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Research status of artificial intelligence in the era of Industry 4.0: A bibliometric analysis

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Abstract

The rapid evolution of Industry 4.0 has had a profound impact on modern industrial ecosystems, with Artificial Intelligence (AI) emerging as a key enabler of intelligent, data-driven operations. This present study presents a large-scale, data-driven bibliometric mapping of AI research in the Industry 4.0 domain, offering novel insights into its intellectual structure and emerging directions. The Biblioshiny framework was utilized to systematically analyze 6,856 Scopus-indexed publications from 2013-2026 through the utilization of RStudio and Microsoft Excel. The findings reveal a conference-driven research landscape, with conference papers contributing 48.25% of total output, followed by journal articles (32%) and book chapters (10%). A distinct geographical shift is observed, with India emerging as the leading contributor, alongside strong participation from the United States, the United Kingdom, and Germany. Keyword density and co-occurrence analysis reveal that "Industry 4.0" is the central knowledge hub, with a high degree of interconnectedness with machine learning, AI, deep learning, digital twin, and cloud computing. These technologies form the technological backbone of the domain. Additionally, the study identifies a transition from core industrial applications towards interdisciplinary frontiers, including smart farming, precision agriculture, and education 4.0, thereby signalling the diffusion of AI-driven Industry 4.0 concepts into broader societal contexts. By quantitatively uncovering research concentration, thematic evolution, and emerging application domains, this study proposes a novel perspective on the dynamic knowledge architecture of AI in Industry 4.0. The findings provide policymakers with actionable insights for designing targeted research funding and innovation strategies that are aligned with emerging interdisciplinary domains. For industry practitioners, the results highlight key technological priorities and application areas that have the potential to drive competitive advantage and operational efficiency. Furthermore, the study offers a strategic roadmap for researchers by identifying themes that have received inadequate concern and future research directions. This fosters more impactful and collaborative advancements in AI-driven Industry 4.0.

Keywords: Industry 4.0; Artificial intelligence; Sustainability; Bibliometric analysis; Research status

1. Introduction

Industry 4.0 refers to a fundamental transformation in manufacturing processes through the integration of the Internet of Things (IoT) with Artificial Intelligence (AI), robotics, cloud computing, and big data analytics [1]. Modern industries are undergoing a transformation, with industries becoming smart, connected, automated networks through this fusion of technology. This integration leads to operational enhancements, enhanced productivity, and greater flexibility [2]. The advancement of AI has been identified as a main catalyst for the advent of Industry 4.0, as it has the capacity to address complex problems across various domains, including manufacturing and healthcare management systems [3]. The replacement of AI technologies, including machine learning, deep learning, computer vision, and natural language processing, facilitates the automation of functions, the enhancement of processes, the optimization of decision-making processes, and the development of new models [4].

The integration of multiple technologies in Industry 4.0 enables software systems and machines to detect situations and

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learn from human operational activities, much as the human mind does. This technology facilitates enhanced efficiency within industrial production system. Industry 4.0 advances at a steady pace, thereby increasing in the manufacturing sector. AI is an emerging technology that enhances operational efficiency and product quality while reducing operational costs. A smart factory is characterized by the integration of production processes through hyperconnectivity, meaning all the equipment works together in a network. Manufacturers have been known to improve their digital operations through the implementation of AI- and ML-enabled data set management purposely to achieve enhanced quality control, standardized operations, and equipment maintenance. AI has been demonstrated to have a number of positive effects on manufacturing operations in Industry 4.0[5-7]. This technology has facilitated the production of enhanced results while requiring less human involvement, thus accelerating work speed. Industry 4.0 is characterized by the integration of digital technologies that have the potential to enhance the intelligence and efficiency of industrial processes. New AI developments are leading to computer systems that possesses the visual, auditory and cognitive capabilities, thereby enabling better platforms for skill development [8]. Industry 4.0 and sustainability are emerging technologies and organizational innovations that have the potential to enhance productivity and sustainable manufacturing [9]. Industry 4.0 technologies aim to address today challenges, such as global competition, market and demand fluctuations, and the need for communication, information, and intelligence to enable more personalized services, innovation cycles, and reduced product life cycles [10]. Industry 4.0 technologies have the potential to make substantial contributions to the voluntary development of organizational and societal sustainability [11]. From the economic perspective, there are tailoring manufacturing processes that reduce set-up times, shorten lead times, reduce labor and material costs, negotiate for production flexibility, increase usage, and enable gigantic customization [12-14].

Despite the growing body of bibliometric and review literature analysing AI, Industry 4.0, smart manufacturing, etc., most studies are quite narrow in scope, focusing on individual technologies, small datasets, or short time frames. Moreover, previous research typically focuses on either performance analysis or conceptual reviews, without integrating them thematically, intellectually, or collaboratively into a single framework. Consequently, the current literature is deficient in providing a comprehensive, longitudinal picture of the evolution of AI studies within the broader Industry 4.0 system.

The novelty of the current work lies in the comprehensive, integrated mapping of the research, considering AI and Industry 4.0. This study, in contrast to the earlier ones, examines recent, comprehensive data that encompasses the latest developments in the area. The study adopts a time-sliced bibliometric framework to systematically examine the evolution of research themes, thereby enabling a deeper understanding of how key topics have emerged, developed, and transformed over time. Moreover, the research employs the latest science-mapping methods to identify and categorise themes into motor, basic, niche, and emerging, providing a systematic perspective on the knowledge field.

Moreover, the study is not only a conventional bibliometric analysis but also a study of global collaboration networks among authors, institutions, and countries. This provides information about the social structure of the research area. By integrating performance analysis, thematic mapping, and evolutionary trends into a single framework, the study provides a multidimensional perspective that distinguishes it from prior research. Such a holistic view has the potential to improve understanding of the state of research and to guide the directions and opportunities that will arise in AI-driven Industry 4.0. Given the rapid development of the field, there is a need to critically assess the research environment and its main contributors, and to define emerging trends. Bibliometric analysis is a robust quantitative method used to map scientific knowledge, assess research impact, and identify structural patterns in the literature [15].

Based on these aforementioned points, the present paper proposes five key Research Objectives (RO) to be investigated. The research is thus designed to accomplish these objectives. The five objectives identified for this article are as follows:

RO1: To identify the major trends in research publications on AI in Industry 4.0 over time.

RO2: To identify and analyze the most productive and influential journals, authors, and institutions in the field.

RO3: To identify and examine the dominant research themes and emerging topics in AI for Industry 4.0.

RO4: To identify the evolution of research collaboration across countries and institutions in this area.

This paper offers an in-depth overview of the scholarly landscape of AI during the Industry 4.0 age based on a systematic bibliometric review. It assists in determining the main publication trends, their contributors, and the leading journals, thereby providing a comprehensive overview of the field's development. The present study combines thematic analysis and evolution to identify the prevailing areas of research and new topics that warrant further investigation. Furthermore, it is instrumental in the identification of patterns of collaboration between countries and institutions, facilitating a comprehensive understanding of the dynamics of research on a global scale. The results allow the researchers to identify knowledge gaps and future research areas. The research is also useful to policymakers and industry practitioners in the decision-making process about innovation and technology adoption. In general, it is the contribution to both academic and practical work in the context of AI-based Industry 4.0 systems.

This paper is structured as follows. Section 1 introduces the research background and outlines the study objectives. In Section 2, a comprehensive review of the literature on Industry 4.0 and artificial intelligence is presented, thereby establishing the foundation for bibliometric analysis. Section 3 describes the research methodology, including data collection, processing, and the analytical and visualisation techniques employed. In Section 4, the results and discussion are presented, covering publication trends, citation analysis, keyword distribution, and research collaboration networks. Section 5 highlights the primary outcomes of the study and summarizes key findings. Section 6 discusses the practical implications for researchers, industry practitioners, and policymakers. Section 7 outlines the study's limitations and suggests directions for future research. Finally, Section 8 concludes the paper by summarizing the overall contributions and key insights.

2. Literature review

The following sections presents a review of bibliometric studies focusing on Industry 4.0, along with AI.

Bibliometric studies have been established as powerful tools for researchers across different academic fields to explore publication landscapes and identify emerging subjects for strategic research development [16]. Statistical and mathematical procedures are utilized to measure and analyze scientific publication features by studying publication counts, citation frequencies, keyword co-occurrences, and collaboration networks [17]. In their bibliometric studies Researchers employ visualization software such as VOS Viewer and RStudio to develop network graphs and group related research topics [18].

The modern revolution in manufacturing operations is driven by AI, which today analyses data in real time to make smart decisions. AI systems, powered by AI, are capable of performing real-time data analysis from sensors and other sources purposely to identify anomalies that result in scrap and rework. Through AI-powered solutions, it is possible for the companies to reduce expenses while increasing operational efficiency and sustainability by enhancing strategic planning, predictive equipment maintenance, quality inspections, and supply chain management [19]. The application of AI in the field of manufacturing enables the examination of energy patterns, facilitating the identification of opportunities for the process enhancement, and optimization of energy utilization. System algorithms that utilize AI have the capacity to modify production parameters, together with equipment optimization tools and production scheduling, to reduce energy consumption [20]. AI powers urban development and production activities for building energy-efficient buildings [21]. AI has the potential to contribute to a reduction in waste by stabilizing industrial operations, improving quality assurance, and detecting potential issues [22]. The utilization of AI, together with cloud services, big data analytics, blockchain technology, and the IoT, assists SSCM in making informed decisions that drive circular development. AI can facilitate the transition of product development to the circular economy by optimizing product design, remanufacturing, reuse, and recycling [23]. The utilization of AI-driven systems has the potential to enhance the resource recovery while addressing environmental concerns by examining product composition, content consumption, and end-of-life choices. Indeed, companies could enhance their internal processes, create more sustainable products and processes and therefore more effectively utilize the potential of AI and other digital tools [24]. An Intelligent chain is created by Industry 4.0 technologies such as AI, Machine Learning, automation, robotics, the IoT, Big Data Analytics, and Blockchain. These technologies facilitate faster decision-making, optimization of current practices, all-around transparency, enhancement of collaboration, and support for warehouse management [25]. AI algorithms analyze large datasets to identify trends and insights that aid decision-making and optimize processes [26]. The use of past data to predict future event is a key component of proactive maintenance, quality control and resource management [27]. AI algorithms are capable of executing complex operations and processes to remove waste, save energy, and maximize efficiency. AI-driven digital twins defined as virtual clones of physical assets that can be used for the purpose of to monitoring, respect timing, simulation, and optimization. The combination of AI with other Industry 4.0 technologies, such as IoT, digital twins, and blockchain, is predicted to yield more efficient results than the use of these technologies individually [28]. AI is a key enabler of sustainable Industry 4.0, enabling the optimization of resources utilization, reduction of waste, improvement of energy efficiency, and the acceleration of the shift towards a circular economy. Nevertheless, various obstacles and limitations need to be overcome to fully utilize AI in sustainable production [29]. These factors encompass data availability and quality, skills and knowledge, connection with legacy systems and ethical factors [30].

2.1. Major enabling technologies for developing sustainable Industry 4.0

Industry 4.0 technologies comprise two major groups: physical and digital technologies. Additive manufacturing, together with sensors and drones, constitutes the bulk of the physical technologies employed primarily for production [31]. Modern information and communication technologies, including digital technologies such as cloud computing, blockchain, big data analytics, and simulation, are of importance [32]. The various technology systems for sustainable Industry 4.0 are presented in Table 1.

Table 1. Description of various Industry 4.0 technologies.

Technologies	Description	References
Blockchain	• It facilitates decentralization and distribution of data management, minimization of reliance on centralized authorities. • It has the potential to secure IoT devices and networks, protecting against cyber threats. • It has the capacity to enhance supply chain transparency, accountability, and efficiency.	[33,34,35]
Additive Manufacturing (3D printing)	• AM facilitates the direct conversion of digital design into physical products, streamlining the production process. • AM reduces material waste, energy consumption, and production time, thereby providing a more sustainable and accurate manufacturing process. • The advancement of standardized processes and materials is pivotal for widespread acceptance of AM in Industry 4.0.	[36,37,38]
Robotics	• This technology is being integrated with AI, facilitating robots to understand from the past, adjust to different situations, and make decisions independently. • The increased utilization of robotics technology in Industry 4.0 raises cybersecurity concerns, highlighting the need for robust security measures. • The selection of robotics technology in Industry 4.0 requires workforce transformation, including training and upskilling of workers.	[39,40,41]
Artificial Intelligence	• AI-powered quality control enables machines to inspect and evaluate products in real-time, resulting in enhanced product quality and reduced waste. • The selection of AI in Industry 4.0 requires workforce transformation, encompassing training and upskilling of workers.	[42,43]
Cybersecurity	• Industry 4.0, classified by the incorporation of AI and the IoT (IoT), and automation, transforms the manufacturing landscape. • It enhances connectivity and reliance on digital technologies.	[44,45]
Industrial IoT (IIoT)	• It facilitates machines to make connections, permitting machines to communicate with each other and with humans, enhancing productivity and efficiency. • It facilitates real-time data analytics, permitting predictive maintenance, quality control, and improvement of manufacturing processes.	[46]
Cloud computing	• This technology provides scalable and flexible infrastructure, enabling manufacturers to adapt to changing demand and production requirements quickly.	[47]
Big Data analytics	• This technology enables supply chain optimization, thereby enhancing inventory management, logistics and transportation.	[48]
Augmented reality (AR)	• This technology provides real-time information and feedback, thereby enabling workers to make informed decisions and take corrective action. • This technology enables the provision of guidance and support to workers, thus reducing the need for physical presence and enhancing knowledge transfer.	[49,50]
Machine Learning	• This technology enables real-time quality control, enhanced product quality and reduces waste. • It optimizes the efficiency of logistics and supply chain management.	[51]
Digital Twins	• It produces an essential replica of physical assets, systems and processes, thus facilitating real-time monitoring.	[52]
Simulation	• It enables the optimization of processes, improving efficiency and reducing waste.	[53]
Radio Frequency Identification Device (RFID)	• This technology facilitates real-time tracking of objects, enhancing inventory management, logistics and supply chain management.	[54]

3. Methodology

The data for this bibliometric analysis have been collected exclusively from the Scopus database, which is widely recognised as one of the most comprehensive and reliable sources of peer-reviewed literature, covering journals, conference proceedings, and book series across multiple disciplines. The selection of Scopus as the sole data source is justified by its broad coverage, high-quality indexing standards, and inclusion of both engineering and interdisciplinary research domains, which are essential for studies related to AI and Industry 4.0. In comparison to other databases, Scopus offers more comprehensive journal coverage and more extensive data, thus enabling robust bibliometric analysis and minimising issues related to data duplication and inconsistency. Furthermore, Scopus is commonly employed in bibliometric studies due to its standardised data structure and compatibility with analytical tools, ensuring consistency and reproducibility of results [55]. In this study, the R package was utilized for quantitative data analysis, including citation, co-authorship, and keyword analysis. Additionally, VOS viewer has been utilized to visualize and explore bibliometric networks, including co-occurrence and citation networks. In addition, Microsoft Excel has been employed for data analysis and to create a summary of the data. The present study focuses on articles and reviews published between 2013 and 2026, as they provide current, relevant information on the issue. Following a comprehensive search, 6856 research papers from Scopus were identified as customized. The search term employed were "AI" OR "AI" OR "machine learning" OR "Cyber physical systems" AND "industry 4.0" OR "Fourth industrial revolution" OR "I4.0". Fig. 1 presents the methodology for document selection in the form of a flow diagram.

4. Result and Discussion

This section is divided into the essential metrics for bibliometric analysis. An exploration was conducted to ascertain its status from various perspectives, such as sources, publications, authors, references, keywords, universities, and countries. Additionally, a comprehensive analysis of these elements is necessary, encompassing their effects, productivity, citation frequency, and collaborative networks. These analyses offer novel insights into scientific research.

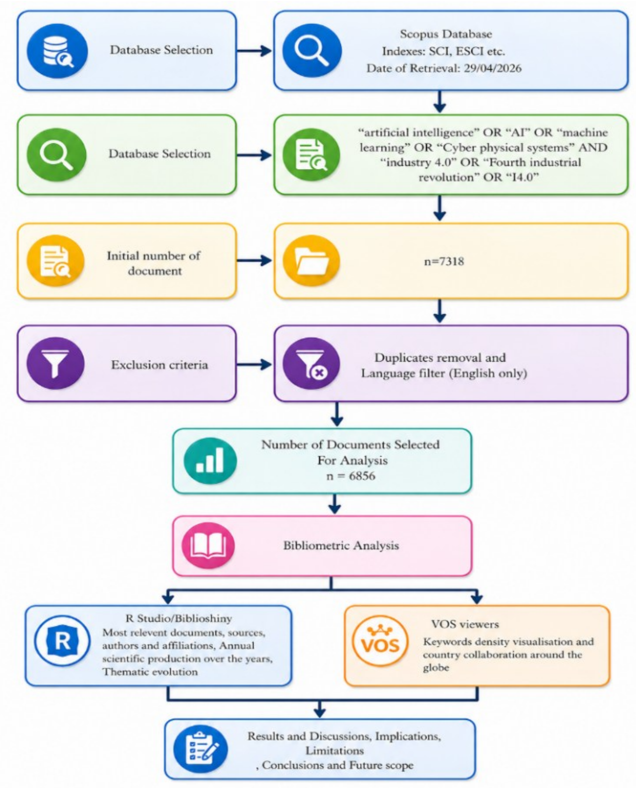

Fig. 1. Flow diagram for bibliometric analysis

Table 2. Major Information about the collected paper

Description	Results and Analysis
Article	2197
Book	103
Book chapter	719
Conference paper	3,308
Conference review	1
Editorial	15
Letter	1
Note	4
Retracted	9
Review	492
Short survey	7
Time span	Years (2013-2026)
	Keywords plus (22037)
	Author's Keywords (DE) (12576)
	Authors (19323)
Authors collaboration	Single authors' docs (543)
	Co-authors per docs (3.92)
International co-authorships (%)	26.84
Sources (Journals, books, etc.)	2471
Documents	6856
Annual growth rate %	42.56
Documents average age	3.7
Average citation per doc	32.05
References	504,108

4.1 Major information about the collected data

As depicted in Table 2, a total of 6856 publications were retrieved from the Scopus database using the keywords. The database contains a total of 22037 keywords, 19323 authors, and 543 single-authored documents. In addition, the database contains 3308 source conferences, and more than 504,000 references. The pie chart (Fig. 2) depicts the classification of documents recovered during the last 14 years. Initially, it is evident that articles are more representative, with 3308 (48.25%) of the conferences; secondly, and thirdly, we have, respectively, articles 2197 (32%) and book chapters 719 (10%).

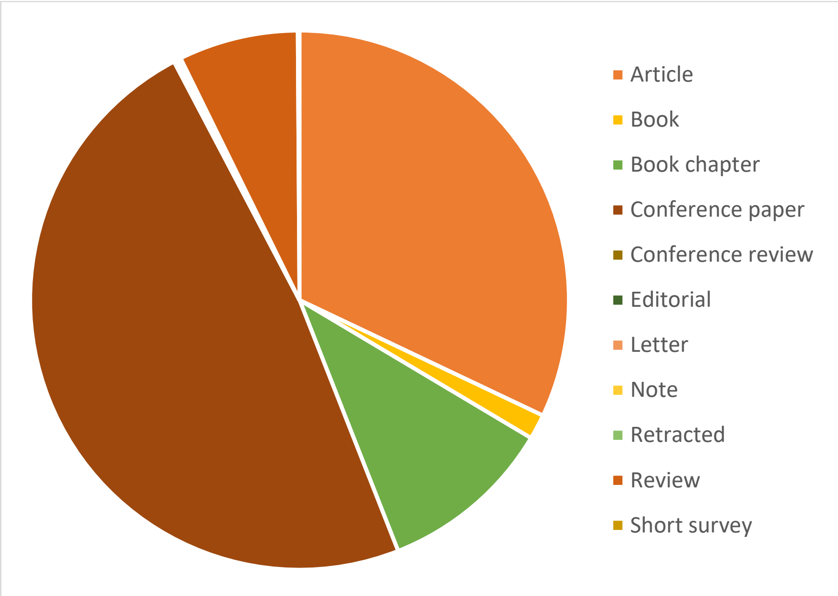

Fig. 2. Pie chart: Documents retrieved over the last 14 years

4.2. Most global cited documents

As illustrated in Fig. 3, the most globally cited documents are identified. An article entitled “A cyber physical systems architecture for Industry 4.0-based manufacturing systems” by Lee, B. and Kao [56] has been identified as the most frequently cited publication based on Scopus data. This article has garnered a total of 4234 citations (352.83 citations per year). Google Scholar data reveals that the same paper has also received the maximum number of citations, with a total of 7796 and 708 citations per year. These most-cited documents have had a significant impact on the research community, as evidenced by the large number of citations they have received.

4.3. Most relevant affiliations

Biblioshiny utilizes bibliometric analysis to identify relevant linkages within bibliographic data. The procedure includes data importation, counting, relevance analysis, and result visualisation. The significance of affiliations is assessed by a number of factors, including publication frequency, citation counts, and journal impact [57]. Institutions have been identified as those with the most affiliations: the University of Johannesburg, the University of Minho, Notre ported, Uttaranchal University, Politecnico di Milano, Lovely Professional University, RWTH Aachen University, Norwegian University of Science and Technology, the University of Texas at San Antonio, and the Hong Kong Polytechnic University. Fig. 4 demonstrates the most relevant affiliations in Industry 4.0.

4.4. Most relevant authors

The identification of the most significant authors in bibliographic analysis is achieved by employing bibliometric techniques to evaluate their relevance and importance in Industry 4.0 research using the stated keyword. Citation records that include key author information are essential for precise and meaningful results. Biblioshiny is a bibliometric analysis tool that can be used to identify significant authors in research papers. As illustrated in Fig. 5, Kumar A. has 34 documents, followed by Kumar S. with 33. Additionally, Wuest T has 27, Romero D has 221, and Leitao P has 20, respectively. Fig. 5 depicts the most relevant authors.

4.5. Most relevant sources

To detect significant sources in bibliographic data, it is recommended to employ the following approach in Biblioshiny: first, import the data, clean it, evaluate source metrics, examine citations, estimate relevance, and finally operate visualization tools. To find the most important sources, the study considered their impact, citation impact, and subject coverage. Fig. 6 demonstrates various journals with the maximum number of documents.

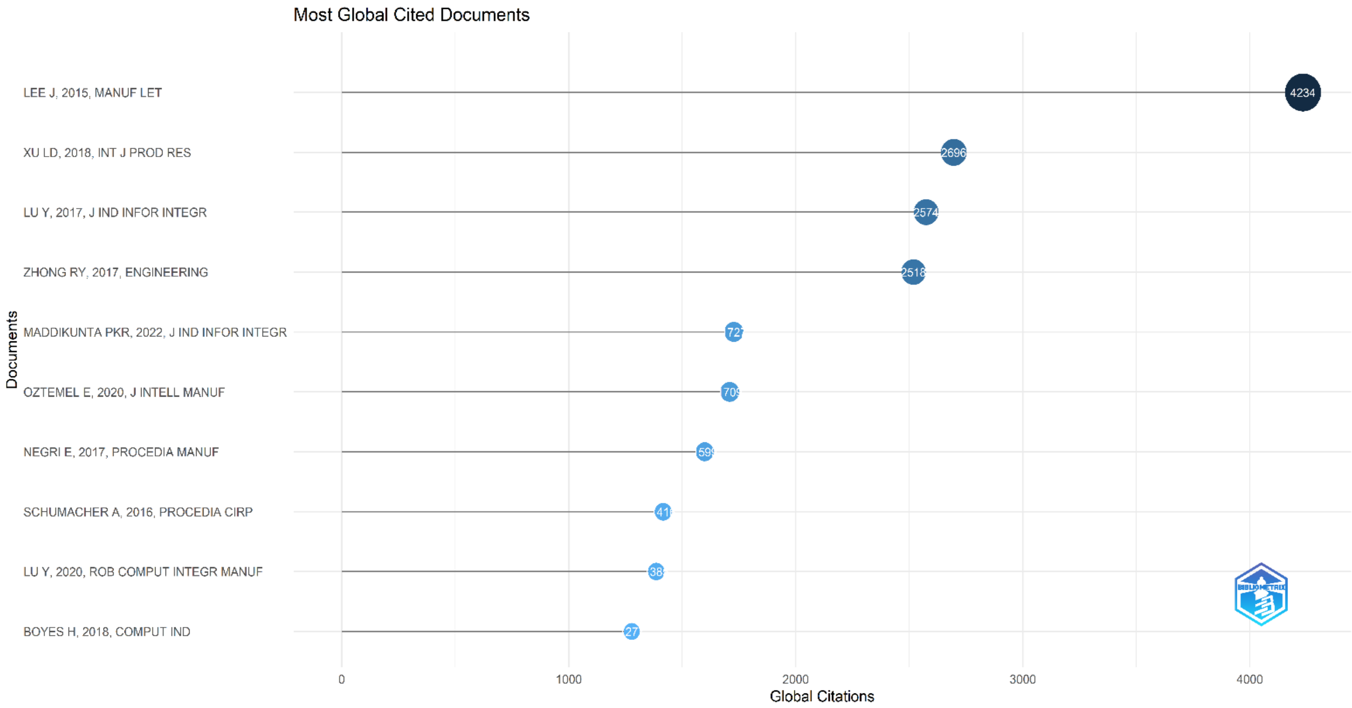

Fig. 3. Most globally cited documents in Industry 4.0

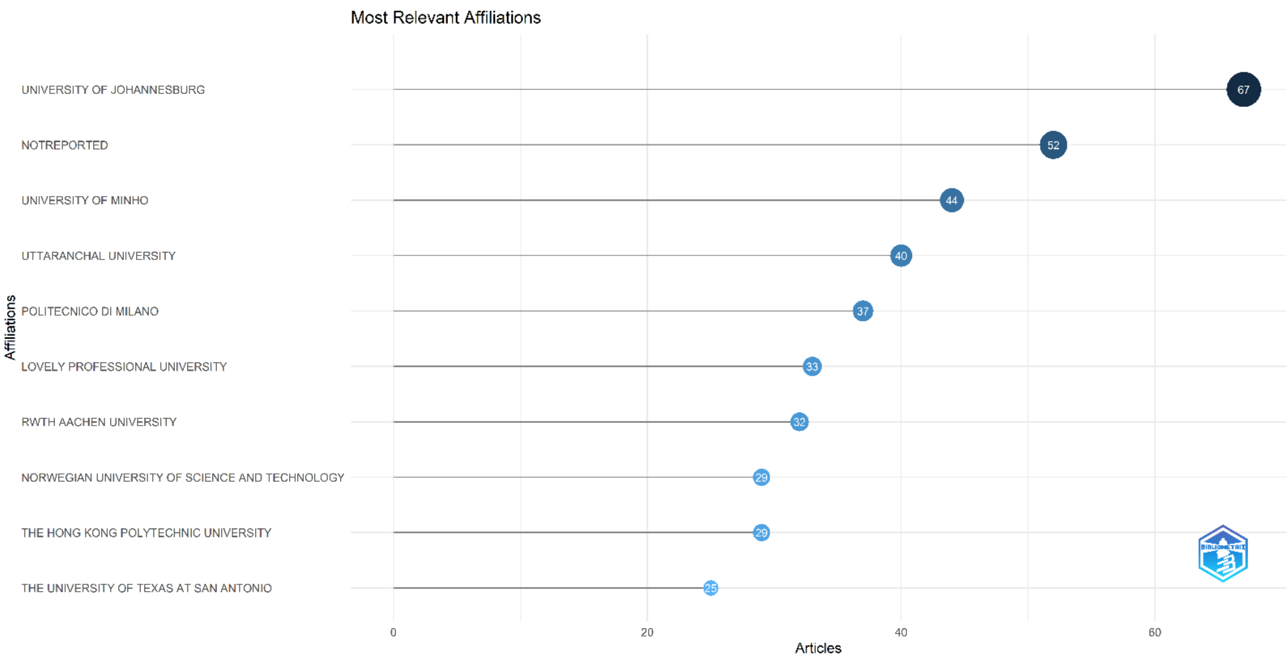

Fig. 4. Most Relevant Affiliations in Industry 4.0

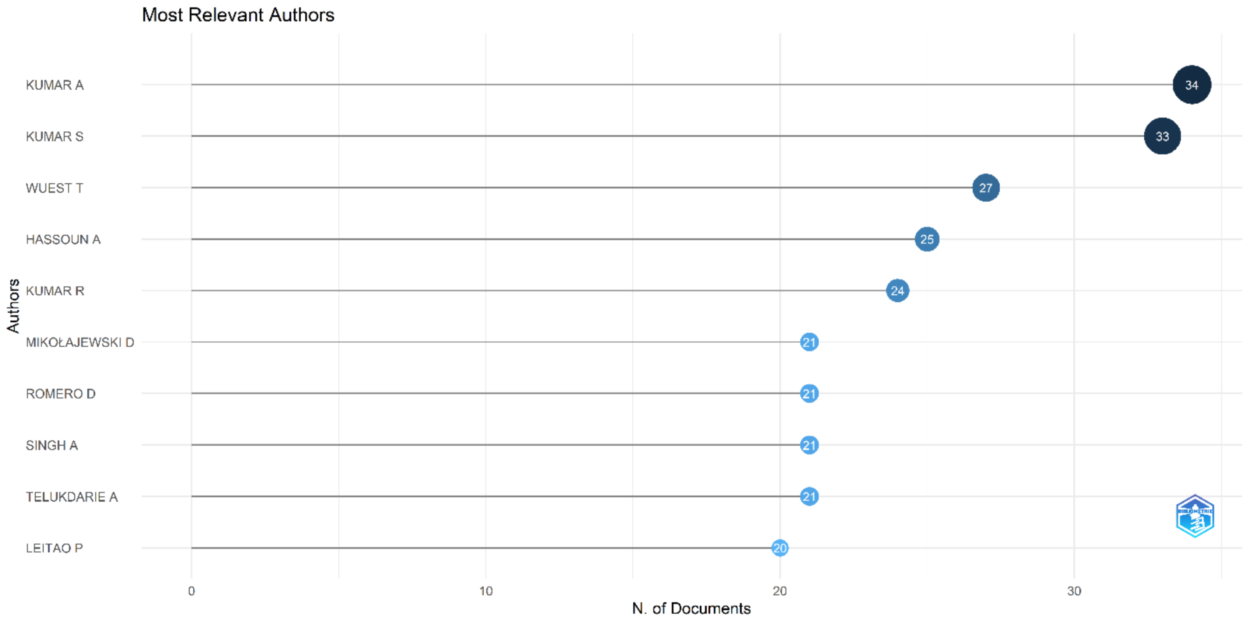

Fig. 5. Most relevant authors

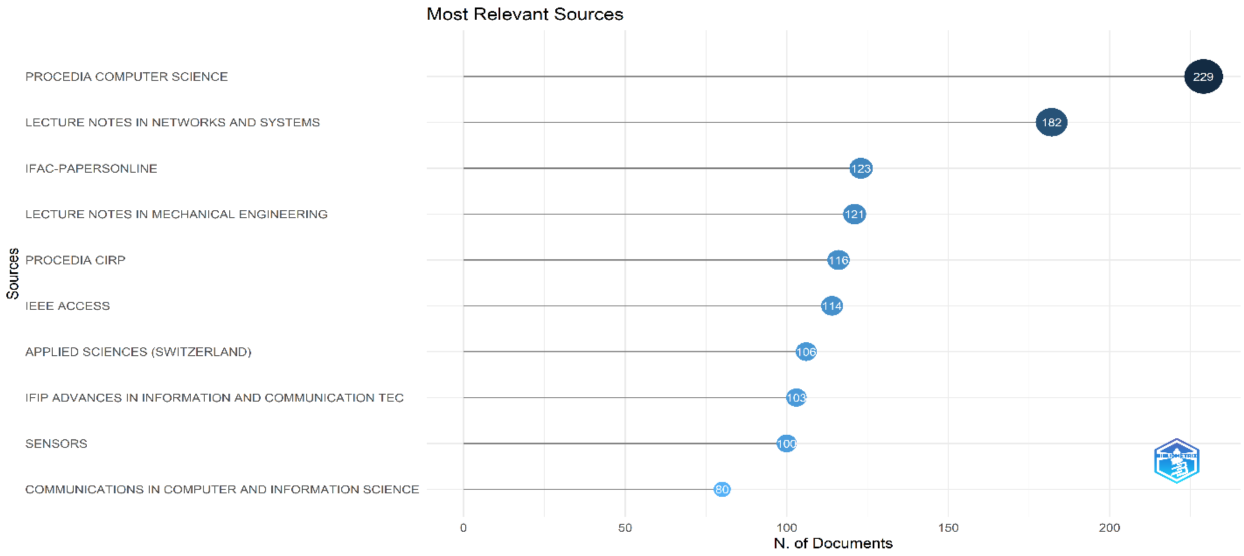

Fig. 6. Most relevant sources

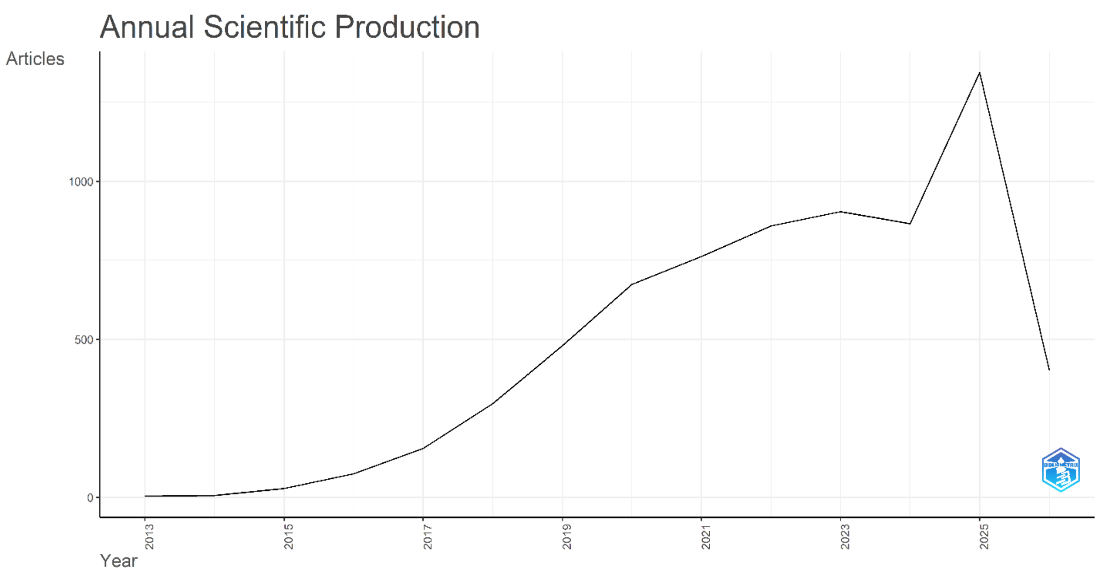

Fig. 7. Annual scientific production

4.6 Annual scientific production

Annual scientific production in Industry 4.0 refers to the total number of publications published each year. The publication experienced an increase from 2013 to 2026, reaching a peak of approximately 1344 publications. Fig. 7 depicts the annual scientific production.

4.7. Keywords collaboration density visualisation analysis

Keywords are highly compressed representations of an article's content, and keyword analysis enables us to swiftly identify popular research areas in a particular sector [58]. Fig. 8 demonstrates the keyword synchronization of the papers containing a total of over 1200 keywords. The keyword density visualisation created with the help of VOS viewer presents a clear picture of the most influential and most frequent research themes in the dataset. The color scheme employed in this map is blue to green and then to yellow, with yellow indicating the highest density of keywords. This signifies the areas where research is focused on and frequent co-occurrence. The term Industry 4.0 is placed in the center with a bright yellow area indicating that it will be the central and most powerful theme. In close proximity to these terms are closely related high-frequency keywords, including machine learning, deep learning, AI, digital twin, and cloud computing, which collectively serve to underscore the pivotal role these technologies play in shaping the landscape of Industry 4.0 research. The closeness of the words indicates strong interrelationships and frequent co-occurrence in relevant literature. A shift towards green and blue themes is evident, accompanied by a decline in density. Consequently, areas that are less explored or emerging are emphasized. These include smart farming, precision agriculture, education 4.0, and COVID-19. These peripheral themes suggest the proliferation of Industry 4.0 concepts across various areas. The visualisation demonstrates that while the research field is strongly centered on AI-driven technologies, it is gradually diversifying into interdisciplinary and application-oriented areas.

4.8. Country collaboration network

Fig. 9 demonstrates the leading countries by number of publications on AI technologies in the context of Industry 4.0. The color gradient represents the number of publications, with darker shades indicating more publications and lighter shades denoting the fewer number. The United States, India, the United Kingdom, and Germany lead in the number of publications, with India recording the highest number between 2013 and 2026. The United States, Germany, Spain, France and the United Kingdom are also countries with a high number of publications.

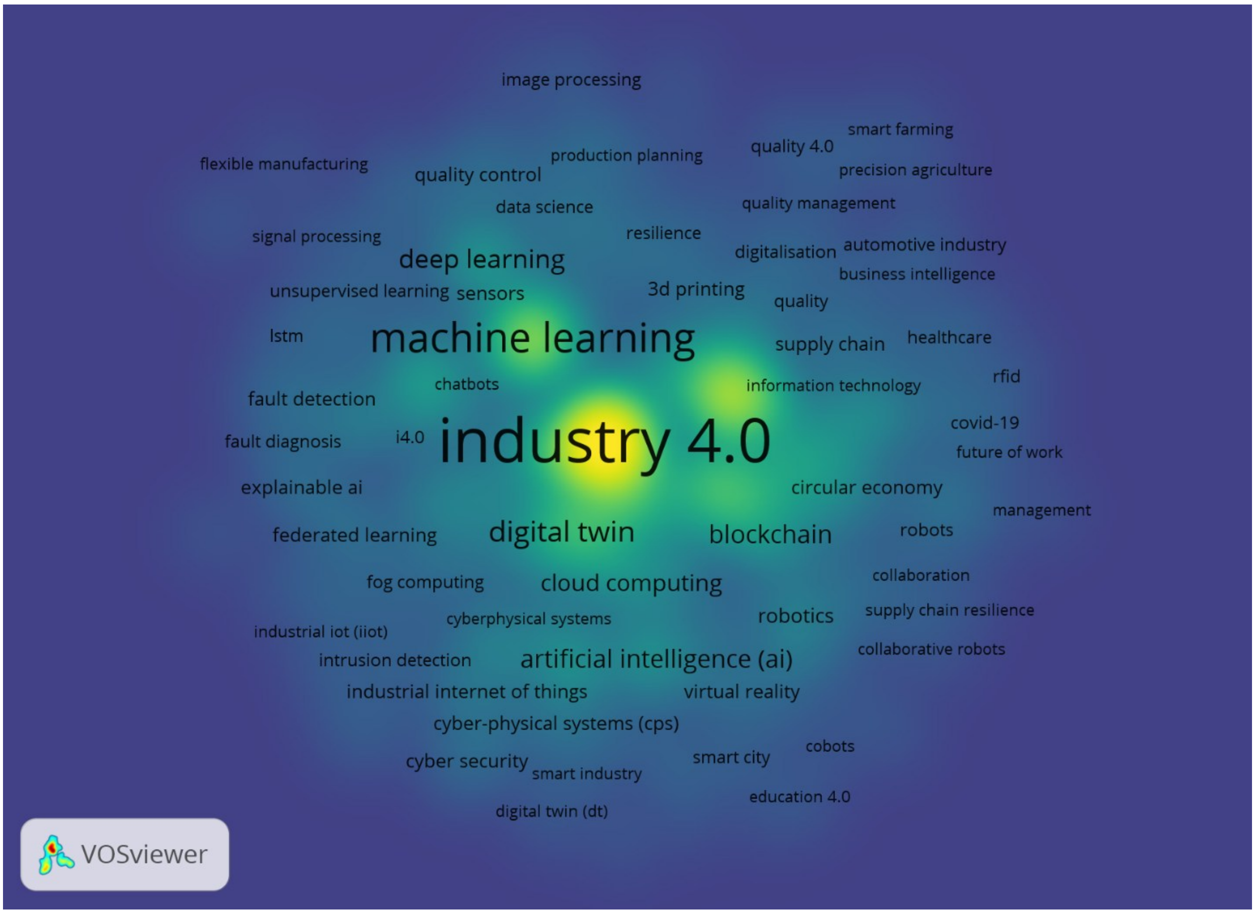

Fig. 8. Keywords density visualisation

4.9 Thematic evolutions

Thematic evolution is the process by which major themes and issues develop across fields including literature, film, scholarly studies, and broader cultural discourse. It facilitates comprehension of the transformation and development of societal values, knowledge systems, and creative expressions [59,60]. This approach entails the strategic emphasis of themes, emphasizing their significance and up-to-date status of themes. The thematic elements are presented as a group within a two-dimensional map or diagram in accordance to their degree of development and topicality. The location of any given cluster is determined by two important measures: centrality and density. Centrality determines the importance of a theme by quantifying the degree of its relationships with other themes. In other words, the more connections a theme bears to other themes, the more central it is regarded. Conversely, density is a measure of a cluster's internal development and maturity, reflecting the strength of relationships among its related keywords. The aforementioned formula can be mathematically expressed as d:100($\sum e_{ij}$/w), where 'w' is the number of keywords in a theme, and 'i ' and 'j' are keywords linked to that theme [61,62]. Time slicing is utilized to systematically explore the evolution of research themes across periods, thereby facilitating a more profound comprehension of the emergence, growth, and change of topics over time [63]. The subdivision of time slices is determined by a combination of factors. Thse include such as ensuring equal representation of publications across periods, reflecting significant stages of technological or research development, reflecting major thematic changes, and adhering to common bibliometric principles, which suggest splitting the study period into a couple of meaningful intervals. Fig. 10 presents the thematic evolution flow diagram.

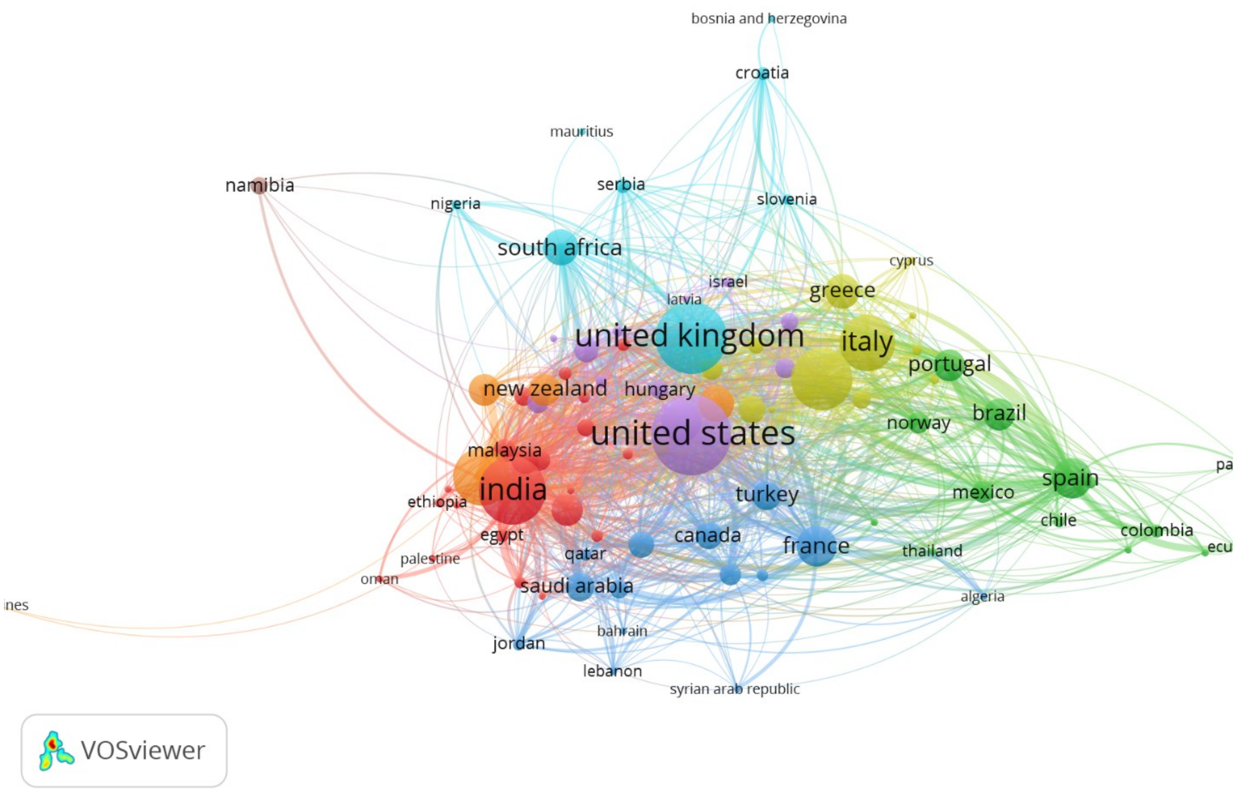

Fig. 9. Country collaboration network

4.9.1. Time slice 1 (2013-2017)

This time-slice (2013-2017) strategic diagram classifies themes based on centrality (importance) and density (development level). Motor themes (e.g., manufacturing, CPSS) are both well-developed and highly relevant, and they are the drivers of the research field. Basic themes (e.g., Industry 4.0, embedded systems) are important but less developed, forming the foundation for other topics. Niche themes (e.g., AI, learning systems) are well developed but exhibit a lack of connection to the broader field. In contrast, theme that in the early stages of development or that are declining themes (e.g., big data, smart manufacturing) demonstrate limited development and relevance, suggesting that they are in the early stages of growth or that research attention has been reduced. Technological advancements have been identified as a key driver of shifts in themes across quadrants, increased integration of digital and intelligent systems, and evolving research priorities. As themes gain more connections and maturity, they move towards motor themes. Conversely, others either merge into broader areas or decline over time [64]. Fig. 11 depicts time slice 1.

4.9.2. Time slice 2 (2018-2020)

This time-slice (2018-2020) strategic diagram visualises themes in terms of centrality (relevance) and density (development). Embedded systems and cyber-physical systems manifest as motor themes indicate a high level of development and the issue's significance. Industry 4.0, AI, and IoT are found towards the centre, highlighting their pivotal role and facilitating the integration of themes. In the meantime, machine learning, learning systems, and predictive maintenance can be classified as emerging or declining themes, as development and connectivity are less prevalent in this stage. The transition can be explained by the growing integration of technologies, in which the principles of fields such as AI and IoT become part of broader models, such as Industry 4.0, and take on broader themes at the system level (e.g., CPS). Consequently, certain areas appear to be less centralized as they are integrated into broader research [65]. Fig. 12 depicts time slice 2.

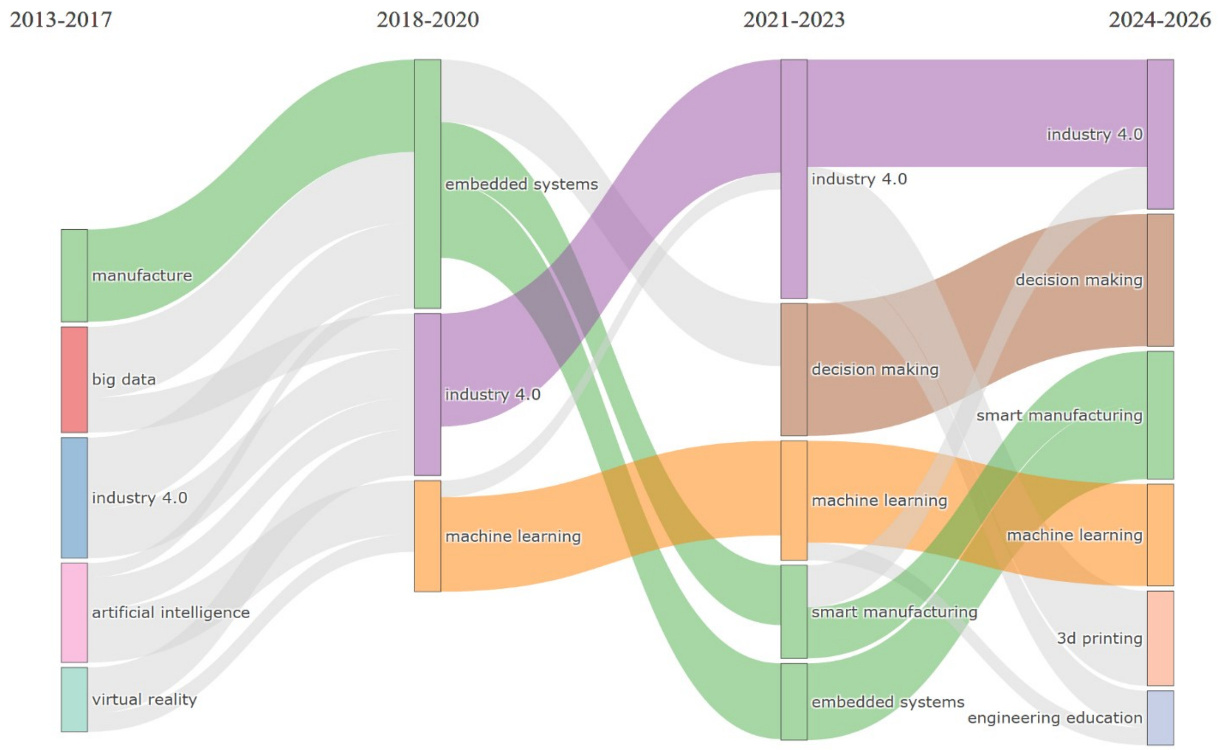

Fig. 10. Thematic evolution

4.9.3 Time slice 3 (2021-2023)

The strategic model of this time-slice (2021-2023) provides the themes by centrality (relevance) and density (level of development). At this stage, machine learning and learning systems are reflected in the form of motor themes, implying that both are well-developed and deeply intertwined, i.e. driving the research area. Industry 4.0, AI, and IoT will serve as pillars and will be positioned as basic themes, with high relevance but relatively low internal development. Embedded systems and cyber-physical systems are at the centre of development, representing linking or transitional themes. In the meantime, smart manufacturing and industrial research demonstrate minimal development and less significant relations during this period. The change can be attributed to the increasing dominance of data-driven technologies, in which machine learning assumes a more central and mature role, and is increasingly integrated into motor themes. Simultaneously, previously core areas, such as Industry 4.0 and IoT, stabilise as base and application-specific topics (e.g., decision-making), either evolving further or temporarily decreasing in prominence. This shift corresponds to a shift from conceptual frameworks to more advanced, data-centric implementations [66]. Fig. 13 depicts time slice 3.

4.9.4. Time slice 4 (2024-2026)

Industry 4.0, AI, and IoT can be observed as motor themes in this time slice (2024-2026), owing to their advanced state of development and their role in propelling the research field.

Machine learning and learning systems are also well-established and increasingly focused on motor themes, which signifies their increased influence. Basic themes include Smart manufacturing and cyber-physical systems, which are important but need to be developed internally. Conversely, 3D printing/additive manufacturing is classified as a niche theme, with strong growth but limited linkage to other themes. In the meantime, the domains of decision-making and engineering education are positioned in the emerging or declining quadrant, suggesting lower relevance and maturity at this stage. The transition is influenced by the growing level of integration and the maturity of digital technologies. Such central ideas as AI, IoT, and Industry 4.0 become dominant and highly interconnected, becoming motor themes. Simultaneously, the development of domains such as smart manufacturing is progressing slowly. In contrast, specific or application-based themes (e.g., decision-making, education) are either lagging in development or being shifted to broader themes. This phenomenon is indicative of a transition from a more fundamental, isolated research to more integrated, intelligent, and application-driven systems [67]. Fig. 14 depicts time slice 4.

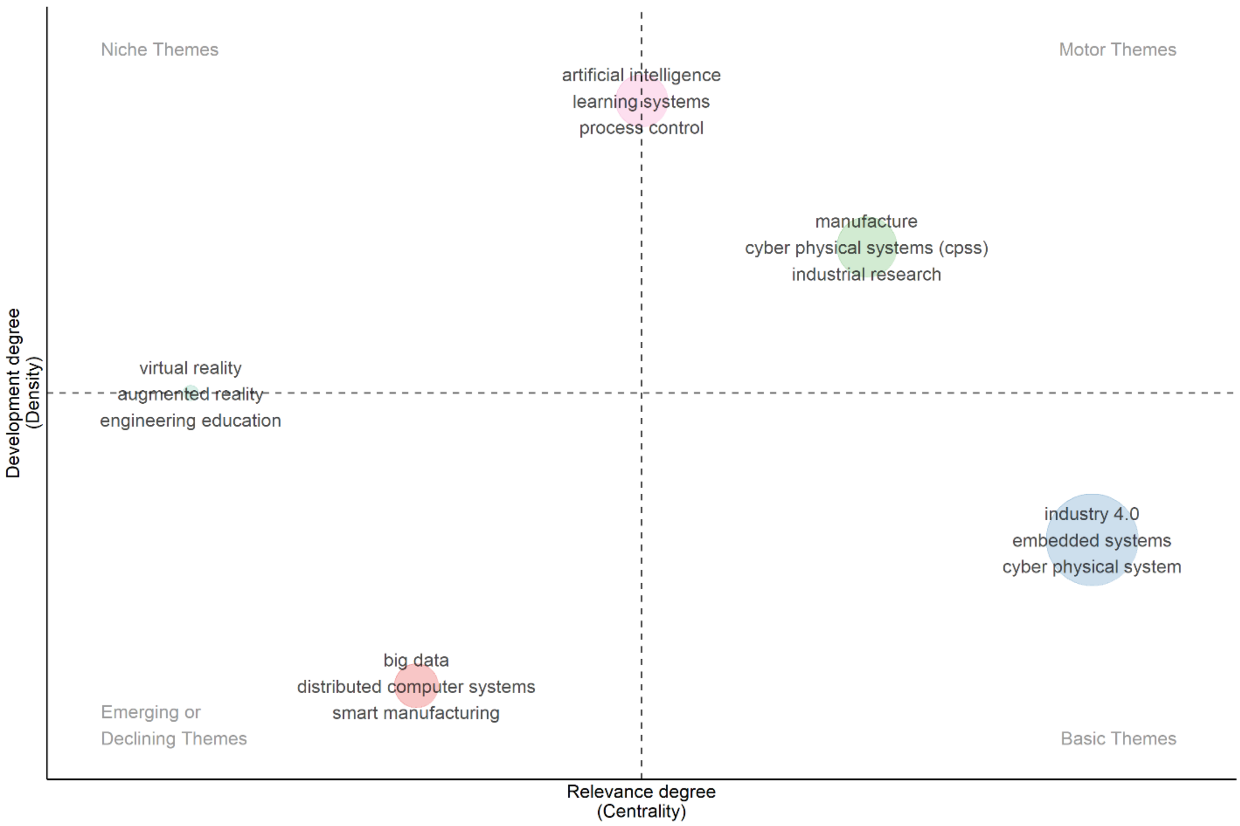

Fig. 11. Time slice 1 (2013-2017)

5. Discussion on Key Findings

The bibliometric analysis demonstrates that some highly-cited publications, in particular, the work by Lee J. and Kao H.-A., have influenced the intellectual base of the Industry 4.0 research to a significant extent, particularly in the introduction of scalable architectures such as cyber-physical systems that addressed real-world industrial challenges and enabled the integration of digital and physical processes. The influence of major institutions and authors is driven by effective funding of research, the development of high-tech infrastructure, and transnational cooperation, which concentrate knowledge production and promote innovation. The marked increase in publications per year between 2013 and 2026 is driven by the global trend towards digital transformation, supported by the rapid development of AI, data analysis, and automation technologies. Keyword analysis also confirms that core technologies such as machine learning, digital twins, and cloud computing have become prominent due to their proven effectiveness in streamlining operations, cutting costs, and enabling real-time decision-making. Emerging trends indicate their growth into interdisciplinary domains. The thematic evolution demonstrates a natural progression from foundational concepts to integrated and data-driven systems, and finally to mature, intelligent applications. This progression is driven by technological convergence and industry demand for smarter, autonomous solutions. These trends have had a great impact on various sectors, including manufacturing (with the emergence of smart factories and predictive maintenance), healthcare (through AI-assisted diagnostics and robotic systems), agriculture (with the development of precision farming), and education (with the emergence of digital and adaptive learning systems). Comprehensively, the results of the study demonstrates that the development and future orientation of research are not solely driven by technological advances, but are also relevant to the practical needs of industry, policy support, and the increasing demand for efficiency, sustainability, and intelligent decision-making across various sectors.

6. Implications of this study

This present research has several implications in theoretical, methodological, practical, and policy aspects. Theoretically, it contributes to understanding of AI in the context of Industry 4.0 by mapping the intellectual structure, key themes, and emerging research areas, thereby providing a solid foundation for future interdisciplinary research. From a methodological perspective, the study provides evidence that bibliometric methods are effective for the analysis of large volumes of scientific literature. It is recommended that such approaches be more widely encouraged in scientific fields. In practice, the research results enable industrial stakeholders to identify high-impact AI applications and align their innovation and investment strategies with the latest technological trends. At the policy level, the study offers valuable insights into global research patterns, leading contributors, and collaboration networks. These insights support policymakers in formulating informed strategies, promoting international partnerships, and strengthening digital infrastructure and skill development initiatives for AI adoption.

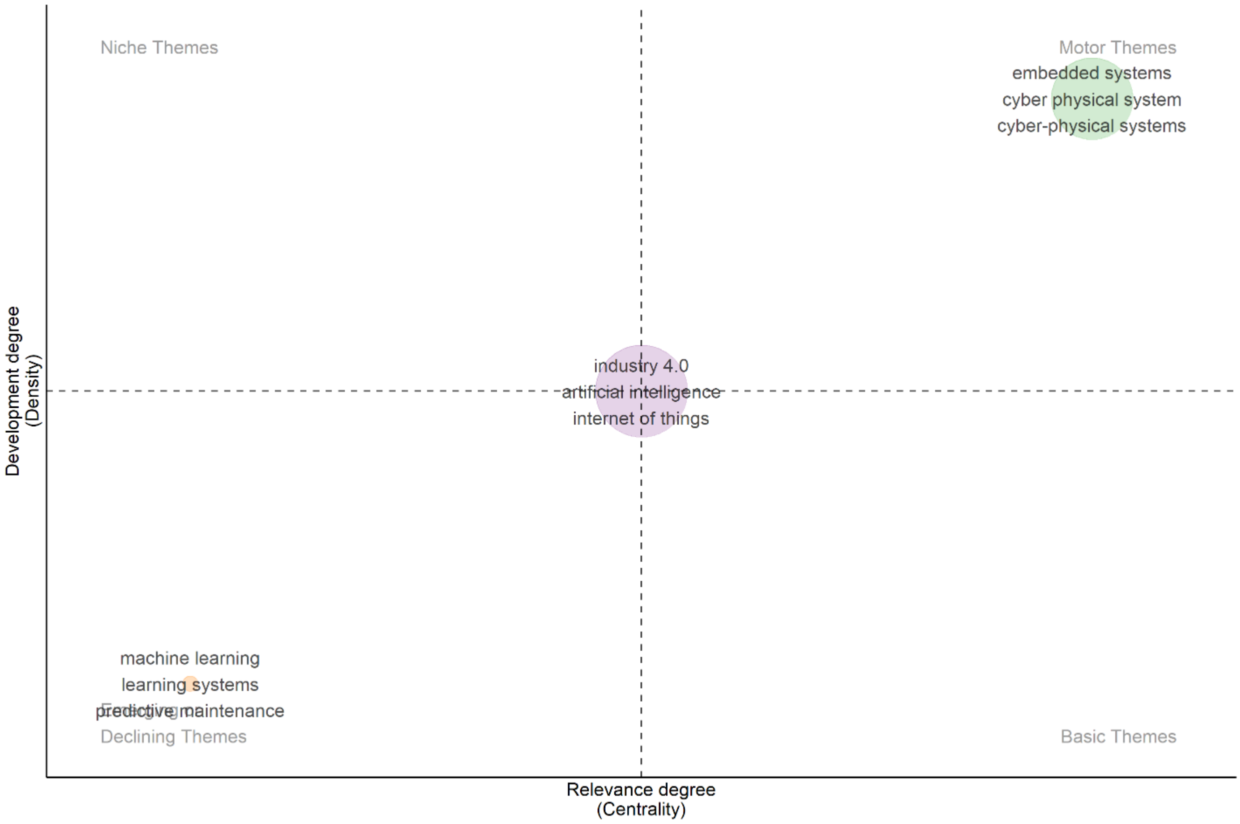

Fig. 12. Time slice 2 (2018-2020)

This present research has several implications in theoretical, methodological, practical, and policy aspects. Theoretically, it contributes to the understanding of AI in the context of Industry 4.0 by mapping the intellectual structure, key themes, and emerging research areas, thereby providing a solid foundation for future interdisciplinary research. From a methodological perspective, the study provides evidence that bibliometric methods are effective for the analysis of large volumes of scientific literature. It is recommended that such approaches be more widely encouraged within scientific fields. In practice, the research results enable industrial stakeholders to identify high-impact AI applications and align their innovation and investment strategies with the latest technological trends. At the policy level, the study offers valuable insights into global research patterns, leading contributors, and collaboration networks. These insights support policymakers in formulating informed strategies, promoting international partnerships, and strengthening digital infrastructure and skill development initiatives for AI adoption.

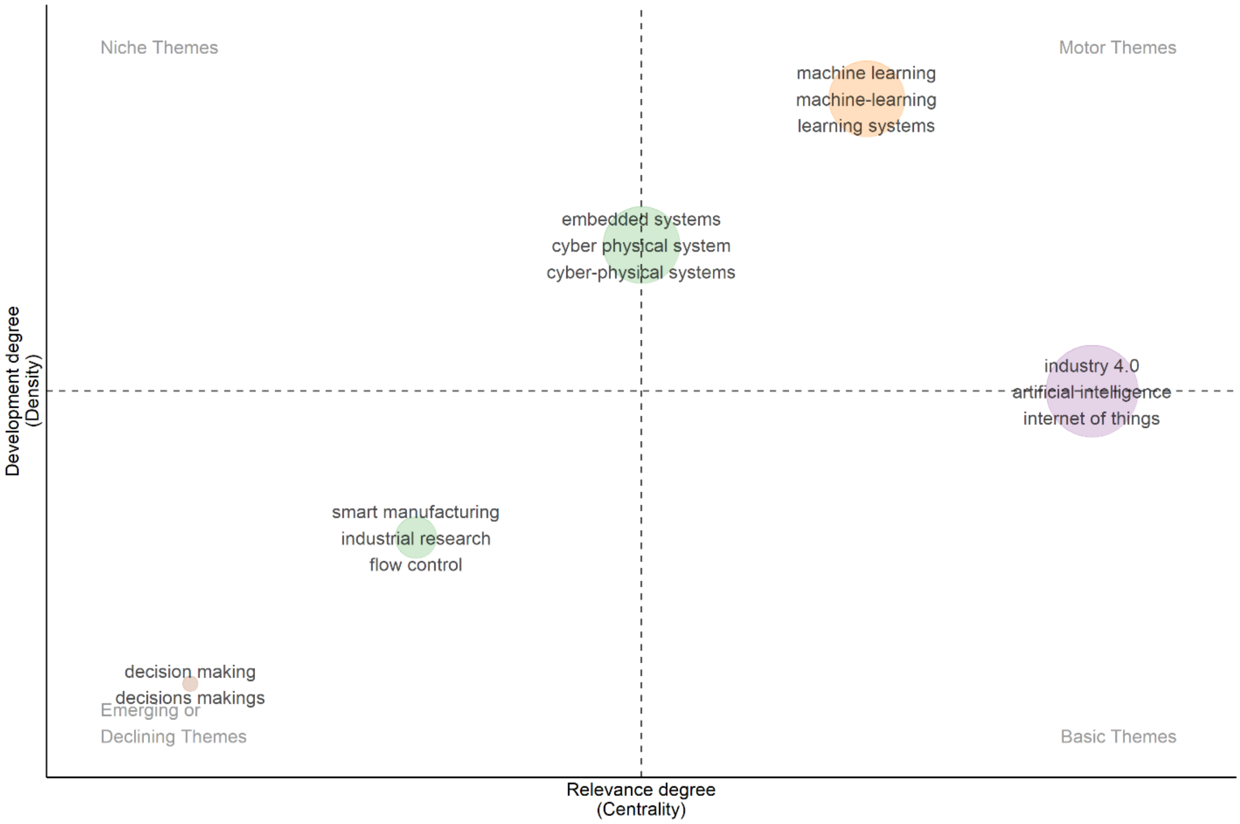

Fig.13. Time slice 3 (2021-2023)

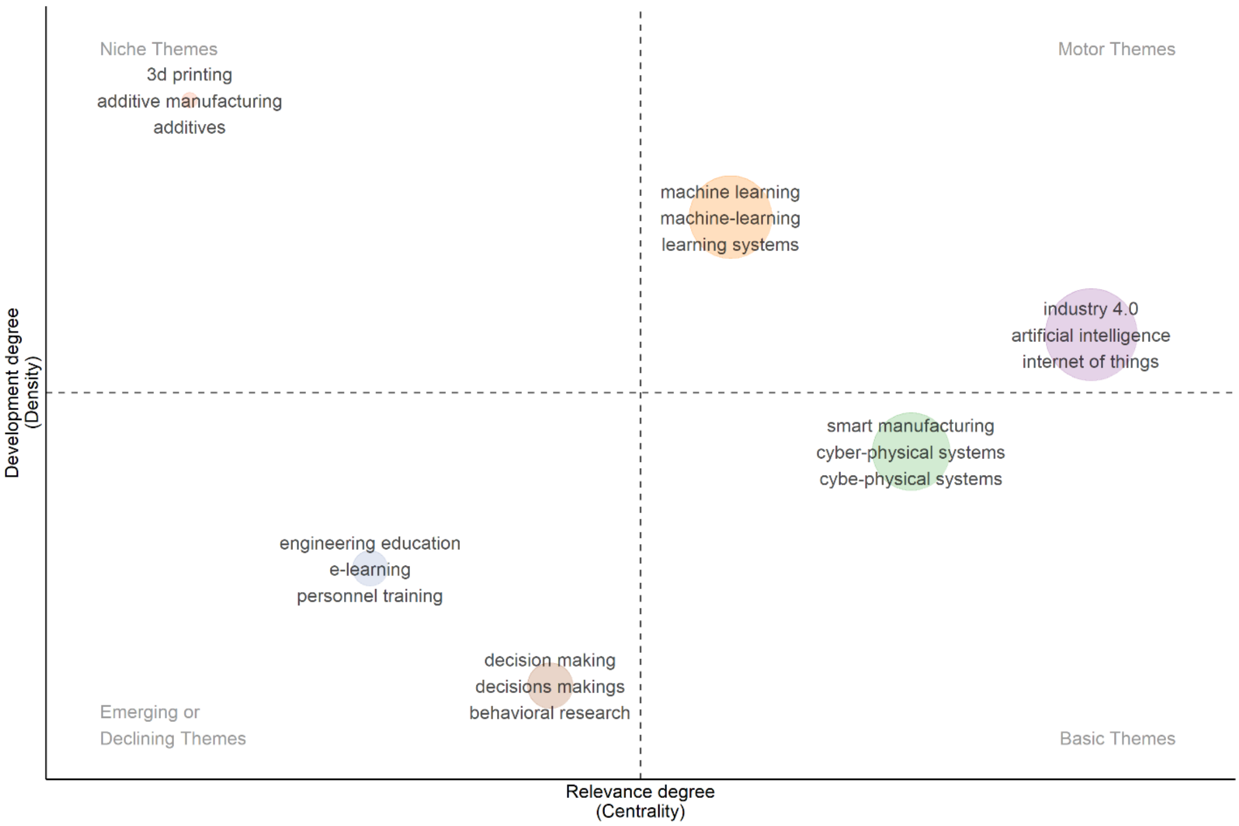

Fig. 14. Time slice 4 (2024-2026)

7. Limitations and Future Scope

It is imperative to note that the validity of the findings presented in this research study is restricted by multiple factors. The analysis relies on Scopus data, yet it omits many industry publications. The method used to identify publications via the search query proved to be incomplete, as it was susceptible to missing relevant research material. The utilization of publication count data and citation frequency indicators in this research may not yield a comprehensive evaluation of research impact or quality. The examined publications herein cover the years 2013-2026, though it is acknowledged that these trends may shift over time. The evaluation of keywords alongside research themes can be influenced by individual interpretations and the researcher's personal perspective.

It is recommended that future research should centre on the findings established in this study. Research analysis might be improved by extending the database evaluation to include Web of Science and Google Scholar to gain a broader perspective on the research field. A qualitative review of Industry 4.0 research materials enables a comprehensive understanding of AI research approaches, investigative results, and the practical consequences of Industry 4.0 applications. It is important that future research should quantify the influence of AI on the economic, social, and environmental effects during Industry 4.0 operations. The ethical ramifications of AI within Industry 4.0 warrant further research attention because it poses privacy risks, algorithmic bias, and workforce displacement.

8. Conclusion

This present paper presents a comprehensive, evidence-based bibliometric review of AI research pertaining to the Industry 4.0 domain. The identification of key publications, contributors, and thematic trends was facilitated. The results suggest that a small number of highly cited works, especially those by Lee J. and Kao H.A., have played a formative role in shaping the field, with leading institutions and authors continuing to drive knowledge production. The current global interest is reflected in the consistent increase in publications from 2013 to 2026, as well as in the high contributions from countries such as the United States, India, the United Kingdom, and Germany. Using both keyword and thematic analysis, it becomes clear that there is a transition towards foundational concepts and more integrated, data-based, and application-oriented AI systems. The findings indicate that technological convergence and industrial demand are the major drivers of AI growth in Industry 4.0; however, the observed influences in areas such as manufacturing and healthcare are indicative rather than universally generalisable. In summary, the study can serve as a systematic source of knowledge for researchers, industry professionals, and policymakers, as it identifies key trends, factors, and research gaps. The study further highlights the imperative for future studies to prioritize ethical AI, sustainability, and interdisciplinary integration, while also acknowledging the necessity of a comprehensive and systematic bibliometric approach.

Declaration of Competing Interest

The authors affirm that they have no known financial conflicts of interest or personal relationships that could have influenced the research presented in this paper.

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