods in manufacturing. This limitation can hinder the adoption of AI solutions, as the ability to clearly interpret results is essential for decision-making in industrial settings. However, the authors identify a significant opportunity in anomaly detection, a fundamental process for quality monitoring. Their proposal to use the Isolation Forest algorithm, which does not require labeled data, opens new possibilities for the initial adoption of machine learning in the industry, thus facilitating the integration of AI into manufacturing processes.

In a complementary approach, Antosz et al. [16] explore the application of AI in lean maintenance within the manufacturing sector. They highlight the main challenge as the insufficiency of means to adequately assess the degree of implementation of maintenance strategies, which can impact both operational efficiency and business policy formulation. Despite this, they identify significant opportunities in the use of intelligent systems that enhance decision-making and increase operational efficiency. This approach not only optimizes maintenance management but also improves overall equipment effectiveness (OEE), providing a competitive advantage in the sector.

Continuing the exploration of the opportunities offered by AI, Williams et al. [17] emphasize how the implementation of this technology is intrinsically linked to the optimization of business processes. Through cognitive algorithms, AI enables greater efficiency and accuracy in production. However, these advances are not without challenges, among which integration with the Internet of Things (IoT) and the need for robust data structures are crucial aspects. Additionally, they point out the need for significant organizational adaptation to overcome technological and investment barriers that could limit the impact of these innovations.

In this context, Cassoli et al. [18] provide a perspective on predictive maintenance, highlighting how recent advances in AI are expanding capabilities in manufacturing. Despite the opportunities this represents, such as preventing unexpected downtime, the authors note that few manufacturers have succeeded in developing AI-based products or services that are commercially viable. This challenge underscores the lack of understanding in integrating AI solutions into new business models, a significant barrier to the adoption of these technologies.

Shifting the discussion towards process optimization, Liu et al. [21] address the implementation of machine learning techniques in the manufacturing of perovskite solar cells. Their focus is on a sequential learning framework that improves process efficiency with a limited experimental budget. This study reflects the opportunities AI offers for process optimization in manufacturing while also highlighting challenges, such as the need to integrate prior knowledge and human observations into decision-making. This underscores the complexity of implementing AI in advanced manufacturing environments.

On the other hand, Dinmohammadi [22] identifies that, although AI is a key driving force for sustainable development in Industry 4.0, there are significant challenges in scaling its implementation beyond the proof-of-concept phase. The main obstacles include the lack of adequate infrastructure, the shortage of specialized talent, poor data quality, and complications related to policies and regulations. His SWOT analysis offers strategic recommendations to overcome these challenges, allowing industries to move toward more effective use of AI.

In line with these studies, Soni et al. [23] emphasize that the integration of physical and cyber technologies, driven by AI, presents opportunities to improve efficiency, quality, and transparency in manufacturing. However, they highlight that to fully take advantage of these opportunities, it is essential to advance sensor technology and ensure its accessibility at low cost. This advancement in sensors is crucial for automation in Industry 4.0, although it also brings technical and economic challenges that need to be overcome.

Finally, Podder et al. [24] highlight the growing importance of MEMS-based sensors in manufacturing, facilitated by advances in semiconductor technology. Despite being powerful and low-cost, these sensors exhibit errors due to the complexity of their fabrication. Here, AI emerges as a crucial tool to improve the quality and reliability of sensors, but it also poses challenges related to quality control and adaptation in the industrial environment.

Closing this review, TurandasjiPatil et al. [25] and Gabsi [26] offer a broad perspective on the challenges and opportunities of AI in Industry 4.0. While TurandasjiPatil et al. emphasize the difficulty of applying AI solutions from one sector to another due to the specific customization of each industry, Gabsi explores how digitalization, automation, and connectivity have led to the creation of "smart factories." Both agree that although the challenges are significant, the opportunities to enhance productivity, efficiency, and decision-making in manufacturing are immense.

In conclusion, the literature review provides a solid framework for the development of the present bibliometric study. The reviewed studies offer insight into the complexity and diversity of AI implementation in this sector, from process optimization to overcoming technological and organizational barriers. This theoretical foundation will enable the analysis of emerging trends and patterns in AI research in manufacturing, providing an understanding of the key areas of opportunity and challenge.

3. Materials and Methods

3.1. Study Design

The present study adopts a bibliometric design with a quantitative approach, whose general objective is to analyze trends, identify key contributions, and assess the challenges and opportunities in the adoption of AI in manufacturing between 2019 and August 2024 in the Scopus database (Figure 1). Bibliometric analysis is a key tool for identifying the growth of the scientific literature, the most influential authors, and the main collaboration networks in a specific field, as highlighted by Donthu et al. [20]. This design allows for a structured analysis of scientific production and collaboration relationships, providing a comprehensive view of the development of research on AI applied to manufacturing. Following the recommendations of Todeschini y Baccini [27], quantitative tools are used to measure scientific performance and visualize the evolution of collaboration networks in this emerging field.

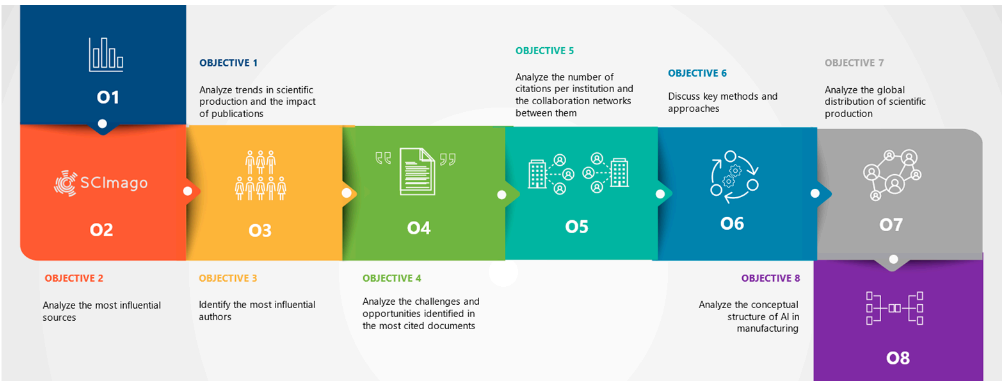


Figure 1. Specific objectives timeline.

3.2. Data Collection

To conduct this analysis, the data were collected from the Scopus database, recognized for its curation and high quality, as highlighted by Baas et al. [28] and Burnham [29]. The initial search was conducted in the "Title" field, using a series of key terms that were strategically selected to encompass the central theme of the study: the implementation of AI in manufacturing. These terms included "artificial intelligence", "AI", "machine learning", "deep learning", "manufacturing", "industry 4.0", "smart manufacturing", and "industrial automation". The choice of these terms was based on their ability to identify relevant studies on the adoption of emerging technologies within industrial settings. As a result of this initial search, 2546 documents were obtained.

To refine the results and capture the specific challenges and opportunities in AI implementation, additional key terms related to these aspects were added. These included: "implementation challenges", "barriers", "obstacles", "investment costs", "capital expenditure", "cost analysis", "skill development", "workforce skills", "reskilling", "upskilling", "competitive landscape", "market competition", "emerging competitors", "business opportunities", "revenue generation", "monetization", "efficiency improvement", "operational efficiency", "process optimization", "business models", "innovative business models", "servitization", "data-driven services", "data-driven business", and "data monetization". This second phase reduced the number of documents to 562, covering the period from 1979 to August 2024.

Subsequently, the search was limited to the period from 2019 to August 2024, as prior years' scientific production in this field was significantly lower (fewer than two studies published per year). The final reduction yielded a total of 537 documents after applying filters that excluded 9 documents such as editorials, errata, notes, short surveys, and retractions (Figure 2).

The inclusion of these key terms and the date refinement ensures that the bibliometric analysis captures the most relevant trends and pertinent studies on AI implementation in manufacturing. This meticulous process was designed to guarantee the quality and specificity of the selected documents, minimizing the risk of including tangential studies. The choice of Scopus as the primary data source is supported by its relevance in bibliometric studies, as argued by Kulkanjanapiban and Silwattananusarn [30], who highlight its usefulness in evaluating academic productivity.

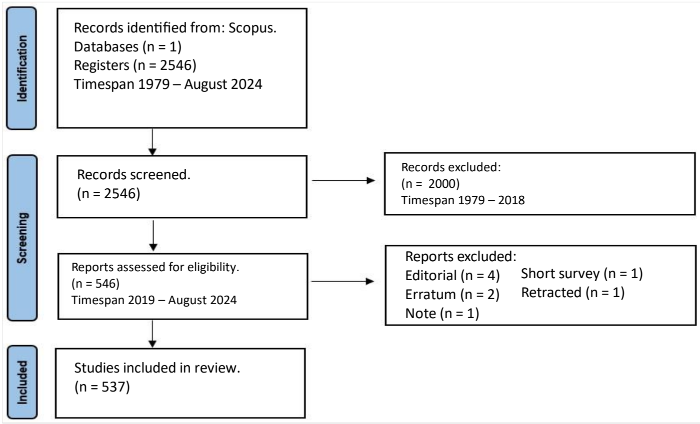


Figure 2. Document selection flowchart.

3.3. Analyzed Variables and Methods of Analysis by Objective

For the analysis of trends in scientific production and the impact of publications (Objective 1), variables such as annual scientific production, the average number of citations per year, the average number of citations per article, and the most worked-on themes were examined. These metrics were processed using RStudio version 2024.04.2+764, following the recommendations of Aria and Cuccurullo [31], who suggest the use of tools like bibliometrix for the visualization and quantitative analysis of scientific data. The resulting graphs, generated with Microsoft Excel 365 version 2408 [32,33], allowed for the observation of how scientific production in AI in manufacturing has evolved and its impact in terms of citations over the studied period.

Regarding the analysis of the most influential sources (Objective 2), variables such as the h, g, and m indexes of the main sources, as well as the number of citations and the production of documents per source, were analyzed. Following the principles of Bradford's Law, RStudio version 2024.04.2+764 was used to identify the most productive and cited sources, an approach recommended by Bradford [34], who explains that this type of analysis is key to identifying core journals in a field of study.

To identify the most influential authors (Objective 3), the h, g, and m indexes of the authors were analyzed, as well as their collaboration networks. VOSviewer version 1.6.20 and RStudio version 2024.04.2+764, tools recommended by van Eck and Waltman [35] and Aria and Cuccurullo [31], were used to generate citation maps that visualized the relationships among the most prominent authors. The minimum threshold was set at 3 documents and 99 citations per author, which made it possible to identify the researchers with the greatest impact in the field of AI applied to manufacturing, following the recommendations of McAllister et al. [36] on creating citation maps.

Regarding the analysis of the challenges and opportunities identified in the most cited documents (Objective 4), the number of citations per document and the key topics addressed were examined. RStudio version 2024.04.2+764 was used to identify the 20 most-cited documents, following the methodology proposed by Donthu et al. [20] to identify the most recurring challenges, such as AI integration, process optimization, and the improvement of labor skills.

Regarding the global distribution of institutions and collaboration networks (Objective 5), the number of citations per institution and the collaboration networks between them were analyzed. VOSviewer version 1.6.20 was used to map institutional connections, in line with the approach proposed by Mongeon and Paul-Hus [37], who highlight the importance of analyzing institutional collaboration in bibliometric studies. This analysis allowed for the identification of the main institutions involved in AI research in manufacturing and their collaboration relationships at a global level.

For the analysis of key methods and approaches in AI research applied to manufacturing (Objective 6), the main methods used, such as machine learning and big data analysis, as well as the challenges in their application, were examined. By using keyword co-occurrence analysis in VOSviewer version 1.6.20, prevalent methodological approaches were identified, following the suggestions of Derviş [38] and Aria and Cuccurullo [31], who recommend the use of bibliometrix to identify methodological patterns in the scientific literature.

In the analysis of the global distribution of scientific production (Objective 7), the production by country and the impact of publications in terms of average citations per article were evaluated. The global production analysis was conducted using RStudio version 2024.04.2+764, as recommended by Mongeon and Paul-Hus [37], allowing for the visualization of each country's contribution to AI research applied to manufacturing.

Finally, to analyze the conceptual structure of AI in manufacturing (Objective 8), the bibliometric technique of 'co-word' was employed with the purpose of analyzing the authors' keywords as the unit of analysis, applying the statistical technique of 'thematic mapping' through RStudio version 2024.04.2+764. This approach enabled the identification of motor, basic, emerging, and niche themes, following the recommendations of Aria and Cuccurullo [31], who highlight the usefulness of these methods in mapping the evolution of topics in a research field.

3.4. Visualization and Interpretation

Visualization tools, such as RStudio version 2024.04.2+764, VOSviewer version 1.6.20, and Microsoft Excel 365 version 2408, enabled the creation of graphs and maps that helped to clearly represent the relationships between authors, sources, institutions, and topics. These visualizations facilitated the interpretation of trends in scientific production, the impact of institutional collaborations, and the evolution of key themes in AI applied to manufacturing. According to McAllister et al. [36] and Aria and Cuccurullo [31], network visualization and thematic analysis are essential for gaining a deeper understanding of how a scientific discipline develops.

3.5. Use of AI-Assisted Technologies

We have employed various technological tools that incorporate artificial intelligence (AI) to enhance our research. Microsoft Word helped with grammar, style suggestions, and text prediction, improving the clarity of the manuscript. Microsoft Excel facilitated data analysis, offering visualization suggestions and optimizing the management of large volumes of information. DeepL and ChatGPT were used for high-quality translations, comparing their results to select the best option before expert review. Google Search was key in retrieving relevant and up-to-date information. While these technologies helped improve the writing, they did not replace the interpretation of data or scientific conclusions in any way.

4. Results and Discussion

4.1. Evolution and Trends of AI Research in Manufacturing (2019–August 2024)

The objective (O1) of this section is to analyze the underlying factors that have influenced the evolution of scientific production and the impact of research on the implementation of AI in the manufacturing sector between 2019 and August 2024, to understand the development of the field during this period. For this analysis, RStudio version 2024.04.2+764 was used. Data on the number of documents published per year, average citations per year, and average citations per article were obtained from the analysis level termed "Overview", using the metrics "Annual Scientific Production" and "Average Citations per Year". These data are presented in Figure 3, generated with Microsoft Excel 365.

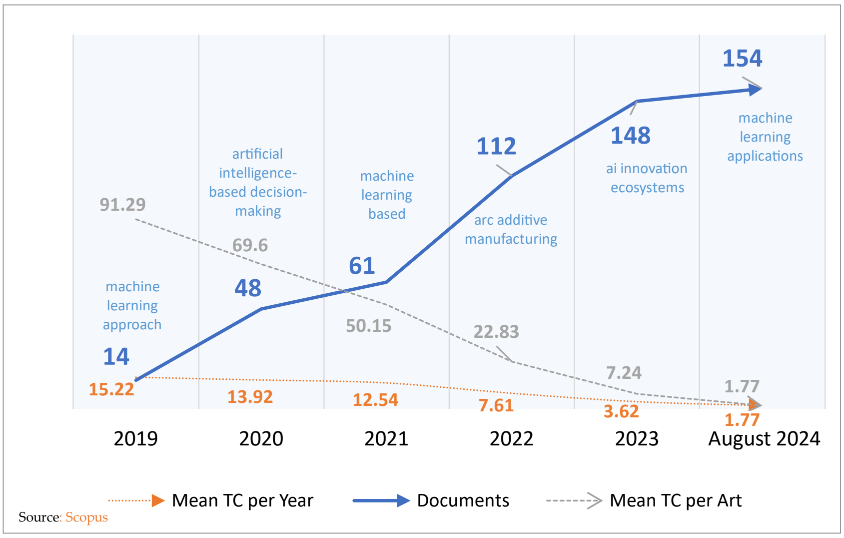


Figure 3. Evolution and trends in research.

Regarding document production, there has been a progressive and significant increase from 2019 to August 2024. In 2019, only 14 documents were published, while in 2023 and 2024, the number of publications reached 148 and 154, respectively. This consistent growth indicates a rising interest from the academic community in applying artificial intelligence to the manufacturing sector, a phenomenon that reflects technological maturity and the adoption of these solutions in various industrial processes.

Despite the increase in document production, the average citations per year have shown a decreasing trend since 2019. That year, the average citation was 15.22, gradually decreasing to 1.77 by August 2024. This decline is common in rapidly expanding fields, as the increase in the volume of publications can spread citations across more articles, reducing the relative impact of each individual work. This phenomenon has been observed in various academic contexts where rapid growth in document production leads to a dilution of citation frequency per article as readers distribute their attention across a larger number of studies [39–41]. Additionally, more recent publications have not yet had enough time to accumulate significant citations. It is important to note that innovative topics in the early years of the study, such as the focus on "machine learning" in 2019 and AI-based decision-making in 2020, likely received a higher number of citations due to their pioneering nature.

In parallel, the average citations per article have followed a similar trend, decreasing from 91.29 in 2019 to 1.77 by August 2024. This pattern reflects not only the increase in the number of published studies but also the inherent challenge of capturing researchers' attention in an increasingly saturated field. During the early years, topics such as the focus on "machine learning" had a significant impact, as they were innovative areas at the time. However, as the field has matured, attention has diversified towards other more specific applications, such as additive manufacturing in 2022 or AI-based innovation ecosystems in 2023, which may have dispersed citations.

The evolution of the most studied topics over the years is also revealing. In 2019, the "machine learning approach" was the central theme [42–44], indicating that the scientific community was exploring the potential of machine learning to optimize processes in manufacturing. In 2020, interest shifted towards AI-based decision-making [45,46], reflecting the need to automate and improve efficiency in industrial processes through decision support systems. In 2021, the focus on "machine learning" remained relevant [47,48], but with a greater emphasis on concrete applications. However, by 2022, the most studied topic was "arc additive manufacturing" [49,50], showing a shift towards applying AI in specific manufacturing processes, such as additive manufacturing.

In 2023, attention focused on "AI innovation ecosystems" [51,52], highlighting the importance of collaborative ecosystems and innovation networks to advance the adoption of AI in manufacturing. Finally, in 2024, although "machine learning" remains a central theme [53,54], it now focuses on more practical and specialized applications to solve specific problems in the manufacturing sector.

Based on these data, it can be concluded that the field of AI research in manufacturing is in full expansion and diversification. Although the average citation per article has decreased, which might suggest a dilution of the individual impact of the works, the topics addressed remain relevant and respond to the emerging needs of the industry. The challenge lies in maintaining the relevance of publications in a field with increasingly growing scientific production. Despite this, opportunities for innovation in this field are vast, especially in integrating AI into collaborative areas, such as innovation ecosystems and the more advanced applications of machine learning in solving specific problems in manufacturing.

4.2. Impact and Trends of the Leading Sources

The objective (O2) of this section is to analyze the factors influencing the variation in impact and productivity of the leading scientific sources in the field of AI research applied to manufacturing. To conduct this analysis, RStudio version 2024.04.2+764 was used, selecting "Sources" as the level of analysis. The metrics employed were the "Sources' Local Impact" and the "Bradford's Law". Analysis of the top 20 sources according to the "Sources' Local Impact" reveals several important observations (see Table 1).

First, journals such as "Applied Sciences (Switzerland)", "Additive Manufacturing", and "Technological Forecasting and Social Change" stand out for having the highest h, g, and m indexes compared to other sources. The h-index, which measures the number of articles with at least h citations, is an indicator of the productivity and impact of a source's publications. "Applied Sciences (Switzerland)" has an h-index of 9, the highest in this analysis, closely followed by "Additive Manufacturing" and "Technological Forecasting and Social Change", both with an h-index of 8. This indicates that these journals have been consistently cited in studies on AI in manufacturing, reflecting their relevance in the field.

The g-index, which considers the distribution of citations received by a source's articles, reinforces the position of "Applied Sciences (Switzerland)" and "Journal of Intelligent Manufacturing", with g-indexes of 14 and 11, respectively. This suggests that these journals not only have a considerable number of cited articles but also that some of their articles are highly cited, which increases their g-index.

The g-index is a bibliometric metric created by Leo Egghe in 2006 that measures academic performance by considering both the number of publications and the accumulation of citations. Unlike the number of publications, the g-index focuses on the distribution of citations, giving more weight to highly cited articles. This means that the g-index is not the same as the number of publications, as it reflects the impact of citations, not just the quantity of articles. Such is the case of IFIP Advances in Information and Communication Technology, which has a g-index of 3 and a total of four publications. Egghe demonstrated that this index is more effective in capturing the influence of a researcher or source with high-impact publications [55].

The m-index is a bibliometric metric that adjusts the h-index based on the number of years since a researcher's first publication, providing a more balanced measure of impact over time. It is calculated by dividing the h-index by the number of years since the first publication. The m-index is useful because it allows for comparisons between researchers who have been active for different lengths of time. Egghe and Hirsch highlighted that, unlike the h-index, the m-index prevents giving an unfair advantage to researchers with longer careers by focusing on relative productivity per year [55,56].

Table 1. Influential sources and their impact.

Source	h Index	g Index	m Index	TC	NP	PY Start	Q	SJR 2023
Applied Sciences (Switzerland)	9	14	1.800	289	14	2020	Q2	0.51
Additive Manufacturing	8	10	1.600	941	10	2020	Q1	2.84
Technological Forecasting and Social Change	8	9	1.600	1194	9	2020	Q1	3.12
Journal of Intelligent Manufacturing	7	11	2.333	237	11	2022	Q1	2.07
Sustainability (Switzerland)	7	11	1.400	525	11	2020	Q1	0.67
Economics, Management, and Financial Markets	6	6	1.200	211	6	2020	N/A	N/A
IEEE Access	5	7	1.000	181	7	2020	Q1	0.96
International Journal of Advanced Manufacturing Technology	5	8	0.833	146	8	2019	Q2	0.7
Journal of Manufacturing Systems	5	8	1.000	260	8	2020	Q1	3.17
Archives of Computational Methods in Engineering	4	4	1.000	77	4	2021	Q1	1.8
Materials Today: Proceedings	4	4	0.800	110	4	2020	N/A	0.47
IFIP Advances in Information and Communication Technology	3	3	0.600	12	4	2020	Q3	0.24
International Journal of Production Research	3	3	0.750	166	3	2021	Q1	2.67
JOM	3	3	0.600	345	3	2020	Q2	0.55
Journal of Cleaner Production	3	3	0.600	157	3	2020	Q1	2.06
Journal of Industrial Integration and Management	3	3	1.000	204	3	2022	Q1	1.14
Journal of Manufacturing Processes	3	3	0.600	113	3	2020	Q1	1.39
Journal of Materials Processing Technology	3	3	1.000	69	3	2022	Q1	1.58
Procedia CIRP	3	5	0.500	82	5	2019	N/A	0.56
Robotics and Computer-Integrated Manufacturing	3	3	1.000	139	3	2022	Q1	2.91

Note: N/A (not applicable); NP (number of publications); Q (quartile); SJR (Scimago journal rank).

The m-index is notable in "Journal of Intelligent Manufacturing", with a value of 2.333, the highest among all analyzed sources. This value indicates a rapid and sustained growth in the number of citations that this journal has received in a short period of time since its first publication, which could indicate the growing importance of AI in smart manufacturing.

On the other hand, "Technological Forecasting and Social Change" leads in terms of total citations (TC) with 1,194 citations, demonstrating its significant influence in the field. However, the journals "Additive Manufacturing", with 941 citations, and "Sustainability (Switzerland)", with 525 citations, also show a significant impact. This suggests that these journals are attracting a high volume of attention within the academic community interested in the application of AI in manufacturing.

It is important to note that some journals with lower h and g indexes, such as "IFIP Advances in Information and Communication Technology" and "Journal of Manufacturing Processes", although they have a lower impact in terms of citations and productivity, may be covering specific niches or emerging areas within the field of AI in manufacturing, justifying their inclusion in more specialized studies.

Finally, the distribution of the "PY_start" (the start year of the considered publications) shows that most sources began publishing relevant work on AI in manufacturing starting from 2020, with some exceptions such as "International Journal of Advanced Manufacturing Technology" and "Procedia CIRP", which started in 2019. This suggests that research related to the implementation of AI in manufacturing has gained considerable momentum in recent years, coinciding with the increased interest in digital transformation and Industry 4.0.

Bradford's Law, formulated by Samuel C. Bradford in 1934 [34], is a bibliometric theory that describes how scientific articles on a specific subject tend to be concentrated in a small number of specialized journals, while a larger number of articles are spread across many less relevant journals. According to this law, if journals are organized into three groups with an equal number of relevant articles, the first group will have a few journals, the second an intermediate number, and the third significantly more. This law is valuable for identifying the most important sources in a field of study.

In the context of this analysis, Bradford's Law is confirmed by observing that 35 journals out of a total of 345 contain most of the articles in the field, as shown in Figure 4. These journals, referred to as "Core Sources," include publications such as *Applied Sciences* (Switzerland), *Journal of Intelligent Manufacturing, and Sustainability* (Switzerland), which stand out for their high productivity and relevance. These sources are crucial for disseminating relevant research and significantly contribute to advancing knowledge in this area. On the other hand, although many other journals (n = 310) publish on the subject, their contribution is much smaller, as suggested by Bradford's curve, which reflects this uneven distribution in the relevance of publications.

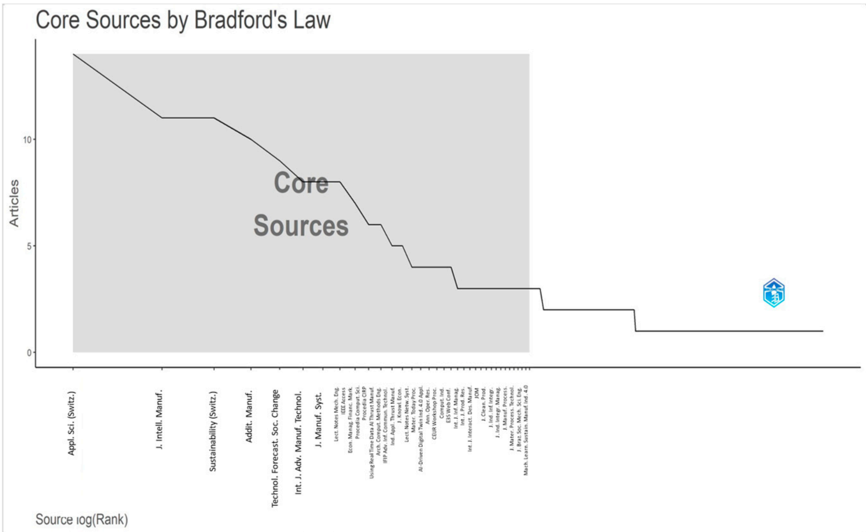


Figure 4. Bradford's Law.

4.3. Key Authors: Influence and Trends

The objective (O3) of this section is to analyze the determinants influencing the collaboration structure and academic impact of the most influential authors in AI research applied to manufacturing. For this analysis, RStudio version 2024.04.2+764 was used, selecting "Authors" as the level of analysis and applying the metric "Authors' Local Impact". Additionally, VOSviewer version 1.6.20 was employed for citation analysis, using "authors" as the unit of analysis. A minimum threshold of 3 documents per author and a minimum of 99 citations per author were established. The results obtained are presented in Table 2.

Table 2. Influential authors.

Author	h-Index	g-Index	m-Index	TC	NP	PY-Start
Lăzăroiu G [57–61]	5	5	1.000	391	5	2020
Agrawal R [62–66]	4	5	1.000	112	5	2021
Haleem A [7,67–69]	4	4	1.000	255	4	2021
Kumar A [63,64,67,70]	4	4	1.333	122	4	2022
Liu Z [21,71–74]	4	5	0.667	233	5	2019
Cao J [43,75–77]	3	4	0.500	99	4	2019
Darwish MMF [47,78,79]	3	3	0.750	298	3	2021
Dwivedi YK [80–82]	3	3	0.750	737	3	2021
Elsisi M [47,78,79]	3	3	0.750	298	3	2021
Huang S [83–87]	3	5	0.500	134	5	2019
Javaid M [7,68,69]	3	3	0.750	229	3	2021
Lee J [88–90]	3	3	0.600	409	3	2020
Lehtonen M [47,78,79]	3	3	0.750	298	3	2021
Li J [91–95]	3	5	0.750	197	5	2021
Li X [88,96–99]	3	5	0.600	207	5	2020
Liu C [100–103]	3	4	1.000	108	4	2022
Liu J [104–108]	3	5	0.600	280	5	2020
Liu Q [71,84,98,99]	3	4	0.500	169	4	2019
Mahmoud K [47,78,79]	3	3	0.750	298	3	2021
Qin J [6,49,109]	3	3	0.600	216	3	2020

The analysis of the 20 authors from a total of 1,948 reveals a clear picture of the most influential researchers in the study of the variables under investigation. This analysis is based on several indicators, such as the h-index, g-index, m-index, total citations (TC), number of publications (NP), and the year of publication start (PY_start).

First, Lăzăroiu G stands out as the most influential author, with an h-index and g-index of 5, indicating that he has published at least five articles, each with at least five citations. His m-index of 1.000, which measures normalized impact over time, suggests steady growth in his impact since he began publishing in 2020. With 391 citations across just five publications, Lăzăroiu has maintained significant relevance in his field.

Authors such as Agrawal R and Haleem A also show considerable influence, both with an h-index of 4 and an m-index of 1.000. This indicates that they have maintained a high level of impact relative to the time since they started publishing in 2021. Agrawal R, with five publications and 112 citations, and Haleem A, with four publications and 255 citations, have established themselves as key contributors to AI research in manufacturing. Kumar A, although he started publishing more recently in 2022, has an h-index of 4 and an m-index of 1.333, indicating an even greater impact in the short time since his first publication. This author appears to be in a phase of rapid growth in terms of influence and academic visibility.

On the other hand, authors like Liu Z and Cao J, who began publishing earlier, in 2019, show h-indexes of 4 and 3, respectively. However, their m-index of 0.667 and 0.500 suggests a more modest impact over time. Liu Z has accumulated 233 citations across five publications, while Cao J has received 99 citations in four publications. Although they have had a significant impact, their growth in terms of citations seems more moderate compared to authors who started publishing more recently. Dwivedi YK and Darwish MMF are other notable authors, both with an h-index of 3 and an m-index of 0.750, reflecting a solid and consistent impact since they started publishing in 2021. Dwivedi YK has achieved a total of 737 citations with only three publications, indicating that his works have been highly cited and possibly fundamental in the field.

Overall, the data suggest that authors with higher h-index and g-index tend to be those who have published in recent years and have maintained a consistent impact over time. However, there are also authors who, despite a more recent start, are quickly achieving a high level of influence in AI research applied to manufacturing. These patterns indicate that the field is attracting a diverse group of researchers who are making significant contributions to the advancement of knowledge, with some emerging rapidly as leaders in academia.

The analysis of Figure 5 generated by VOSviewer reveals several clusters and connections among the authors, as well as some disconnections that provide insights into collaborations and thematic focus within the field under study. One of the most notable clusters includes Kumar A, Dwivedi YK, and Agrawal R (green color), showing a strong connection between these authors. This suggests that they have collaborated on joint projects or work in very similar research areas, leading them to frequently cite each other. This citation network could indicate that these researchers are exploring topics related to AI implementation in manufacturing from complementary perspectives.

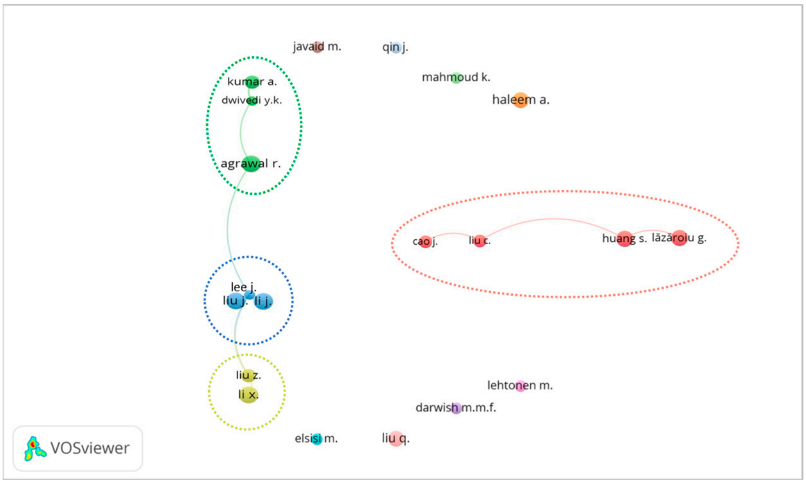


Figure 5. Citation analysis of the top 20 authors.

Another significant cluster is formed by Lăzăroiu G, Huang S, Liu C, and Cao J (red color), suggesting an active collaboration network or a shared focus in their research. These authors are likely working on more specific or advanced aspects of AI in manufacturing, placing them in a central position within this thematic network. Additionally, the cluster including Lee J, Liu J, and Li J (blue color) shows an interrelationship within a possibly more technical or applied area of AI in manufacturing. The presence of connections among them suggests cooperation or alignment in the research topics they are exploring. Similarly, Liu Z and Li X form another small cluster (yellow color), indicating possible collaboration in specific AI in manufacturing research, or at least mutual recognition in their citations.

On the other hand, some authors such as Javaid M, Qin J, Mahmoud K, and Haleem A appear more isolated or with few direct connections to other main clusters. This could be because these authors are exploring more specialized or emerging areas within AI in manufacturing that have not yet been widely integrated into the main research network. Alternatively, these authors may be focused on specific contexts or applications not being addressed by the authors in the more connected clusters. Likewise, Elsisi M, Liu Q, Darwish MMF, and Lehtonen M show a lower degree of connection, which could indicate that their research, while relevant, is aimed at specific subdomains of AI in manufacturing that have not generated broad collaborations or extensive citations within the analyzed group.

In summary, Figure 5 displays a clear segmentation of authors into different clusters, reflecting collaboration networks and shared research themes, while the disconnections highlight the existence of niches or emerging areas in the field that are not yet fully integrated into the main research network on the studied variables.

4.4. Most Cited Documents

The objective (O4) of this section is to identify and analyze the determinants that influence the challenges and opportunities highlighted in the most cited documents on the application of AI in manufacturing. For this analysis, RStudio version 2024.04.2+764 was used, selecting "Documents" as the level of analysis and employing the metric "Most Cited Documents Worldwide". The results are presented in Table 3. The analysis of Table 3, which includes the 20 most-cited documents out of a total of 537, in research on the studied variables, focusing on challenges and opportunities, reveals data that shape the direction of the field and underscore areas that will require future attention.

Table 3. Most cited documents.

Author	Paper	Total Citations	TC per Year	Normalized TC
Wang et al. [110]	"Machine learning in additive manufacturing: State-of-the-art and perspectives"	450	90.00	6.47
Diez-Olivan et al. [14]	"Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0"	441	73.50	4.83
Bag et al. [82]	"Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities"	426	106.50	8.49
Dubey et al. [111]	"Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations"	409	81.80	5.88
Çinar et al. [11]	"Machine Learning in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0"	350	70.00	5.03
Cavalcante et al. [44]	"A supervised machine learning approach to data-driven simulation of resilient supplier selection in digital manufacturing"	325	54.17	3.56
Meng et al. [89]	"Machine Learning in Additive Manufacturing: A Review"	294	58.80	4.22
Chatterjee et al. [80]	"Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model"	250	62.50	4.99
Liu et al. [104]	"Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors"	231	46.20	3.32
Mhlanga [112]	"Industry 4.0 in Finance: The Impact of Artificial Intelligence (AI) on Digital Financial Inclusion"	212	42.40	3.05
Zhan and Li [113]	"Machine learning based fatigue life prediction with effects of additive manufacturing process parameters for printed SS 316L"	172	43.00	3.43
Javaid et al. [7]	"Artificial Intelligence Applications for Industry 4.0: A Literature-Based Study"	170	56.67	7.45
Qin et al. [6]	"Research and application of machine learning for additive manufacturing"	160	53.33	7.01
Johnson et al. [114]	"Invited review: Machine learning for materials developments in metals additive manufacturing"	154	30.80	2.21
Huang et al. [92]	"A Survey on AI-Driven Digital Twins in Industry 4.0: Smart Manufacturing and Advanced Robotics"	131	32.75	2.61

Table 3. *Cont.*

Author	Paper	Total Citations	TC per Year	Normalized TC
Sahu et al. [115]	"Artificial intelligence (AI) in augmented reality (AR)-assisted manufacturing applications: A review"	130	32.50	2.59
Ahmad et al. [116]	"Energetics Systems and artificial intelligence: Applications of industry 4.0"	127	42.33	5.56
Wan et al. [96]	"Artificial-Intelligence-Driven Customized Manufacturing Factory: Key Technologies, Applications, and Challenges"	127	31.75	2.53
Elsisi et al. [78]	"Deep Learning-Based Industry 4.0 and Internet of Things towards Effective Energy Management for Smart Buildings"	126	31.50	2.51
Sing et al. [117]	"Perspectives of using machine learning in laser powder bed fusion for metal additive manufacturing"	125	31.25	2.49

One of the main challenges identified in these studies is the complexity of integrating disruptive technologies such as machine learning and big data into traditional industrial processes. For example, the paper by Wang et al. [110], with 450 citations and an average of 90 citations per year, highlights the difficulties involved in adapting these technologies to conventional manufacturing environments, which not only require advanced infrastructure but also adequate technical training for operators and managers. Similarly, the study by Çinar et al. [11], with 350 citations and an average of 70 citations per year, emphasizes the challenge of implementing machine learning in predictive maintenance within smart manufacturing. These publications reflect how the integration of AI into industrial processes faces significant barriers in terms of technological complexity and organizational adaptation.

Sustainability and resilience are other significant challenges addressed in these documents. Cavalcante et al. [44], with 325 citations and an average of 54.17 citations per year, and Liu et al. [104], with 231 citations and an average of 46.20 citations per year, focus on how to apply AI to improve these aspects in manufacturing. However, both studies underline the difficulties in balancing technological optimization with minimizing environmental impact, all while maintaining competitiveness and operational efficiency. These works indicate that, although AI has the potential to make manufacturing processes more sustainable, implementing these changes in practice is a considerable challenge.

Another major challenge is the adoption of AI technologies in an institutional environment that is often resistant to change. The work of Bag et al. [82], which has received 426 citations with an impressive average of 106.50 citations per year, highlights how institutional barriers and the lack of adequate resources complicate the implementation of big data and AI in sustainable manufacturing. Regulatory, economic, and cultural pressures emerge as obstacles that hinder the rapid adoption of these technologies, reflecting a mismatch between technological capabilities and current regulations.

Additionally, the lack of interoperability between different systems and technological platforms presents a critical challenge. Javaid et al. [7], with 170 citations and an average of 56.67 citations per year, suggest the urgent need to develop common standards to facilitate a smooth and efficient integration of emerging technologies into complex manufacturing processes. Although data security and privacy are not always directly addressed, these aspects underlie as critical concerns in the context of using big data and AI, as implied in works like that of Dubey et al. [111], which has been cited 409 times with an average of 81.80 citations per year.

On the other hand, the most cited documents also highlight several significant opportunities. One of the most notable is the optimization of predictive maintenance through AI, as illustrated by the work of Çinar et al. [11]. AI's ability to anticipate failures and optimize equipment use, reflected in its 350 citations, not only improves operational efficiency but also reduces costs and minimizes downtime, offering a clear return on investment in the implementation of these technologies. Furthermore, AI presents key opportunities to advance sustainability within manufacturing. The study by Bag et al. [82], with its high citation rate, along with that of Liu et al. [104], highlights how AI can analyze large volumes of data and optimize processes in real-time. This approach translates into waste reduction and more efficient use of energy resources, aligning manufacturing operations with global sustainability goals.

The development of new materials and manufacturing processes also benefits from the use of AI, as evidenced by the study of Johnson et al. [114], which has accumulated 154 citations. This approach enables innovation in the creation of customized materials, optimizing properties and processes that were previously difficult to achieve with conventional technologies. Additionally, AI facilitates mass customization and flexibility in manufacturing processes, as noted by Wang et al. [110] and Meng et al. [89], which have received 294 citations with an average of 58.80 citations per year. This allows companies to quickly respond to market demands and adjust their production lines without the need for costly and complex changes.

Finally, improvement in decision-making is a highlighted opportunity, especially when AI is integrated with technology adoption models, as shown by Chatterjee et al. [80], which has been cited 250 times with an average of 62.50 citations per year. The ability of AI to provide real-time analysis and accurate predictions empowers managers to make more informed and agile decisions, significantly enhancing business competitiveness.

In conclusion, this analysis highlights both the challenges and opportunities that AI presents in manufacturing according to the most cited documents. While technological integration, sustainability, institutional adoption, interoperability, and data security emerge as critical challenges, the opportunities to optimize processes, improve sustainability, innovate in materials, customize production, and enhance decision-making offer a clear path for the advancement of Industry 4.0 (Figure 6). These documents, with their high citation rates, not only reflect the relevance of AI in modern manufacturing but also lay the groundwork for future research that addresses these challenges and capitalizes on emerging opportunities.

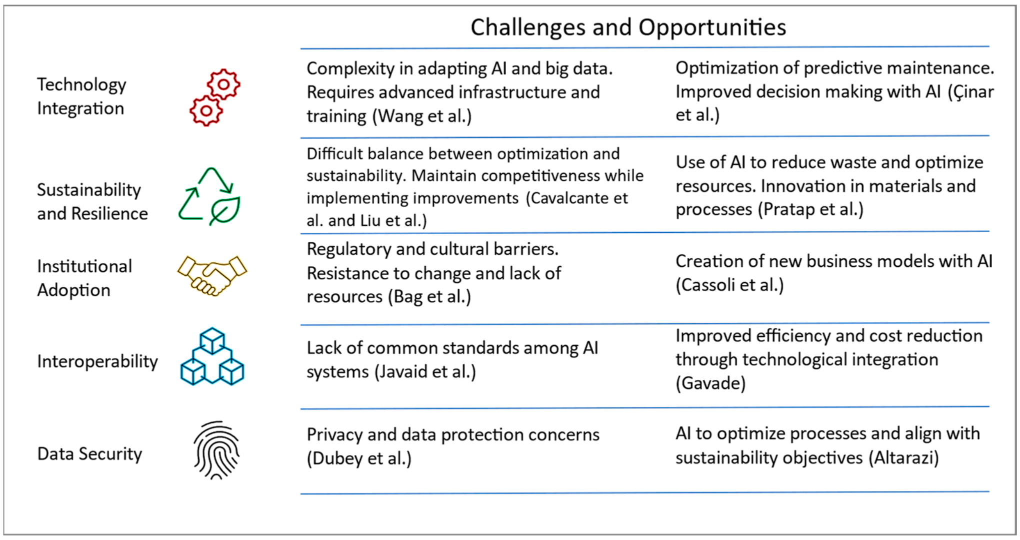


Figure 6. Summary of the challenges and opportunities. Based on studies by Wang et al. [110], Çinar et al. [11], Cavalcante et al. [44], Liu et al. [104], Pratap et al. [118], Bag et al. [82], Cassoli et al. [18], Javaid et al. [7], Gavade [2], Dubey et al. [111], and Altarazi [119].

4.5. Global Analysis of Leading Institutions in AI Research Applied to Manufacturing

The objective (O5) of this section is to analyze the global distribution of the main institutions researching AI applied to manufacturing, identifying the challenges and opportunities that emerge from their interaction in technological and industrial development. For this analysis, VOSviewer software, version 1.6.20, was used, applying the "citations" analysis and using "organizations" as the unit of analysis. A minimum threshold of one document per organization was established. A total of 1329 organizations were identified, and for each, the total strength of citation links with other organizations was calculated. Subsequently, the 20 organizations with the highest total link strength were selected, and the results are presented in Figure 7 generated by VOSviewer.

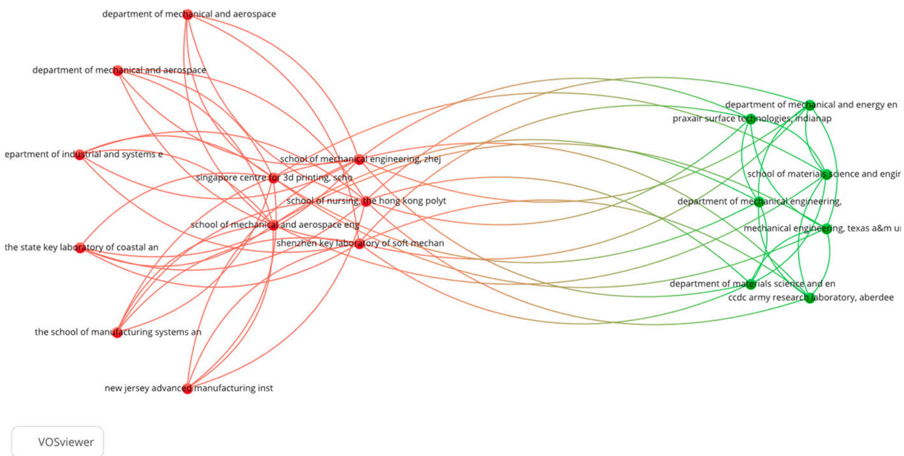


Figure 7. Institutions with the highest citations.

The analysis of the 20 most relevant institutions worldwide that are involved in research on AI in manufacturing, according to Table 4, reveals important patterns in terms of citations and collaboration link strength.

The analysis of the 20 most relevant institutions in AI research applied to manufacturing shows clear correlations with the trends observed in the literature. First, Nanyang Technological University of Singapore, through its School of Mechanical and Aerospace Engineering and the Singapore Centre for 3D Printing, leads with 450 citations each and a link strength of 9. This confirms Singapore's key role as a global innovation hub, particularly in 3D printing, reflecting a significant concentration of research and collaborations in AI. These findings align with what Diez-Olivan et al. [14] highlighted, emphasizing the use of emerging technologies as a fundamental part of Industry 4.0. Singapore's ability to lead collaboration networks, as evidenced by its high link strength, underscores the importance of central nodes in the global expansion of AI.

In the United States, the CCDC Army Research Laboratory, with 294 citations and a link strength of 6, demonstrates American leadership in research applied to manufacturing. Institutions such as Indiana University-Purdue University and Rutgers University show a multidisciplinary approach aligned with the need to monitor and prevent anomalies in industrial machinery, as emphasized by Carletti et al. [15]. The literature highlights the importance of interpretability in machine learning, something that U.S. institutions seem to be addressing through research focused on process optimization and predictive maintenance [18].

South Korea also plays a prominent role in AI research applied to manufacturing, with institutions such as Changwon National University and Gyeongsang National University that have a strong collaborative presence, reflecting Antosz et al.'s [16] analysis of the importance of intelligent systems for decision-making in manufacturing. Although South Korea still has room to grow in citations, its ability to establish global connections suggests a rapid evolution in this field.

Table 4. Most relevant institutions.

Institution	City/Country	Citations	Total Link Strength
School of Mechanical and Aerospace Engineering, Nanyang Technological University	Singapore	450	9
Singapore Centre for 3D Printing, School of Mechanical and Aerospace Engineering, Nanyang Technological University	Singapore	450	9
CCDC Army Research Laboratory	Aberdeen, MD, United States	294	6
Department of Materials Science and Engineering, Changwon National University	Changwon, South Korea	294	6
Department of Mechanical and Energy Engineering, Indiana University-Purdue University Indianapolis	Indianapolis, IN, United States	294	6
Praxair Surface Technologies	Indianapolis, IN, United States	294	6
Department of Industrial and Systems Engineering, Rutgers University-New Brunswick	Piscataway, NJ, United States	108	5
Department of Mechanical and Aerospace Engineering, Case Western Reserve University	Cleveland, OH, United States	108	5
Department of Mechanical and Aerospace Engineering, Rutgers University-New Brunswick	Piscataway, NJ, United States	108	5
New Jersey Advanced Manufacturing Institute, Rutgers University-New Brunswick	Piscataway, NJ, United States	108	5
The School of Manufacturing Systems and Networks, Arizona State University	Mesa, AZ, United States	108	5
The State Key Laboratory of Coastal and Offshore Engineering, Dalian University of Technology	Dalian, China	108	5
Department of Business and Economics, School of Business and Information Systems, York College, CUNY	Jamaica, NY, United States	11	0
Department of Mechanical Engineering, CVR College of Engineering	Hyderabad, Telangana, India	4	6
Mechanical Engineering, Texas A&M University College Station	College Station, TX, United States	4	6
School of Materials Science and Engineering, Gyeongsang National University	Jinju, South Korea	4	6
School of Mechanical Engineering, Zhejiang University	Hangzhou, China	3	10
School of Nursing, The Hong Kong Polytechnic University	Hong Kong	3	10
Shenzhen Key Laboratory of Soft Mechanics & Smart Manufacturing, Southern University of Science and Technology	Shenzhen, China	3	10
Department of Mechanical and Production Engineering, Guru Nanak Dev Engineering College	Ludhiana, Punjab, India	1	0

China, through Zhejiang University and the Southern University of Science and Technology, stands out for having a high linkage strength (10) despite having only 3 citations. This reflects what was observed by Dinmohammadi [22] and Soni et al. [23], who highlight that although the infrastructure and data quality in AI manufacturing can be limiting, Chinese universities are well positioned to influence future development through strategic international collaborations.

The case of non-academic institutions, such as Praxair Surface Technologies in the United States, demonstrates the impact of tech companies on applied research. With

294 citations, Praxair emphasizes the importance of collaboration between the private and academic sectors, an aspect that Williams et al. [17] also stress in their review. Such alliances are crucial for the adoption of AI in advanced manufacturing.

Several challenges arise from this analysis. The geographical concentration of research in countries like Singapore, the United States, China, and South Korea reflects a lack of participation from other regions, which may limit the diversity of approaches in the application of AI in manufacturing. Moreover, the reliance on collaboration networks between specific institutions can create bottlenecks in knowledge exchange, as indicated by the difficulties in scaling AI solutions beyond the proof-of-concept phase [22]. This concentration, both geographical and institutional, presents a challenge regarding equity in knowledge production.

On the other hand, the resulting opportunities are equally significant. The expansion of collaboration networks, particularly through institutions with high connectivity, such as the universities of Hong Kong and Shenzhen, can foster more equitable growth in global scientific production. This type of collaboration is also in line with the recommendations of Liu et al. [21], who suggest that integrating accumulated knowledge with human observations in AI manufacturing can accelerate its adoption in industrial environments.

In conclusion, although AI manufacturing research is led by a few institutions in key countries, strengthening global collaboration networks and including more international actors offer significant opportunities for advancing the sector. Consolidating these alliances will be key for more regions to benefit from advanced technologies in manufacturing, as suggested by TurandasjiPatil et al. [25] and Gabsi [26]. Below, Figure 8 presents a summary of the challenges and opportunities derived from the analysis.

Figure 8. Challenges and opportunities arising. Based on studies by Diez-Olivan et al. [14], Carletti et al. [15], Liu et al. [104], Antosz et al. [16], Dinmohammadi [22], Soni et al. [23], TurandasjiPatil et al. [25], and Gabsi [26].

4.6. Key Methods and Approaches in AI Research in Manufacturing

The objective (O6) of this section is to analyze the most prevalent methods and study approaches in AI research in manufacturing, as well as to assess the challenges and opportunities that arise from their application. For this analysis, VOSviewer software, version 1.6.20, was used with the 'co-occurrence' analysis type, the unit of analysis 'author keywords', and the counting method 'Full counting'. The minimum occurrence threshold for a keyword (1) was set. Out of a total of 1322 keywords, 1332 met the threshold. The 40 keywords most related to methods and study approaches were selected, as shown in Figure 9 generated by VOSviewer.

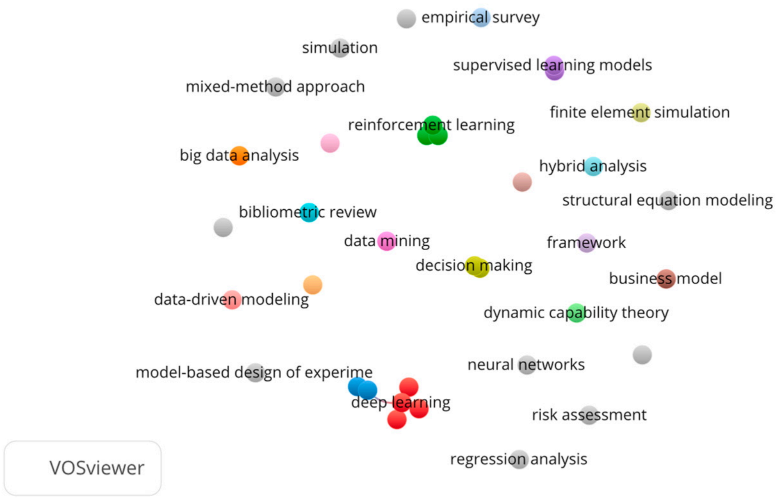


Figure 9. Methods and study approaches.

Below is a description of the 40 methods and study approaches identified in the co-occurrence analysis:

(1) Augmented Statistical Fatigue Life Model: A model that combines statistical methods with experimental data to predict the fatigue life of materials, improving the accuracy of estimations [120].
(2) Bibliometric Review: A method that uses quantitative analysis of the scientific literature to identify patterns, trends, and relationships in a field of study based on citations and references [63,121].
(3) Big Data Analysis: An approach that involves collecting, processing, and analyzing large volumes of data to extract meaningful patterns and support data-driven decision-making [13].
(4) Building Information Modeling (BIM): A process that involves the generation and management of digital representations of the physical and functional characteristics of a built space, used to enhance the planning and execution of construction projects [122].
(5) Business Model: A structure that defines how an organization creates, delivers, and captures value, focusing on business strategy and key operations [123].
(6) Conceptual Framework: A theoretical structure that guides research, defining key concepts, variables, and their relationships, providing a framework for analysis [124,125].
(7) Data-Driven Models: Models that use empirical data to build mathematical or computational representations of phenomena, enabling informed predictions and decisions [126].
(8) Data Mining Techniques: A set of methods used to discover patterns and relationships in large datasets, applied in areas such as marketing, biomedicine, and computer science [127].
(9) Decision-Making Models: Systematic approaches to evaluate and select options among alternatives, optimizing outcomes based on predefined criteria [44].
(10) Deep Learning Models: A subcategory of machine learning models that use deep neural networks to analyze large volumes of unstructured data, such as images or text [128].
(11) Dynamic Model: A mathematical model that describes how a system evolves over time, capturing the dynamics of the processes involved [96].
(12) Empirical Analysis: A research method that uses observable and measurable data to evaluate theories, testing hypotheses through experimentation and observation [129].

(13) Finite Element Analysis (FEA): A computational technique that divides an object into small parts (finite elements) to analyze its behavior under various conditions, commonly used in engineering [130].
(14) Fuzzy Logic Models: Models that handle uncertainty and imprecision by allowing degrees of truth instead of binary values, applied in control systems and decision-making [116].
(15) Hybrid Modeling: Combines different models or methods to leverage the strengths of each, enhancing predictive accuracy and capacity in complex situations [131].
(16) Literature Review: A critical and systematic review of the existing literature on a topic, identifying knowledge gaps and establishing context for future research [132,133].
(17) Machine Learning Models: Algorithms that enable computers to learn from data and improve their performance on specific tasks without being explicitly programmed for them [134,135].
(18) Mathematical Modeling: The creation of mathematical models to represent, analyze, and predict the behavior of real-world systems, applicable across various disciplines [75].
(19) Meta-Analysis: A statistical technique that combines the results of multiple studies to derive a more robust and generalizable conclusion about a research topic [61].
(20) Mixed Methods Approach: A research approach that integrates qualitative and quantitative methods to provide a more comprehensive understanding of a phenomenon [136].
(21) Model-Based Systems: An approach that uses mathematical and computational models to design, analyze, and manage complex systems, optimizing their performance [137].
(22) Multi-Criteria Decision Analysis (MCDA): A method that evaluates options based on multiple criteria, facilitating decision-making in complex contexts where various factors must be balanced [138].
(23) Multivariate Analysis: A set of statistical techniques that analyze more than two variables simultaneously, allowing for the understanding of complex relationships between them [130].
(24) Neural Networks Model: A computational model inspired by the structure of the human brain, primarily used in machine learning for tasks like pattern recognition and classification [94].
(25) Optimization Models: Mathematical models that seek the best solution within a set of options, maximizing or minimizing an objective function under certain constraints [139].
(26) Predictive Modeling: The use of statistical or machine learning models to make predictions about future events based on historical data [140].
(27) Quantitative Analysis: Analysis based on numerical data, using statistical and mathematical techniques to measure variables and analyze relationships between them [2,141].
(28) Regression Analysis: A statistical technique that examines the relationship between a dependent variable and one or more independent variables, used for making predictions and understanding causal relationships [142,143].
(29) Reinforcement Learning Models: A subfield of machine learning where an agent learns to make optimized decisions through trial and error, rewarded for its actions [108].
(30) Risk Analysis: The process of identifying, evaluating, and prioritizing risks, using models to forecast and mitigate negative impacts on projects or systems [144].
(31) Scenario Analysis: A technique used to anticipate possible future scenarios and their implications, facilitating strategic planning and decision-making in uncertain situations [145].
(32) Simulation Modeling: The use of computational models to imitate the behavior of real systems, allowing for experimentation and analysis of scenarios without real risks [146].

(33) Statistical Analysis: A set of techniques for collecting, reviewing, analyzing, and interpreting data, helping to uncover significant patterns and trends in research [147].
(34) Structural Equation Modeling (SEM): A statistical technique that allows for the analysis of complex relationships between latent and observable variables, combining factor analysis and regression models [59,148].
(35) Supervised Learning Models: A type of machine learning model where the algorithm learns from labeled data, improving its ability to predict or classify new data [12].
(36) Systematic Review: An exhaustive and structured review of the existing literature on a specific research question, applying a rigorous approach to minimize bias [149,150].
(37) Topic Modeling: A technique used to identify underlying themes in a set of documents, typically using probabilistic models that group related words [151].
(38) Training Data Model Development: The process of creating and refining machine learning models using training datasets, aiming to improve their accuracy and generalization [152].
(39) Unsupervised Learning Models: Machine learning models that find patterns in unlabeled data and are used for tasks such as clustering and dimensionality reduction [12].
(40) Wavelet Analysis: An analysis technique that decomposes complex signals into frequency components, allowing for the study of phenomena in both the time and frequency domains simultaneously [153].

These descriptions summarize each method and study approach, highlighting their application and relevance in research and professional practice. From this analysis, both significant challenges and opportunities can be inferred. On the one hand, innovation in models and techniques represents a major opportunity for the manufacturing industry. The use of advanced methods such as machine learning, predictive modeling, and big data analysis allows for improved accuracy, efficiency, and predictive capability in manufacturing processes.

These approaches enable the development of solutions better tailored to the specific needs of the industry, which can lead to productivity improvements and more informed, data-driven decision-making. This same aspect is addressed by Williams et al. [17], who emphasize how cognitive algorithms improve efficiency in business processes, although the authors recognize that integrating these technologies also brings significant challenges, such as creating robust data structures.

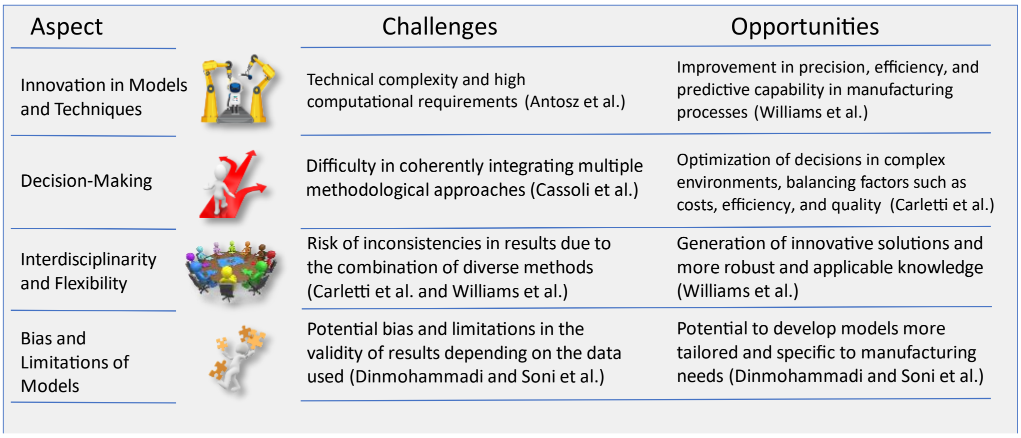
Another highlighted opportunity is improved decision-making, facilitated by approaches like multi-criteria decision analysis (MCDA) and decision models. These methods offer tools for optimizing decisions in complex environments where it is necessary to balance multiple factors such as costs, efficiency, quality, and sustainability. Additionally, the interdisciplinarity and flexibility provided by integrating hybrid approaches and data-driven models open new possibilities for innovation.

Combining the best of different disciplines and methods allows for addressing complex problems with greater robustness, generating more applicable and relevant knowledge for professional practice. This decision-making improvement approach is similar to that discussed by Carletti et al. [15], who highlight the need to enhance the interpretability of machine learning models to facilitate their adoption in manufacturing, especially in quality monitoring.

However, significant challenges are also faced. The complexity and high technical requirements of many of these methods, such as dynamic modeling and finite element analysis, represent a barrier to their widespread adoption, particularly in companies that lack the necessary technical capabilities or computational resources. This challenge is also highlighted by Antosz et al. [16], who mention that inadequate means to assess the implementation of maintenance strategies may limit the potential of AI to optimize operational efficiency.

Furthermore, the coherent integration and applicability of a variety of methodological approaches can be problematic. Companies may face difficulties trying to implement multiple methods in a coordinated manner, which could lead to inconsistencies in results and inefficient use of available resources. This challenge aligns with the observations of Cassoli et al. [18], who note that while AI has the potential to transform predictive maintenance, the commercial viability of AI-based solutions remains a hurdle.

Finally, another key challenge is the potential bias and inherent limitations of some models, such as regression and statistical analysis. Although these methods are powerful, they are subject to the limitations of the data used, which can affect the validity and applicability of the conclusions derived. In this regard, authors such as Dinmohammadi [22] and Soni et al. [23] identify data quality as one of the main obstacles to AI adoption in manufacturing. In summary, the analysis suggests that while there are enormous opportunities to advance manufacturing through AI and advanced methods, there are also significant challenges that need to be addressed to maximize the positive impact of these approaches on the industry. Figure 10 shows the summary of the challenges and opportunities from this analysis.



Aspect	Challenges	Opportunities
Innovation in Models and Techniques	Technical complexity and high computational requirements (Antosz et al.)	Improvement in precision, efficiency, and predictive capability in manufacturing processes (Williams et al.)
Decision-Making	Difficulty in coherently integrating multiple methodological approaches (Cassoli et al.)	Optimization of decisions in complex environments, balancing factors such as costs, efficiency, and quality (Carletti et al.)
Interdisciplinarity and Flexibility	Risk of inconsistencies in results due to the combination of diverse methods (Carletti et al. and Williams et al.)	Generation of innovative solutions and more robust and applicable knowledge (Williams et al.)
Bias and Limitations of Models	Potential bias and limitations in the validity of results depending on the data used (Dinmohammadi and Soni et al.)	Potential to develop models more tailored and specific to manufacturing needs (Dinmohammadi and Soni et al.)

Figure 10. Summary of the challenges and opportunities. Based on studies by Antosz et al. [16], Williams et al. [17], Cassoli et al. [18], Carletti et al. [15], Dinmohammadi [22], and Soni et al. [23].

4.7. Analysis of Global Scientific Production in AI and Manufacturing

The objective (O7) of this section is to evaluate the global distribution of scientific production on AI in manufacturing, assessing the quality, international collaboration dynamics, and participation of different regions to identify their challenges and opportunities. For this analysis, RStudio version 2024.04.2+764 was used, selecting "Countries" as the level of analysis and employing the metric of "Most Cited Countries". The "World Map of Country Collaboration" metric was also selected as the "Social Structure".

4.7.1. Scientific Production by Country

The analysis of Table 5, which includes the 20 most cited countries, reveals that scientific production in the field of AI applied to manufacturing is led by countries with advanced economies and well-established research and development sectors. The United States tops the list with 113 documents and a total of 1553 citations, reflecting its dominant position in generating knowledge in this field. However, countries like France, with only nine documents but an average of 120 citations per article, stand out for the high quality and impact of their research. Singapore and Spain also stand out for their high average citations per article (105 and 83.2, respectively), indicating that although they produce fewer documents in terms of quantity, their research is highly influential.

Table 5. Most cited countries.

Country	TD	Total Citations	Average Article Citations
United States	113	1553	29.9
United Kingdom	42	1245	69.2
China	73	1070	18.1
Germany	52	760	29.2
Singapore	11	735	105
India	111	703	12.6
Spain	16	499	83.2
France	9	480	120
South Korea	22	453	28.3
Italy	22	329	21.9
Malaysia	14	105	17.5
Australia	22	102	11.3
Canada	17	89	14.8
Greece	12	76	8.4
Poland	11	71	11.8
Turkey	11	38	6.3
Saudi Arabia	11	33	16.5
Taiwan	12	13	6.5
Pakistan	9	8	8
Mexico	9	6	2

In contrast, countries such as Pakistan and Mexico show limited scientific production in both quantity and impact, with a significantly low average number of citations per article (eight and two, respectively). This suggests that there is a gap in these countries' ability to contribute to cutting-edge research in AI and manufacturing, possibly due to limitations in resources, infrastructure, or access to international collaboration networks.

4.7.2. Continental Distribution of Scientific Production

The breakdown by continents shows that Europe and Asia are the main drivers of AI research for manufacturing, with 65.22% and 62.22% of countries from each continent contributing to scientific production (Figure 11). This strong leadership reflects the consolidation of these regions as epicenters of technological innovation, especially in countries such as Germany, China, and the United Kingdom. In contrast, America and Africa present significantly lower percentages (22.86% and 20.37%, respectively), indicating a lower concentration of active countries in these continents in terms of AI research for manufacturing.

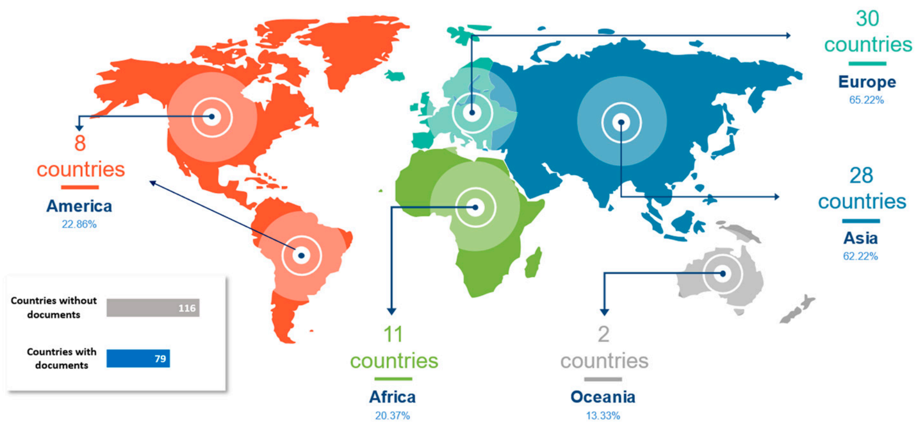


Figure 11. Number of countries with documents by continent.

Oceania, with only 13.33% of its countries participating in this research area, clearly demonstrates a need to strengthen capabilities and investment in research and development to avoid falling behind in such a dynamic and crucial field for the future of manufacturing.

4.7.3. Global Participation in Research

Globally, out of 195 countries [154], only 79 have contributed publications on AI in manufacturing, representing 40.51% (Figure 11). This data highlights that the majority of countries (59.49%) are not involved in research in this critical area, which is concerning given the growing importance of AI in global industrial competitiveness. This lack of participation could be related to economic limitations, a lack of research infrastructure, or barriers to accessing knowledge and technology.

4.7.4. International Collaboration

Figure 12, which shows the global collaboration map, reveals that leading research powers not only excel in production but also act as central nodes in international collaboration networks. For example, China has strong collaborations with the United Kingdom (10 times) [6,155–157] and other significant connections with Singapore [158], Korea [5], Pakistan [155], and Saudi Arabia [159]. Similarly, India maintains crucial collaborations with the United Kingdom [160] and the United States [89], while the United Kingdom itself is a central partner for multiple countries, including the United States [111] and Australia [161].

Country	Main Collaboration	Collaboration Frequency	Other Significant Collaborations	Frequencies
China	United Kingdom	10	Singapore (4), Korea (2), Pakistan (2), Saudi Arabia (2)	4, 2, 2, 2
India	United Kingdom	10	USA (7), Saudi Arabia (3), Australia (3), France (2)	7, 3, 3, 2
USA	China	10	United Kingdom (9), Mexico (5), Germany (3), Korea (3)	9, 5, 3, 3
United Kingdom	Australia	4	USA (9), Mexico (5), Germany (3), Korea (3)	9, 5, 3, 3
Australia	USA	4	United Kingdom (2), Mexico (5), Germany (3), Korea (3)	9, 5, 3, 3

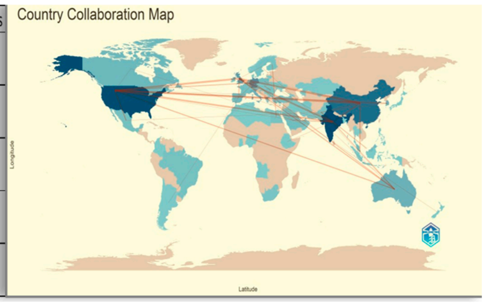


Figure 12. World collaboration map.

These collaboration networks are vital for advancing research, as they facilitate the exchange of knowledge, resources, and technologies between countries, thereby fostering innovation and overcoming technical and scientific challenges. However, reliance on a small number of countries for collaboration can limit the diversity of approaches and perspectives, which is essential for addressing global challenges comprehensively.

4.7.5. Derivation of Challenges and Opportunities

The challenges and opportunities in global scientific production of AI in manufacturing reveal several key considerations. A significant challenge is the inequality in scientific production, reflected in the disparity between countries in terms of the quantity and quality of publications. Countries with lower production and impact are at risk of falling behind in adopting AI in manufacturing, which could affect their industrial competitiveness in the long term. This challenge aligns with what authors like Diez-Olivan et al. [14] have pointed out, emphasizing that despite the growing adoption of smart technologies, many countries face technical and infrastructure difficulties in implementing advanced data monitoring and analysis strategies. This lack of capability can disadvantage less developed economies, slowing their integration into Industry 4.0.

Additionally, the regional concentration of research, primarily in Europe and Asia, highlights a lack of global integration, with less involvement from the Americas, Africa, and Oceania. This situation could limit the applicability of the developed solutions, as they may not be adapted to the diverse contexts of other regions. Cassoli et al. [18] support this idea by noting that many advancements in AI, such as predictive maintenance, are still not commercially viable in many regions due to inadequate infrastructure and low adoption of advanced technological solutions.

Another significant challenge is the limited global participation. With only 40.51% of countries involved in AI research in manufacturing, there is a clear need to encourage more nations, especially developing ones, to ensure that research develops inclusively and its benefits reach a wider variety of economies. This issue is also discussed by Dinmohammadi [22], who points out that the lack of specialized talent and inadequate policies are significant barriers to the global expansion of AI in manufacturing. Moreover, reliance on bilateral collaborations in a few countries could reduce diversity in research and perpetuate inequalities in access to knowledge and resources. This poses a challenge for generating more diverse and holistic solutions in the application of AI in manufacturing.

On the other hand, there are also significant opportunities. Enhancing the quality of research is a key area, where countries with high citation averages per document, such as France and Singapore, can lead with innovative research and serve as models for other countries. Williams et al. [17] also highlight that leadership in AI research can be crucial for improving production efficiency by leveraging cognitive algorithms to optimize complex processes.

Expanding collaboration networks presents another major opportunity, as including underrepresented countries would enrich research with new perspectives and solutions adapted to different contexts. The review by Antosz et al. [16] suggests that intelligent systems, such as those implemented in lean maintenance strategies, can be a gateway for more countries to adopt AI, thus creating global collaboration opportunities.

Furthermore, there is the possibility of incorporating new actors into the global landscape by encouraging their participation through international cooperation programs, research funding, and capacity development, which would significantly expand the global reach and relevance of AI in manufacturing. Soni et al. [23] echo this idea, emphasizing that AI has the potential to significantly improve transparency and efficiency in manufacturing, but advances in sensor technology and other tools must be available at low cost to facilitate adoption in developing countries.

Finally, Europe and Asia, as leading research regions, have a key opportunity to influence the future direction of AI in manufacturing by establishing standards and practices that could be adopted globally. This is consistent with Gabsi's observations [26], who explores how digitalization and connectivity in smart factories are enabling advanced economies to define trends and regulatory frameworks for Industry 4.0. In conclusion, while scientific production in AI and manufacturing is advancing considerably, it is crucial to address existing inequalities to ensure that the benefits of AI are distributed equitably and that the developed solutions are relevant to a broader range of industrial contexts worldwide. Figure 13 shows the summary of the challenges and opportunities of this analysis.

Figure 13. Summary of the challenges and opportunities. Based on studies by Diez-Olivan et al. [14], Cassoli et al. [18], Dinmohammadi [22], Williams et al. [17], Antosz et al. [16], Soni et al. [23], and Gabsi [26].

4.8. Thematic Analysis of AI in Manufacturing

The objective (O8) of this section is to analyze the themes in the conceptual structure of AI applied to manufacturing. To conduct this analysis, RStudio version 2024.04.2+764 was used. The bibliometric technique of 'co-word' was employed with the purpose of analyzing authors' keywords as the unit of analysis, applying the statistical technique of 'thematic mapping'. The parameters used in this process were: number of words (250), minimum cluster frequency 'per thousand documents' (5), and the 'walktrap' clustering algorithm.

The analysis of the "Thematic Map" is presented below, organized according to the four quadrants: motor themes, basic themes, emerging or declining themes, and niche themes (see Figure 14 and Table 6).

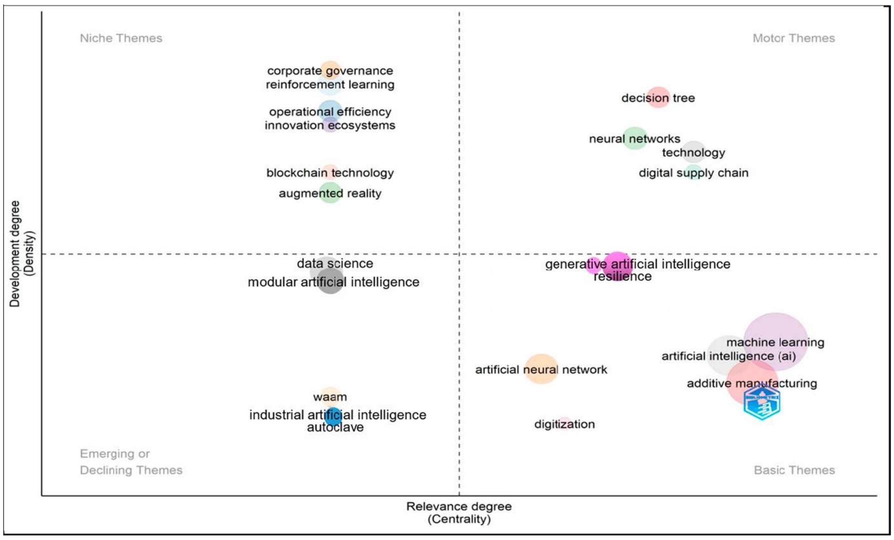


Figure 14. Thematic map generated by RStudio.

Firstly, the motor themes in the analysis of the conceptual structure of AI in manufacturing, such as 'technology', 'digital supply chain', 'neural networks', and 'decision tree', are those that present high centrality and density, meaning they are well connected with other themes and have achieved significant conceptual development. The 'technology' cluster, for example, is key in transforming manufacturing through AI, encompassing fundamental innovations like process automation and improved operational efficiency. The literature review supports this position, where authors such as Williams et al. [17] and Soni et al. [23] highlight how the implementation of AI in manufacturing is intrinsically linked to the optimization of business and operational processes, driven by key technologies such as sensors and cyber–physical systems.

On the other hand, basic themes such as 'machine learning', 'additive manufacturing', 'artificial intelligence (AI)', and 'digitization' have high centrality but are still in the development phase. 'Machine learning' is widely implemented in manufacturing, but its low density indicates that there are still areas to explore, such as the customization of its applications. In the literature, Carletti et al. [15] and Liu et al. [21] emphasize this aspect, particularly in the use of 'machine learning' in advanced manufacturing, where challenges such as result interpretability and the integration of human knowledge in decision-making persist.

Regarding 'additive manufacturing', its crucial role in product customization is highlighted, but as Cassoli et al. [18] point out, there are obstacles in the commercial development of these technologies. Additive manufacturing, although commonly associated with 3D printing, has a significant impact on broader industrial manufacturing processes. When integrated with AI, it enables the optimization of production parameters, such as printing speed and material properties, improving product customization and efficiency in large-scale production. This connects additive manufacturing directly with traditional manufacturing processes, transforming the way products are made within Industry 4.0.

Table 6. Centrality and density of clusters.

Cluster	Callon Centrality	Callon Density	Rank Centrality	Rank Density	Cluster Frequency
machine learning	4.69	48.742	28	8	937
additive manufacturing	3.89	45.312	27	5	208
artificial intelligence (ai)	1.817	47.988	26	7	95
technology	0.75	66.667	24.5	22	9
digital supply chain	0.75	62.5	24.5	20.5	4
decision tree	0.5	87.5	23	26	8
neural networks	0.458	71.875	22	23	10
resilience	0.333	50	21	13.5	5
generative artificial intelligence	0.25	50	20	13.5	2
digitization	0.222	33.333	19	2	3
artificial neural network	0.214	47.718	18	6	25
applications	0	50	9	13.5	5
3D printing	0	50	9	13.5	2
surrogate model	0	50	9	13.5	5
blockchain technology	0	62.5	9	20.5	4
structural equation modeling	0	33.333	9	2	3
manufacturing sector	0	50	9	13.5	5
critical success factors	0	50	9	13.5	2
reinforcement learning	0	90	9	27	11
operational efficiency	0	77.083	9	25	9
data science	0	50	9	13.5	5
augmented reality	0	53.704	9	19	8
waam	0	43.75	9	4	6
corporate governance	0	100	9	28	6
innovation ecosystems	0	75	9	24	4
industrial artificial intelligence	0	33.333	9	2	3
autoclave	0	50	9	13.5	2
modular artificial intelligence	0	50	9	13.5	2

Regarding emerging or declining themes such as ‘data science’, ‘modular artificial intelligence’, and ‘WAAM’ (wire arc additive manufacturing), they show low centrality and density, indicating that they are either in their early stages or declining. ‘Data science’, for example, has great potential to optimize processes in manufacturing but is not yet fully integrated into the industrial ecosystem. This analysis is reflected in the studies by Diez-Olivan et al. [14] and Dinmohammadi [22], who point out that the challenge is not only in applying AI to processes but also in overcoming barriers such as a lack of infrastructure and the quality of available data.

Finally, niche themes such as ‘blockchain technology’, ‘operational efficiency’, and ‘reinforcement learning’ have low centrality but high density, indicating that they are well developed in their specialized areas, although with limited connection to other themes. ‘Blockchain technology’ is relevant for niches like traceability and supply chain security but is not yet fully integrated with AI in manufacturing ecosystems. The literature reflects this with examples such as those highlighted by Gabsi [26], who emphasizes that digitalization and connectivity are driving the creation of smart factories, but these advances still face technical and economic challenges.

Challenges and Opportunities Derived

Regarding the challenges, the integration of emerging technologies remains a significant hurdle. Themes such as data science, modular AI, and reinforcement learning have high potential but face obstacles related to their widespread adoption, as mentioned by Dinmohammadi [22] and Soni et al. [23] in their studies on infrastructure shortages and the need to overcome technological barriers. Similarly, the consolidation of fundamental areas such as digitization and artificial neural networks is crucial to maximize the impact of AI in manufacturing, as noted by Carletti et al. [15] and Cassoli et al. [18], who agree that the commercial development of these technologies is still in early stages.

On the other hand, there are clear opportunities in strengthening key technologies such as 'machine learning' and 'additive manufacturing'. According to Williams et al. [17] and Liu et al. [21], these technologies can optimize customization and automation in production if they are strengthened and integrated more effectively into processes. Additionally, the development of digital supply chains and neural networks is also well positioned to lead digital transformation in manufacturing, providing improvements in resilience and operational efficiency, as suggested by Soni et al. [23] and Gabsi [26].

Finally, innovation in operational efficiency and reinforcement learning offers great potential to enhance real-time processes, which could translate into cost reductions and increased industrial competitiveness, aligning with the perspectives of Williams et al. [17] and Cassoli et al. [18]. Figure 15 below presents a summary of these challenges and opportunities.

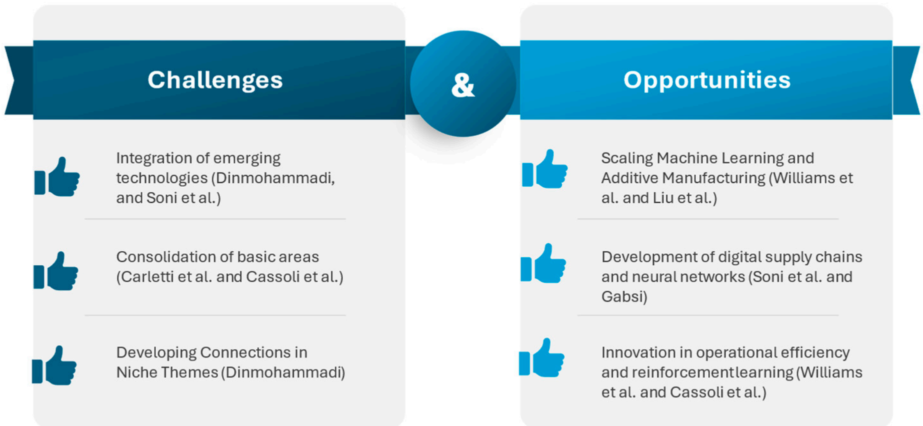


Figure 15. Summary of the challenges and opportunities. Based on studies by Dinmohammadi [22], Soni et al. [23], Williams et al. [17], Liu et al. [104], Carletti et al. [15], Cassoli et al. [18], Gabsi [26], and Dinmohammadi [22].

4.9. Limitations

One of the main limitations of this study is the reliance on the Scopus database as the sole source of information. While Scopus is widely recognized for its scope and relevance in bibliometric studies, the exclusion of other databases, such as Web of Science or IEEE Xplore, may reduce the comprehensiveness of the analysis. This means that some important studies might not have been included, which could skew the results towards authors or institutions that predominantly publish in journals indexed in Scopus, affecting the overall representativeness of the study.

Additionally, the decision not to consider articles published before 2019, due to their scarcity, and to include articles published up until August 2024 may have affected the comparability of the results. While this approach allowed for the capture of more recent research, it does not follow a uniform time structure that ensures greater methodological consistency. In future research, it would be advisable to establish complete or standardized time periods to ensure a more homogeneous and comparable dataset. This consideration will be important to minimize potential biases in identifying trends over time.

From a methodological standpoint, the study utilized tools such as RStudio version 2024.04.2+764 and VOSviewer version 1.6.20 for citation analysis and collaboration networks. Although these tools are effective for identifying quantitative patterns, they have limitations when it comes to analyzing the qualitative depth of relationships between documents and authors. Since citations do not always reflect the intrinsic quality or real impact of research, there is a risk of partially interpreting the influence of certain authors or articles. Furthermore, the selection of keywords used to filter the documents may have excluded important research due to variability in terminology employed by different authors or fields. This limitation in methodology might have restricted the breadth and scope of the thematic analysis.

Another aspect to consider is that the study focused exclusively on the implementation of AI in manufacturing within the context of Industry 4.0. This implies that the results obtained may not be fully applicable to other industries or sectors that are also adopting AI but under different technological or economic conditions. Additionally, since the bibliometric analysis does not evaluate the empirical results of AI implementation, the findings should be interpreted with caution when applying them to practical contexts or policy formulation.

Finally, it is important to note that the most recent articles in the database have a limited number of citations due to the short time since their publication. This particularly affects documents from 2024, which have not had the same opportunity to be cited as those published in 2019 or 2020. This citation dynamic could skew the results towards older publications, offering a partial view of the impact of more recent research.

4.10. Future Research Directions

This bibliometric study has revealed various opportunities and challenges that pave the way for future research in this field. First, several unresolved questions emerged during the analysis. One of the main issues concerns how small- and medium-sized enterprises (SMEs), which lack infrastructure and specialized talent, can effectively adopt and scale these technologies [17,22]. Additionally, the interpretability of machine learning models remains an obstacle, as trust in the results generated by AI is limited, presenting a crucial area for future theoretical and empirical research focused on its implementation [15].

On the other hand, future research could expand the time range of the study by incorporating earlier works to provide a more comprehensive historical view of AI adoption in manufacturing [14]. The sample could also be broadened using other databases such as Web of Science or IEEE Xplore, which would allow for more robust and exhaustive results. Moreover, it would be interesting to extend this analysis to other industries beyond manufacturing, assessing the implementation of AI in sectors such as healthcare, agriculture, or energy, to detect similarities and differences in the challenges faced by these industries [25,26].

From a methodological perspective, this study primarily employed bibliometric tools like RStudio version 2024.04.2+764 and VOSviewer version 1.6.20, which are effective in identifying citation and collaboration patterns. However, future studies could complement this approach with qualitative methods that allow for a deeper understanding of organizational and technological barriers. Expert interviews, case studies, and discourse analysis could provide a more detailed view of the internal challenges companies face when attempting to adopt AI in their operations [16,23].

Another relevant aspect would be to conduct longitudinal studies that track the evolution of AI implementation in manufacturing over time. This would allow observation of how policies, technological advancements, and organizational capabilities influence the adoption of these technologies in the manufacturing sector [18]. Additionally, future studies could include new variables, such as the impact of public policies or the return on investment of AI-based solutions in different types of companies, exploring their long-term economic viability [24].

On the other hand, future research could also focus on the practical application of AI technologies in real industrial environments. Experimental studies evaluating the impact of AI on operational efficiency, predictive maintenance, or cost reduction in factories could provide valuable insights for the sector. Such applied research would offer practical validation of the theoretical results presented in this study, facilitating the development of effective frameworks for AI adoption in manufacturing [21].

Finally, it would be of great interest to conduct comparative studies between different geographic and cultural regions. The implementation of AI in manufacturing varies significantly between developed and developing economies due to differences in infrastructure, regulatory policies, and technological capabilities. Studying the challenges and opportunities in different geographic contexts would allow for a deeper understanding of how these factors influence AI adoption and what strategies might be more effective in each region [14,25].

5. Conclusions

This study has revealed significant growth in scientific production related to the implementation of AI in manufacturing, particularly in areas such as machine learning, additive manufacturing, and predictive maintenance. The results indicate a substantial increase in the number of publications since 2019, with annual production peaking in 2023 at 148 documents. However, despite this growth, a decreasing trend in average citations per article has been observed, dropping from 15.22 in 2019 to 1.77 by August 2024. This phenomenon is common in rapidly expanding fields, where increased production can dilute the impact of individual works.

In terms of the most influential sources, journals such as *Applied Sciences* (Switzerland) and *Additive Manufacturing* have played a key role in disseminating relevant research, achieving high impact scores (h-index of 9 and 8, respectively). These journals have not only shown high productivity but have also been fundamental in addressing the challenges and opportunities of AI in manufacturing. Additionally, emerging areas such as AI-based innovation ecosystems and additive manufacturing present significant opportunities for innovation and the customization of industrial processes.

At the level of authors and institutions, researchers such as Wang, Çinar, Bag, and Cavalcante stand out. Through their highly cited works, they have significantly contributed to developing innovative approaches to AI implementation in manufacturing. These authors, along with their respective institutions, such as Nanyang Technological University and the CCDC Army Research Laboratory, have led in terms of citations and international collaboration. Their research addresses not only technical aspects such as predictive maintenance and process customization but also highlights the importance of establishing collaborative networks to overcome challenges like system interoperability and institutional barriers.

Finally, the data indicate that the main opportunities for advancing AI in manufacturing lie in integrating emerging technologies, optimizing predictive maintenance, and improving decision-making through data-driven models. These findings underscore the importance of continuing to explore the application of AI in specific industry niches while working to overcome the technological and organizational barriers that limit its widespread adoption. This study provides a solid foundation for future research, offering recommendations to the academic and industrial communities on how to maximize the benefits of AI in manufacturing and address the challenges that still persist.

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