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HOT TOPICS AND RESEARCH TRENDS IN THE APPLICATION OF ARTIFICIAL INTELLIGENCE IN SMART MANUFACTURING

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Abstract
With the advancement of Industry 4.0, artificial intelligence that integrates Internet of Things (IoT), big data (BD), edge computing (EC), digital twins, haptic feedback, and other technologies is penetrating various aspects of smart manufacturing, such as predictive maintenance, material design, automatic fault detection, and so on. Based on sampling data extracted from Scopus database between 1986 and 2025, this study employs a bibliometric analysis method to systematically analyse research trends, knowledge structures, and future directions in the field of artificial intelligence and smart manufacturing. The results show that this cross-disciplinary research between artificial intelligence and smart manufacturing has witnessed significant upward growth in recent years, especially since 2017. The top 10 most cited documents, most related documents, some productive authors, and high-frequency keywords have been identified. This study not only helps researchers comprehensively grasp the development trajectory but also provides directional guidance and knowledge map support for subsequent research.
Keywords: artificial intelligence, ChatGPT, smart manufacturing, manufacturing

Abstrak
Seiring kemajuan Industri 4.0, kecerdasan buatan yang mengintegrasikan Internet of Things (IoT), big data (BD), edge computing (EC), digital twins, umpan balik haptik, dan teknologi lainnya semakin merambah berbagai aspek manufaktur cerdas, seperti pemeliharaan prediktif, desain material, deteksi kesalahan otomatis, dan sebagainya. Berdasarkan data sampel yang diekstraksi dari basis data Scopus antara tahun 1986 dan 2025, penelitian ini menggunakan metode analisis bibliometrik untuk menganalisis secara sistematis tren penelitian, struktur pengetahuan, dan arah masa depan di bidang kecerdasan buatan dan manufaktur cerdas. Hasil penelitian menunjukkan bahwa penelitian lintas disiplin antara kecerdasan buatan dan manufaktur cerdas telah mengalami pertumbuhan yang signifikan dalam beberapa tahun terakhir, terutama sejak tahun 2017. Telah diidentifikasi 10 dokumen yang paling sering dikutip, dokumen yang paling terkait, beberapa penulis produktif, serta kata kunci dengan frekuensi tinggi. Penelitian ini tidak hanya membantu para peneliti memahami lintasan perkembangan secara komprehensif, tetapi juga memberikan panduan arah dan dukungan peta pengetahuan untuk penelitian selanjutnya.
Kata kunci: *kecerdasan buatan, ChatGPT, manufaktur cerdas, manufaktur*

INTRODUCTION

The development of the Fourth Industrial Revolution has brought about fundamental changes in various sectors of life, including the manufacturing sector. Digital transformation—characterized by the integration of smart technologies into production processes—has spurred the emergence of the concept of smart manufacturing. This concept not only focuses on the automation of production processes but also emphasizes the ability of manufacturing systems to adapt, learn, and make decisions independently based on data obtained in real time (Kamble et al., 2018). In this context, Artificial Intelligence (AI) has become one of the key technologies driving the transformation toward more efficient, flexible, and sustainable manufacturing systems.

Artificial Intelligence refers to the ability of computer systems to perform tasks that typically require human intelligence, such as pattern recognition, decision-making, problem-solving, prediction, and learning from experience (Russell & Norvig, 2021). In recent decades, the development of AI has accelerated rapidly alongside increases in computing capacity, the availability of large amounts of data, and advancements in machine learning and deep learning algorithms. These advancements have enabled the application of AI across various industrial sectors, including modern manufacturing, which requires fast and accurate data processing to improve operational quality and productivity (Cinar et al., 2020).

Smart manufacturing is a new paradigm in production systems that integrates digital technology, connectivity, and artificial intelligence to create manufacturing processes that are more adaptive and responsive to changes in the business environment. This concept leverages various cutting-edge technologies such as the Internet of Things (IoT), Big Data Analytics, Cloud Computing, Edge Computing, Cyber-Physical Systems (CPS), Digital Twin, Augmented Reality (AR), Virtual Reality (VR), Mixed Reality (MR), Blockchain, and Artificial Intelligence (Zheng et al., 2018). The integration of these technologies enables manufacturing companies to monitor, control, and optimize the entire production chain in real time, thereby improving operational efficiency and the company's competitiveness.

In practice, Artificial Intelligence has made significant contributions to the development of smart manufacturing. One of the most widely used AI applications is predictive maintenance. This technology enables systems to predict machine failures before operational breakdowns occur by analyzing sensor data and the performance patterns of production equipment (Zhao et al., 2021). With this approach, companies can reduce downtime, extend equipment lifespan, and significantly lower maintenance costs. Cinar et al. (2020) explain that AI-based predictive maintenance can improve the reliability of manufacturing systems while minimizing the risk of unexpected production disruptions.

In addition to predictive maintenance, AI also plays a crucial role in quality control. Computer vision and deep learning technologies enable systems to automatically detect product defects with a higher level of accuracy compared to manual inspections. Fan et al. (2025) explain that the use of AI in quality inspection can improve the consistency of production results and accelerate the process of identifying non-conforming products.

This capability is particularly important in modern manufacturing industries that demand high quality and large-scale production.

The application of AI is also expanding in the fields of material design and product optimization. Through machine learning approaches, AI can analyze material characteristics and predict their performance under various operational conditions. Research conducted by Baduge et al. (2022) shows that integrating AI into the development of new materials can accelerate the innovation process and reduce the costs of experiments that have traditionally required significant time and resources. Das Mahapatra et al. (2021) also emphasize that AI can help researchers identify more efficient and sustainable material combinations to meet the needs of future industries.

In the context of manufacturing operations, AI contributes to the automation of complex tasks that previously required human intervention. Intelligent robots powered by AI algorithms are capable of performing various activities such as product assembly, material transport, quality inspection, and automated inventory management (Fan et al., 2025). These capabilities not only boost productivity but also reduce the risk of workplace accidents and human error in the production process.

Furthermore, AI plays a role in optimizing the use of industrial resources. Asif et al. (2024) explain that AI can analyze patterns of energy consumption, raw material usage, and production capacity to generate more efficient recommendations. Consequently, companies can reduce waste, improve energy efficiency, and support sustainable, environmentally friendly manufacturing practices. This aligns with global demands for industrial development that balances economic, social, and environmental aspects.

The development of smart manufacturing is also supported by the integration of AI with smart sensor technology. Sun et al. (2024) point out that AI-based sensing systems are capable of generating more accurate data and responding more effectively to changes in production environment conditions. This information is then used as the basis for automated decision-making, thereby enhancing the system's ability to adapt to dynamic changes.

The digital transformation underway in the manufacturing sector has reshaped business models and the structure of global industrial competition. Sarkar et al. (2024) state that AI is one of the key drivers of digital transition within manufacturing companies. Organizations that are able to effectively adopt AI technology tend to have a greater competitive advantage compared to companies that still rely on conventional systems. Therefore, understanding the latest developments in AI research within smart manufacturing is crucial for supporting future industrial transformation processes.

Although research on Artificial Intelligence and smart manufacturing is growing at a rapid pace, the available studies remain largely fragmented. Most studies focus on specific technologies such as deep learning, machine learning, edge computing, or the Internet of Things without providing a comprehensive overview of the field's overall development (Cinar et al., 2020). Furthermore, many studies highlight AI applications only in specific cases—such as fault diagnosis, predictive maintenance, or material design—making it difficult to grasp the broader knowledge structure within this field.

These conditions indicate a research gap that needs to be addressed through a bibliometric approach. Bibliometric analysis is a quantitative method used to evaluate the development of a scientific field based on the characteristics of scientific publications, citation patterns, collaboration networks, and relationships between research concepts (Donthu et al., 2021). This method enables researchers to systematically and objectively map the development of scientific knowledge, thereby identifying research trends, key themes, influential authors, productive institutions, and the direction of future research.

In the context of Artificial Intelligence and smart manufacturing, bibliometric analysis is crucial because it provides a comprehensive overview of the evolution of research over the past several decades. By analyzing publications indexed in the Scopus database from 1986 to 2025, this study aims to identify patterns of publication growth, citation distribution, the development of research topics, and the academic collaboration networks that have formed in this field. Scopus was selected because it is one of the largest and most widely used scientific databases in bibliometric research, with broad multidisciplinary coverage and high-quality metadata (Baas et al., 2020).

Bibliometric analysis also enables the identification of core literature that serves as the foundation for scientific development in the fields of Artificial Intelligence and smart manufacturing. This core literature can be identified through citation analysis, which highlights scientific works that have had a significant influence on the development of a specific research field. Additionally, keyword co-occurrence analysis can be used to identify key concepts and emerging topics within the scientific community (Donthu et al., 2021).

Keyword mapping is a crucial aspect of bibliometric research because it illustrates the knowledge structure of a scientific field. Keywords that frequently appear together indicate conceptual relationships between specific research topics. Using bibliometric software such as VOSviewer or Biblioshiny, the relationships between keywords can be visualized as networks that highlight major research clusters and emerging themes (van Eck & Waltman, 2010). Through this approach, research can uncover both mature research areas and those that still hold potential for further development.

In addition to analyzing the development of research topics, bibliometric studies also provide information on the contributions of countries, institutions, and authors to the advancement of science. This analysis is crucial for understanding the global distribution of academic contributions and identifying research hubs that serve as key drivers of Artificial Intelligence development in smart manufacturing. This information can serve as a foundation for fostering international collaboration and strengthening research capacity across various countries.

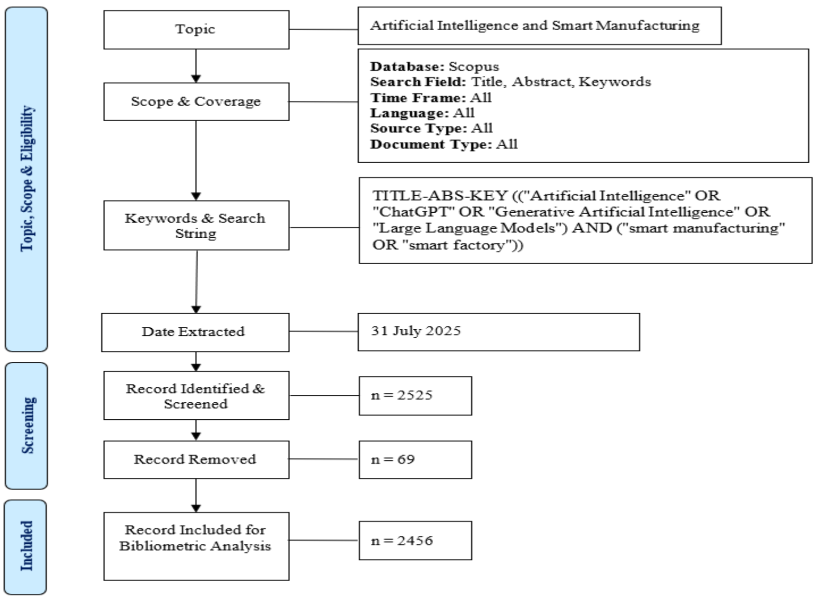
This research is expected to provide both theoretical and practical contributions. Theoretically, the research findings will enrich the literature on the development of Artificial Intelligence in smart manufacturing through a comprehensive bibliometric approach. Practically, the findings can serve as a reference for academics, researchers, industry practitioners, and policymakers in understanding the direction of technological development and determining research and investment strategies relevant to the needs of the future industry.

Based on the above description, this study aims to analyze the development of Artificial Intelligence research in smart manufacturing through a bibliometric approach to publications indexed in Scopus from 1986 to 2025. This study focuses on identifying trends in publication growth, the annual distribution of research, core literature, influential authors, dominant keywords, collaboration networks, primary publication sources, and the future direction of research. Through systematic and comprehensive mapping, this study is expected to provide a comprehensive overview of the scientific landscape of Artificial Intelligence in smart manufacturing and serve as a foundation for further research in the era of AI-driven industrial transformation.

METHOD

Bibliometric analysis is a well-known and well-established way to analyze a bunch of scientific data, and it can be used to track how a particular area is changing and spot new fields that are popping up (Dar et al., 2024; Donthu et al., 2021; Fosso Wamba et al., 2024). The current study applies bibliometric analysis to systematically analyze the hot topics and research trends in the application of artificial intelligence in smart manufacturing. First of all, this study chooses the Scopus database as the main data source, considering its availability for the purpose and content of the present research. Next, the retrieval strategy is ensured: TITLE-ABS-KEY (("Artificial Intelligence" OR "ChatGPT" OR "Generative Artificial Intelligence" OR "Large Language Models") AND ("smart manufacturing" OR "smart factory")). The data extraction date for this study is July 31, 2025, and this study extracted a total of 2,525 records, of which 69 were deleted, keeping 2,456 for further analysis (Figure 1). Noticeably, this study mainly relies on various bibliometric tools, like Excel, Python, VOSviewer, R, and Bibliometrix to deal with data related to artificial intelligence and smart manufacturing.

Figure 1. Data Acquisition Workflow



RESULTS AND DISCUSSION

After finishing the data collection and screening, this part will systematically analyze the collected literature referring to artificial intelligence and smart manufacturing.

Document Category

As can be seen from Table 1, most documents are conference papers (982, 39.98%) and articles (931, 37.91%). The results indicate that artificial intelligence in smart manufacturing research exhibits a dual strengthening of theoretical construction and practical exploration.

Table 1. Document Type

DOCUMENT TYPE	QUANTITY	PERCENTAGE	CUMULATIVE PERCENTAGE
CONFERENCE PAPER	982	39.98%	39.98%
ARTICLE	931	37.91%	77.89%
BOOK CHAPTER	268	10.91%	88.80%
REVIEW	198	8.06%	96.86%
BOOK	54	2.20%	99.06%
EDITORIAL	15	0.61%	99.67%
SHORT SURVEY	5	0.20%	99.88%
OTHERS	3	0.12%	100.00%
TOTAL	2456	100.00%	100.00%

Note: Rounding up or down.

Language

In terms of language, most included documents were published in English, accounting for 97.35% (2391) of the total, suggesting the mainstream language of documents associated with artificial intelligence and smart manufacturing is still English (Table 2). Nevertheless, other languages like Chinese (39, 1.59%), Korean (10, 0.41%), German (9, 0.37%), and Spanish (2, 0.08%) account for a small proportion. As topics related to "Industry 4.0" and "Smart Manufacturing" gradually become globalized, an international dissemination system for scientific research results primarily in English has become one of the crucial paths for scholars to gain influence and promote technology diffusion.

Table 2. Language of Original Document

LANGUAGE	QUANTITY	PERCENTAGE	CUMULATIVE PERCENTAGE
ENGLISH	2391	97.35%	97.35%

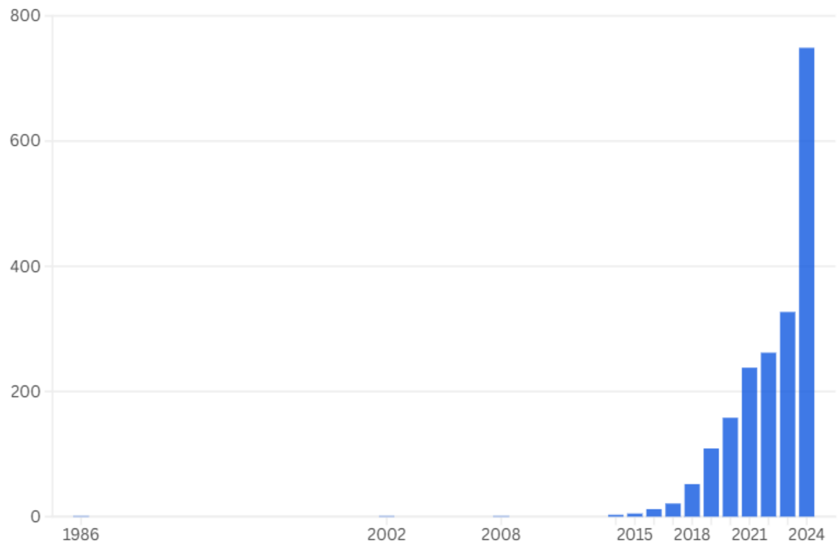
CHINESE	39	1.59%	98.94%
KOREAN	10	0.41%	99.35%
GERMAN	9	0.37%	99.71%
RUSSIAN	3	0.12%	99.84%
SPANISH	2	0.08%	99.92%
ITALIAN	1	0.04%	99.96%
JAPANESE	1	0.04%	100.00%
TOTAL	2968	100.00%	100.00%

Note: Rounding up or down.

Document Number

Cross-disciplinary research between “artificial intelligence” and “smart manufacturing” has witnessed significant upward growth in recent years, especially since 2017 (Figure 2). From an overall trend perspective, the number of research documents published on “artificial intelligence” and “smart manufacturing” displays a three-stage progression characterized by a “slow start—stable growth—explosive rise.” Since 2017, the number of documents has grown rapidly, reaching its first peak in 2024 (approximately 749 articles). Although the data for 2025 is not yet complete, as of July 31, there were already 517 documents included, and it is expected that the high publication rate will continue throughout the year. This trend may be closely related to the birth of ChatGPT, the promotion of “Industry4.0” or “Industry5.0” similar policies in many countries, the industrial maturation of AI algorithms, and the backdrop of digital transformation. As mentioned above, research on the application of artificial intelligence in smart manufacturing is going through a period of rapid growth, which not only shows the popularity of this theme but also gives us a solid foundation for future academic resource integration and research path identification.

Figure 2. Document Number



Top Ten Cited Documents

The number of citations can demonstrate the core knowledge, theoretical foundations, and technical approaches in a particular field, and is one of the important indicators for evaluating the academic influence of literature (Goyal & Kumar, 2021; Pietronudo et al., 2022; Roldan-Valadez et al., 2019; Tahamtan et al., 2016). This study extracts the top 10 most cited documents, which have a cumulative total of 10,252 citations, highlighting the significant "head effect" of a few key results about artificial intelligence and smart manufacturing (Table 3). With the extensive application of sensors and Internet of Things (IoT), Wang et al. (2018) compared some typical deep learning models and proposed a deep learning-based calculation method aimed at enhancing the performance of manufacturing systems (TC per Year = 172.13 and Normalized TC = 9.38). Tao et al. (2018) provide a historical overview of the manufacturing data lifecycle and explore the role of big data in reinforcing smart manufacturing (TC per Year = 168.25 and Normalized TC = 9.17). Overall, the focal themes and technical approaches of highly cited literature provide reference clues for understanding the "paradigm shift" and "technological focus (e.g., deep learning, digitalization-driven, smart manufacturing systems)" of artificial intelligence and smart manufacturing, and also offer theoretical support and methodological insights for subsequent researchers to conduct model expansion and system integration.

Table 3. Top Ten Global Cited Documents

NO.	TC	AUTHORS	TITLE	TC PER YEAR	NORMALIZED TC
1	1377	Wang J.; Ma Y.; Zhang L.; Gao R.X.; Wu D.	Deep learning for smart manufacturing: Methods and applications	172.13	9.38
2	1346	Tao F.; Qi Q.; Liu A.; Kusiak A.	Data-driven smart manufacturing	168.25	9.17
3	1177	Wuest T.; Weimer D.; Irgens C.; Thoben K.-D.	Machine learning in manufacturing: Advantages, challenges, and applications	117.70	10.29
4	1160	Tao F.; Zhang M.	Digital Twin Shop-Floor: A New Shop-Floor Paradigm Towards Smart Manufacturing	128.89	8.58

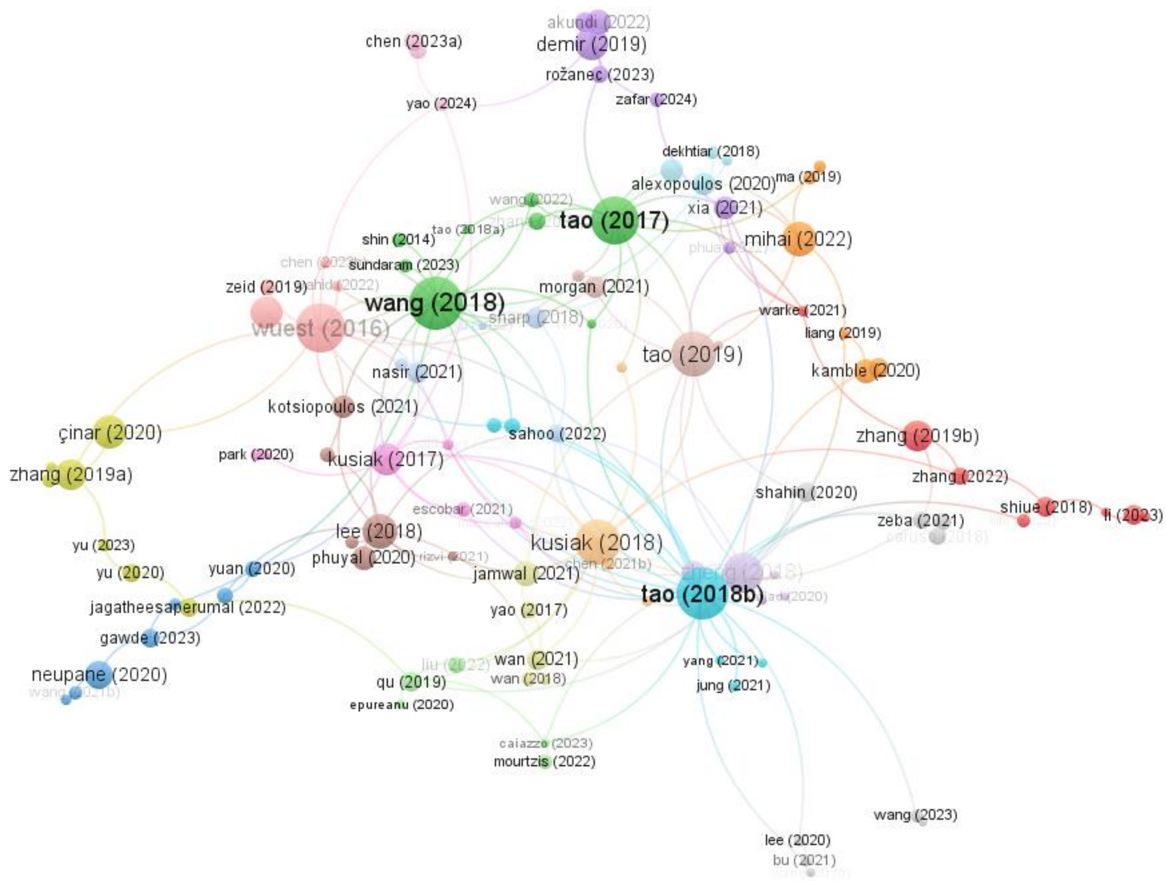
5	1127	Wang X.; Han Y.; Leung V.C.M.; Niyato D.; Yan X.; Chen X.	Convergence of Edge Computing and Deep Learning: A Comprehensive Survey	187.83	20.76
6	1047	Kusiak A.	Smart manufacturing	130.88	7.13
7	990	Tao F.; Qi Q.; Wang L.; Nee A.Y.C.	Digital Twins and Cyber–Physical Systems toward Smart Manufacturing and Industry 4.0: Correlation and Comparison	141.43	19.46
8	819	Zheng P.; wang H.; Sang Z.; Zhong R.Y.; Liu Y.; Liu C.; Mubarok K.; Yu S.; Xu X.	Smart manufacturing systems for Industry 4.0: Conceptual framework, scenarios, and future perspectives	102.38	5.58
9	612	Lee J.; Davari H.; Singh J.; Pandhare V.	Industrial Artificial Intelligence for industry 4.0-based manufacturing systems	76.50	4.17
10	1377	Mihai S.; Yaqoob M.; Hung D.V.; Davis W.; Towakel P.; Raza M.; Karamanoglu M.; Barn B.; Shetve D.; Prasad R.V.; Venkataraman H.; Trestian R.; Nguyen H.X.	Digital Twins: A Survey on Enabling Technologies, Challenges, Trends and Future Prospects	149.25	27.70

Note: TC = Total Citations

Citation Analysis

Because citation analysis is one of the key strategies for measuring the academic influence of literature and knowledge dissemination pathways of academic knowledge and research clusters (Annarelli et al., 2021; Hota et al., 2020; Shiau et al., 2017; Trujillo & Long, 2018), this study utilized the VOSviewer tool to construct a citation network of literature related to artificial intelligence and smart manufacturing (Figure 3). After setting the threshold to 30, VOSviewer automatically identified around 200 documents that met the citation frequency requirement. Some literature (e.g., Tao et al., 2018; Tao & Zhang, 2017; Wang et al., 2018) is located at the core of the citation network, forming multiple academic clusters and constructing the theoretical framework and critical application paths for artificial intelligence in the realm of smart manufacturing.

Figure 3. Citation Documents Diagram



Most Relevant Sources

According to the analysis of sources, the present study found the ten most relevant sources in the intersection of artificial intelligence and smart manufacturing. Among them, Procedia CIRP (n=50), Lecture Notes in Networks and Systems (n=46), Applied Sciences (Switzerland) (n=45), and IEEE Access (n=43) have published the most related literature (See Figure 4). The most representative source journal distribution indicates that artificial intelligence and smart manufacturing research have formed a relatively broad academic dissemination ecosystem, with journals specializing in technical subfields providing indepth professional coverage and transdisciplinary comprehensive journals encouraging systematic integration and innovative convergence.

Figure 4. Relevant Sources

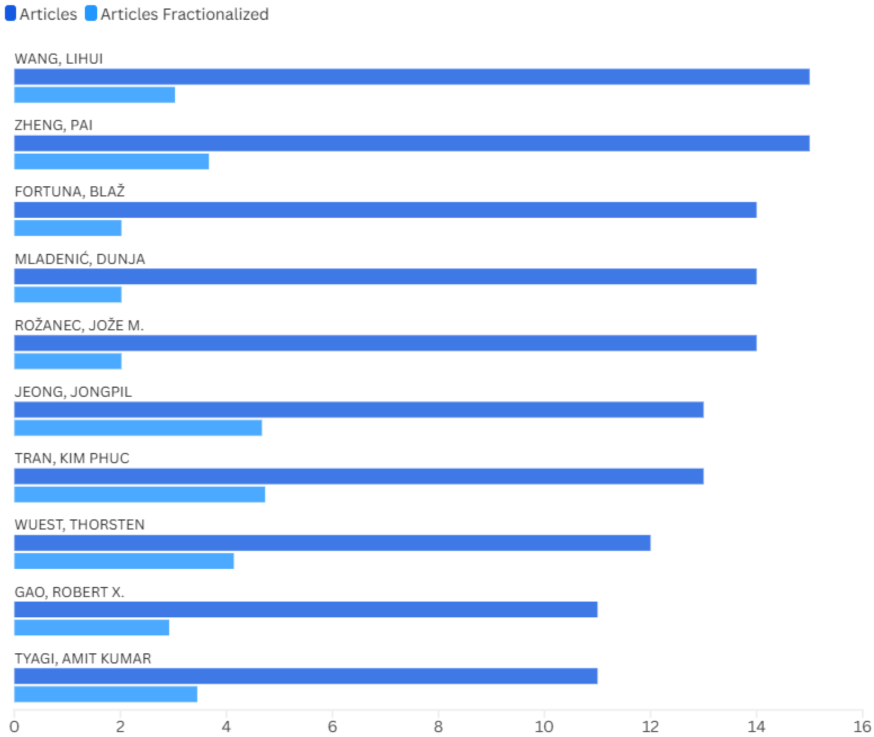
Most Relevant Authors

In the crossover domain of artificial intelligence and smart manufacturing, Table 4 and Figure 5 list the most prolific authors in this field. Research suggests that Wang Lihui (15, 3.03), Zheng Pai (15, 3.67), Fortuna Blaž (14, 2.02), Mladenić Dunja (14, 2.02), Rožanec, Jože M. (14, 2.02), and some others are among the influential scholars in this field.

Table 4. Top Ten Productive Authors

AUTHORS	ARTICLES	ARTICLES FRACTIONALIZED
WANG, LIHUI	15	3.03
ZHENG, PAI	15	3.67
FORTUNA, BLAŽ	14	2.02
MLADENIĆ, DUNJA	14	2.02
ROŽANEC, JOŽE M.	14	2.02
JEONG, JONGPIL	13	4.67
TRAN, KIM PHUC	13	4.73
WUEST, THORSTEN	12	4.14
GAO, ROBERT X.	11	2.92
TYAGI, AMIT KUMAR	11	3.45

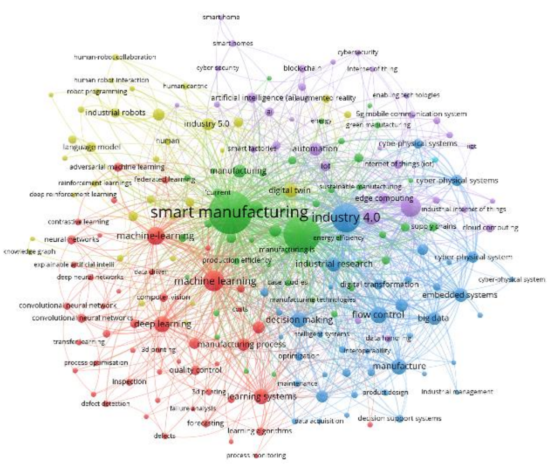
Figure 5. Most Relevant Authors



Keywords Co-occurrence Analysis

This study employed VOSviewer to examine the co-occurrence of keywords in the collected literature, with a minimum occurrence frequency of 20, resulting in the extraction of 12791 keywords, 2011 of which met the co-occurrence criteria (Figure 6). According to the VOS clustering algorithm, the main keywords forming the clusters include artificial intelligence, smart manufacturing, internet of things, industry 4.0, machine learning, deep learning, industry 5.0, manufacturing process, flow control, automation, and so on. The co-occurrence network of keywords reveals the close relationship between artificial intelligence and smart manufacturing as core nodes and multiple subfields, showcasing the multidimensional integration features of AI in the field of smart manufacturing.

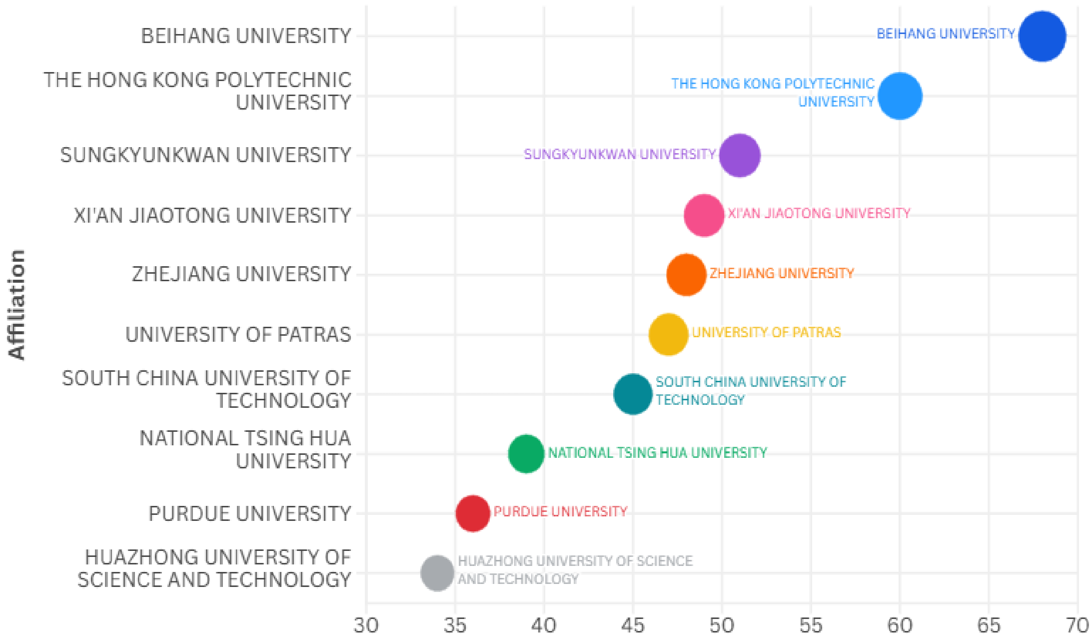
Figure 6. Keywords Co-occurrence Analysis



Affiliations Analysis

In the cross-disciplinary field of smart manufacturing and artificial intelligence, this study has identified some of the most active research affiliations on this topic. Figure 7 illustrates the relevant productive affiliations of artificial intelligence and smart manufacturing currently. The relatively high-ranking affiliations include: Beihang University, the Hong Kong Polytechnic University, Sungkyunkwan University, and more.

Figure 7. Relevant Affiliations



CONCLUSION

This study creates a knowledge map of artificial intelligence and smart manufacturing through systematic bibliometric analysis. The results show that most documents are conference papers (982, 39.98%) and articles (931, 37.91%). Most included documents were published in English (97.35%, 2391), and cross-disciplinary research between “artificial intelligence” and “smart manufacturing” has witnessed significant upward growth in recent years, especially since 2017. This study extracts the top 10 most cited documents, such as “Deep learning for smart manufacturing: Methods and applications” (TC per Year = 172.13 and Normalized TC = 9.38). Meanwhile, some documents that are associated with artificial intelligence and smart manufacturing are recognized at the center of the citation network, forming multiple academic clusters. According to the analysis of sources, this study finds that Procedia CIRP (n=50), Lecture Notes in Networks and Systems (n=46), Applied Sciences (Switzerland) (n=45), and IEEE Access (n=43) have published the most related documents. Some productive authors, such as Wang Lihui (15, 3.03), Zheng Pai (15, 3.67), Fortuna Blaž (14, 2.02), Mladenić Dunja (14, 2.02), Rožanec, Jože M. (14, 2.02), and some others have been identified. The co-occurrence network of keywords that are related to artificial intelligence and smart manufacturing has been built, and the relevant productive affiliations have been identified.

However, this study relied solely on the Scopus database, which may have omitted high-quality articles related to artificial intelligence and smart manufacturing from other databases. Moreover, during the standardization process of authors, affiliations, and keywords, and others, issues such as incomplete synonym merging or author name ambiguity may arise, which perhaps affect the accuracy of the statistical results. In addition, the application of artificial intelligence technology in manufacturing is still in a dynamic evolutionary stage, and the current citation analysis, clustering structure, co-occurrence analysis, and other measurements may not fully predict future research directions.

In the future, artificial intelligence research in smart manufacturing can continue to explore the following directions, for instance: (1) The integration of artificial intelligence IoT, edge computing, 6G, and blockchain may drive the transformation of manufacturing systems toward more intelligent and autonomous operations (2) With the enhancement of large language models (e.g., ChatGPT), there is potential to form industrial large-scale models with judgment, reasoning, and interpretation capabilities, enabling human-machine collaborative decision-making and limited autonomous decision-making. The green AI algorithms and green smart manufacturing, which aim to save resources, reduce waste, protect the environment, and promote sustainable development, are worth further exploration.

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