

Review

The Integration of Additive Manufacturing into Industry 4.0 and Industry 5.0: A Bibliometric Analysis (Trends, Opportunities, and Challenges)

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Abstract: This bibliographic analysis explores the evolving landscape of additive manufacturing (AM) in the context of Industry 4.0 and the emerging paradigms of Industry 5.0. This research critically examines the key literature and scholarly works to clarify the evolution, challenges, and opportunities presented by integrating AM technologies with digital transformation and advanced industrial practices. The exploration begins by tracing the foundational concepts of Industry 4.0, emphasizing the role of cyber–physical systems, data analytics, and automation in reshaping manufacturing ecosystems. It then moves to the developments of Industry 5.0, focusing on human-centric approaches, collaborative robotics, and sustainable manufacturing strategies that extend beyond automation. The impact of AM technologies across various sectors, from aerospace and automotive industries to healthcare and consumer goods, is central to this analysis. This article synthesizes empirical studies, case analyses, and theoretical frameworks to discern the synergies, challenges, and prospects of integrating AM into Industry 4.0 and the evolving Industry 5.0. Through this bibliographic journey, readers gain insights into the transformative potential of AM as a catalyst for innovation, agility, and sustainability in the digital age. The findings underscore the need for interdisciplinary collaborations, policy frameworks, and technological advancements to harness AM's full potential within Industry 4.0 and 5.0.

Keywords: additive manufacturing; Industry 4.0; Industry 5.0; artificial intelligence; bibliometric; Scopus; Web of Science



Academic Editor: Antonio J. Marques Cardoso

Received: 25 November 2024

Revised: 11 January 2025

Accepted: 13 January 2025

Published: 16 January 2025

Citation: Dehghan, S.; Sattarpanah Karganroudi, S.; Echchakoui, S.; Barka, N. The Integration of Additive Manufacturing into Industry 4.0 and Industry 5.0: A Bibliometric Analysis (Trends, Opportunities, and Challenges). *Machines* **2025**, *13*, 62.

<https://doi.org/10.3390/machines13010062>

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1. Introduction

Additive manufacturing (AM), or 3D printing, has revolutionized the manufacturing industry by enabling the creation of intricate designs with exceptional precision, which traditional methods like machining and casting cannot achieve [1,2]. This has opened new possibilities for industries such as the aerospace, automotive, and healthcare sectors. For example, in the aerospace industry, GE Aviation uses AM to produce fuel nozzles for jet engines, which are 25% lighter and five times more durable than those made through traditional manufacturing methods. The capabilities of AM have significantly contributed to more efficient production and design processes, especially when combined with digital technologies. AM's primary advantage is its ability to create complex geometries, offering

designers unprecedented freedom to push the boundaries of innovation [3]. The automotive industry exemplifies this by using AM to design and produce lightweight components, such as the lattice structures in Porsche's 3D-printed car seats, reducing vehicle weight without compromising strength. Additionally, AM has transformed the prototyping phase, reducing lengthy and costly cycles. Companies like Ford have leveraged AM to rapidly prototype vehicle parts, significantly shortening the time to market and reducing prototyping costs by over 50% [4,5]. Moreover, AM facilitates mass customization by enabling on-demand production, tailored to individual needs. Nike, for instance, produces customized soles for its shoes using AM, which allows for unique, personalized designs. Traditional manufacturing often relies on economies of scale, resulting in standardized products. In contrast, AM only produces what is necessary, reducing waste and improving customer satisfaction [6–8]. This shift towards customized, on-demand manufacturing is a key driver of AM's rapid adoption. The global market for AM is projected to reach \$35.6 billion by 2024, fueled by advancements in materials, processes, and applications [9–11]. The adoption of AM is expanding across various industries, including aerospace, automotive, healthcare, and consumer goods, highlighting its increasing relevance and potential for future growth [11,12]. AM is increasingly adopted across industries such as aerospace, automotive, healthcare, and consumer goods sectors, demonstrating broad relevance and potential. For example, in healthcare, 3D printing is used to produce personalized implants and prosthetics, helping to improve patient outcomes. Beyond production, AM is reshaping supply chain dynamics and business models by enabling decentralized production and reducing lead times. Companies like Adidas and IKEA have adopted localized AM to reduce their reliance on centralized factories, thus improving supply chain efficiency and flexibility. As industries continue to integrate AM, its transformative potential promises significant advancements, driving future innovation, promoting sustainability, and leading to disruptions in manufacturing [13–16].

While Industry 4.0 focuses on automation and integrating digital technologies, it tends to prioritize machine efficiency over human involvement. A major limitation of Industry 4.0 is the potential dehumanization of the workforce. In highly automated environments, like automotive manufacturing, robots handle tasks such as assembly, but this can lead to reduced job opportunities for humans. Industry 5.0 addresses this limitation by emphasizing human–machine collaboration. Unlike traditional automation, where machines replace human labor, Industry 5.0 values the complementary strengths of both humans and machines. Collaborative robots (cobots) assist human workers with physically demanding or repetitive tasks, allowing them to focus on more complex problem-solving and innovation.

A prime example of this shift is the integration of cobots into BMW's production lines, where robots assist workers with heavy lifting or repetitive tasks, allowing humans to focus on more complex activities. This collaborative approach enhances productivity and job satisfaction by retaining meaningful human roles. Moreover, Industry 5.0 fosters innovation through human creativity, recognizing that breakthroughs come from combining human insight with machine precision. In the fashion industry, for example, designers use additive manufacturing (AM) technologies in Industry 5.0 to create customized clothing and accessories, optimized for both performance and manufacturability. AI-driven design optimization reduces material waste by up to 30%, and rapid prototyping shortens design cycles by about 40%, demonstrating the benefits of this collaboration.

Industry 5.0 encourages a more holistic approach, where human creativity and machine precision complement each other. By balancing automation with human-centered approaches, Industry 5.0 aims to create sustainable and resilient manufacturing systems that prioritize worker well-being while improving productivity and fostering innovation. The core of Industry 5.0 lies in the harmony between machines, humans, values, tasks, and

knowledge, resulting in personalized products and services. It places worker well-being at the center of the manufacturing process, respects the planet's boundaries, and aims to achieve societal goals beyond jobs and economic growth. Industry 5.0 strives for sustainable development, creating a super-smart society with ecological values, and is becoming a resilient provider of prosperity.

By integrating digital technologies and emphasizing human–machine collaboration, Industry 4.0 and Industry 5.0 together address the challenges of modern manufacturing, aiming for more intelligent, efficient, and sustainable industries. The complementary nature of both paradigms highlights their combined impact on the future of manufacturing.

The introduction of Industry 4.0 and the emerging concept of Industry 5.0 have revolutionized industrial processes, transforming manufacturing with new technologies and ideas. Industry 4.0, the Fourth Industrial Revolution, integrates digital technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data into manufacturing systems, enhancing automation, data exchange, and real-time communication between machines [17,18]. This integration creates smarter, more interconnected factories, improving operational efficiency, predictive maintenance, and agile production systems that adapt quickly to market demands [9,11,19]. By optimizing production processes, minimizing waste, and improving product quality through AI-driven decision-making, Industry 4.0 boosts manufacturing performance [20]. It also focuses on sustainability by optimizing resource and energy consumption across the entire value network, improving efficiency and environmental performance throughout the product lifecycle [17,18,21–26].

However, the rapid adoption of these technologies has raised concerns about the dehumanization of work in automated systems, impacting workers, society, and governments [21,26–28]. In response, Industry 5.0 emphasizes human–machine collaboration, shifting from automation-focused approaches to a model that values human creativity, problem-solving, and innovation [29–31]. Industry 5.0 envisions a future where technology augments human abilities rather than replacing them, fostering more meaningful work experiences. Collaborative robotics (cobots), a key feature of Industry 5.0, enhances productivity and safety by combining the strengths of humans and machines [32–35]. This approach supports the development of more sustainable, resilient, and human-centered manufacturing systems [36–39]. Industry 5.0 ensures that humans remain at the core of innovation and process optimization while balancing technological advancements with human skills [40–44].

As shown in Figure 1, while Industry 4.0 focuses on automation and the integration of digital technologies, it tends to prioritize machine efficiency over human involvement. A major limitation of Industry 4.0 is the potential dehumanization of the workforce. In highly automated environments, like automotive manufacturing, robots handle tasks such as assembly, but this can lead to reduced job opportunities for humans. Industry 5.0 addresses this limitation by emphasizing human–machine collaboration [45,46]. Unlike traditional automation, where machines replace human labor, Industry 5.0 values the complementary strengths of both humans and machines [46]. Collaborative robots (cobots) assist human workers with physically demanding or repetitive tasks, allowing them to focus on more complex problem-solving and innovation.

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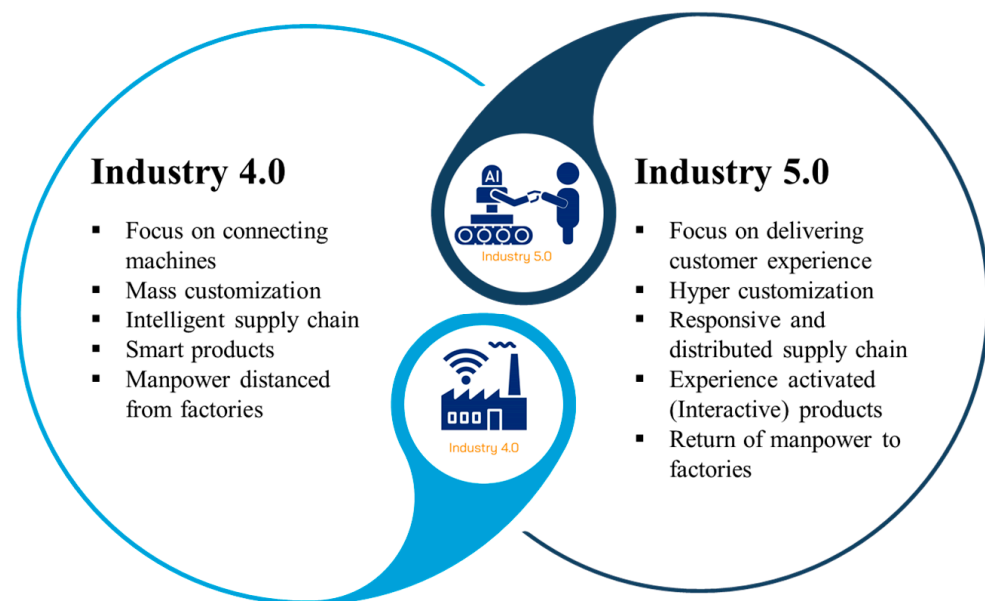


Figure 1. Highlights of Industry 4.0 and Industry 5.0 [17,29].

Industry 5.0 encourages a more holistic approach, where human creativity and machine precision complement each other [47]. By balancing automation with human-centered approaches, Industry 5.0 aims to create sustainable and resilient manufacturing systems that prioritize worker well-being while improving productivity and fostering innovation. The core of Industry 5.0 lies in the harmony between machines, humans, values, tasks, and knowledge, resulting in personalized products and services. It places worker well-being at the center of the manufacturing process, respects the planet's boundaries, and aims to achieve societal goals beyond jobs and economic growth. Industry 5.0 strives for sustainable development, for the creation of a super-smart society with ecological values, and to become a resilient provider of prosperity [48,49].

AM is a key player in the opportunities presented by Industry 4.0 and Industry 5.0. It offers transformative capabilities that align with the core principles of these industrial paradigms [50,51]. AM becomes part of smart manufacturing when it integrates digital technologies, real-time monitoring, data-driven optimization, connectivity, customization, predictive maintenance, and human–machine collaboration. This ensures that AM processes are efficient, adaptable, and aligned with smart manufacturing. Smart manufacturing uses IoT, AI, big data, and cyber–physical systems (CPS) to optimize production, enhance productivity, and improve quality. AM, or 3D printing, is integral to this system, enabling precise and customized production. Figure 2 highlights the advantages of integrating Industry 5.0 with AM over Industry 4.0, with improved efficiency, precision, human roles, customization, sustainability, and innovation. Industry 5.0 introduces human-centric collaboration, enhancing AM's potential in modern manufacturing.

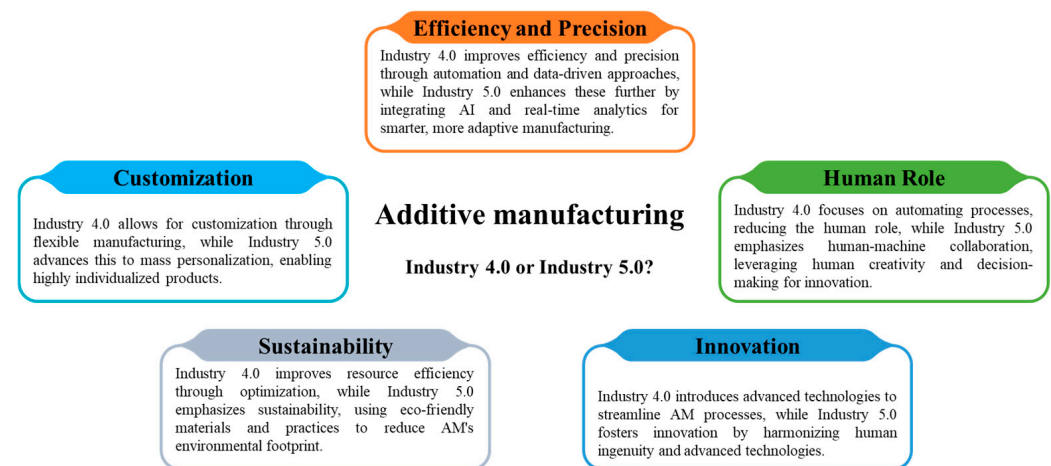


Figure 2. Implementation of AM in Industry 4.0 and 5.0.

AM leverages digital design tools such as Computer-Aided Design (CAD) to create complex and customized designs. Smart manufacturing utilizes data analytics and AI to optimize these designs in terms of performance and manufacturability. Digital twins simulate and optimize AM processes, predicting and mitigating potential issues to ensure higher quality and efficiency [52,53]. In smart manufacturing, IoT sensors and advanced monitoring systems continuously collect data during the AM process [34]. This real-time monitoring enables the immediate detection of anomalies, ensuring high-quality outputs. Adaptive control systems can adjust AM parameters on the fly based on real-time data, ensuring consistent quality and reducing material waste [34]. Smart manufacturing integrates AM into the broader supply chain, enabling just-in-time production and reducing inventory costs [41]. Distributed manufacturing networks use AM to produce parts closer to the point of use, reducing lead times and transportation costs while enhancing supply chain responsiveness. Additionally, the optimize resource usage, improve energy efficiency, minimize waste, and reduce the environmental footprint. Lifecycle management tracks the entire lifecycle of additively manufactured products, ensuring sustainable practices from raw material usage to end-of-life recycling. AM's ability to produce customized parts is enhanced by smart manufacturing's data-driven approach, which manages production for individualized products at scale. Customer feedback is integrated into the design and production process, allowing for rapid iteration and improvement [41]. Leveraging AI and big data, smart manufacturing predicts when AM equipment requires maintenance, reducing downtime and extending the machinery's lifespan. Advanced analytics and machine learning ensure continuous quality control, reducing defects and improving overall product quality. This synergy accelerates prototyping, speeds up innovation cycles, and reduces the time to market for new products [19,27,54]. Smart manufacturing platforms enable collaboration across teams and locations, integrating AM to develop new products more efficiently. By incorporating digital technologies and emphasizing human-machine collaboration, smart manufacturing and AM address modern manufacturing challenges [55]. This combination drives innovation, efficiency, and sustainability, creating a smarter, more sustainable industry. AM has revolutionized how we design and produce objects, enabling rapid prototyping, complex geometries, and on-demand production. Industry 5.0 elevates this transformation by prioritizing human-centric collaboration with intelligent technologies, moving beyond the automation focus of Industry 4.0 [44,56].

Figure 3 illustrates the interplay between additive manufacturing (AM), Human-Centric Technologies (HCTs), and Environmental Sustainability (ES) within the framework of Industry 5.0. Positioned centrally, Industry 5.0 acts as the integrative platform that con-

nects and enhances these elements. It emphasizes the harmonious coexistence of advanced manufacturing technologies with human skills and environmental stewardship. By integrating AM, HCTs, and ES, Industry 5.0 fosters a holistic approach to manufacturing, where technological advancements align with human well-being and ecological preservation. This approach aims to create a more innovative, efficient, and sustainable manufacturing environment. Industry 5.0 empowers AM to embrace mass customization, with localized manufacturing hubs producing parts based on real-time customer needs. This reduces lead times and inventory costs, and opening possibilities for the development of innovative products with personalized features. AI-powered design optimization within Industry 5.0 enhances AM capabilities by analyzing extensive datasets, including design parameters, material properties, and printing process data. This enables designers to create lighter, stronger, and more efficient parts, tailored to specific printing processes. Industry 5.0 also integrates AM into the broader manufacturing ecosystem. Real-time production data from other machines inform the AM process, enabling adjustments to printing parameters based on upstream production variables. This integration ensures seamless operations and avoids bottlenecks. Predictive maintenance, powered by sensor data, identifies potential equipment failures, minimizing downtime and ensuring consistent production quality. Automated post-processing workflows reduce human error and increase efficiency. The vast quantities of data generated throughout the AM process, from design to printing and post-processing, provide valuable insights into Industry 5.0. Advanced analytics detect anomalies, optimize printing parameters, and predict the remaining lifespan of printed parts, allowing for preventative maintenance or replacement planning. Industry 5.0 fosters mass customization by utilizing real-time customer data and AI-powered tools to produce customized parts on demand, reducing lead times and inventory costs while enabling innovative product offerings. While Industry 5.0 introduces significant automation and intelligent decision-making, the human element remains crucial. AM specialists are essential in areas like advanced design expertise, material mastery, quality control, and strategic planning. Their creativity, understanding of design principles, and innovation drive the boundaries of technology, leading to the exploration of new applications across diverse industries and the development of new business models. Cross-industry collaboration enables AM specialists to bridge gaps and revolutionize various fields. The combination of AM and Industry 5.0 has the potential to redefine how goods are manufactured [41,56,57]. For example, lightweighting to enhance performance can improve aviation efficiency, with aircraft components designed and printed through AM with AI optimization. In healthcare, personalized medical solutions like custom implants and prosthetics can improve patient outcomes. On-demand parts and supply chains, utilizing localized AM, can streamline supply chain efficiency, eliminating the need for large inventories and ensuring critical parts are readily available. Sustainable production can be achieved by optimizing printing processes and material usage and using renewable energy and recycled materials. Traditional manufacturing constraints are broken, empowering designers to create complex, organic shapes and intricate internal structures that were previously impossible. As AM and Industry 5.0 continue to evolve, groundbreaking innovations are expected to redefine manufacturing, personalize products, and usher in a new era of sustainable, efficient production.

Conducting a bibliometric analysis to connect AM with Industry 4.0 and 5.0 is vital for various reasons. This analysis aids in identifying research trends, collaboration networks, and crucial areas of innovation, offering comprehensive insights into the intersections and developments of these technologies. While existing bibliometric studies, such as that of Krishna et al. on AM [15], Kumar et al. [59] on AI, and Bibby and Dehe on Industry 4.0 [60], emphasize increasing research interest and potential advancements, there exists a gap in

the literature that focuses specifically on the amalgamation of AM with Industry 4.0 and 5.0. This underscores the necessity for further exploration in this domain.

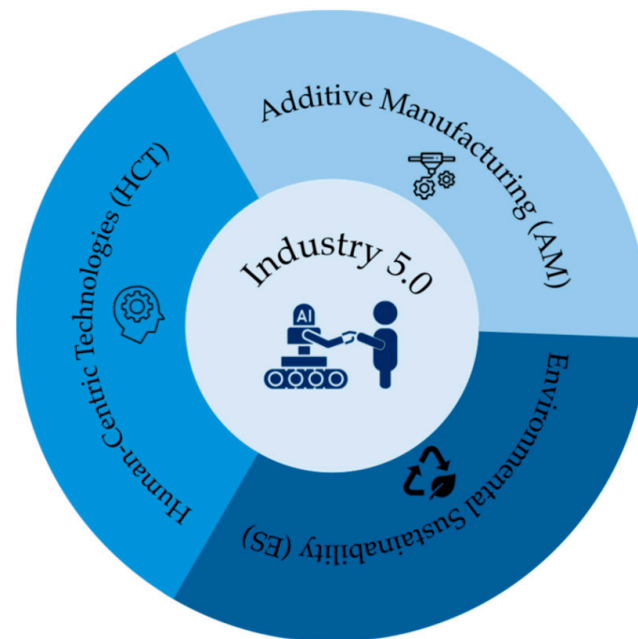


Figure 3. Relationship between AM and Industry 5.0 [58].

This bibliometric analysis aims to provide a comprehensive overview of the research surrounding AM in the context of Industry 4.0 and 5.0. By using bibliometric indicators and analytical techniques, this study aims to uncover key trends, influential works, and emerging themes in the field. The findings of this analysis will provide valuable insights for researchers, industry practitioners, policymakers, and other stakeholders interested in understanding the evolution, impact, and future directions of AM in the era of Industry 4.0 and 5.0. Furthermore, this study lays the groundwork for further research and exploration in areas that are critical for advancing knowledge and innovation in advanced manufacturing technologies.

The main contributions of this work include the following:

- Detailed insights into AM's potential within Industry 4.0 and 5.0.
- Analysis of publication trends, citation patterns, and keyword clusters to identify current research topics in AM.
- The identification of collaboration networks among researchers, institutions, and countries, fostering knowledge exchange and expertise sharing.
- Citation analysis to assess the impact of research, recognizing seminal works and influential authors.
- The identification of emerging technologies and innovative approaches within AM, helping stakeholders to prioritize investments and anticipate market trends.

AM, also known as 3D printing, began to be developed in the late 20th century [61]. Charles Hull's invention of stereolithography (SLA) in 1986 was a significant milestone, enabling the creation of 3D objects by curing photopolymer resin with ultraviolet light [62]. Hull established 3D Systems, a key player in the industry. Similarly, Carl Deckard developed Selective Laser Sintering (SLS), while Scott Crump patented fused deposition modeling (FDM), leading to the formation of Stratasys [63–65]. During the 1990s, AM gained traction, especially in rapid prototyping, shortening product development cycles and impacting industries like the aerospace, healthcare, and automotive sectors [66]. In the 2000s, AM made advances with the introduction of materials such as metals and ceramics,

expanding its applications for high-performance parts, including the development of technologies like Direct Metal Laser Sintering (DMLS) and Electron Beam Melting (EBM) [66]. In the 2010s, AM was integrated with Industry 4.0, merging IoT, big data, and artificial intelligence (AI) to create intelligent manufacturing systems that facilitated real-time monitoring, predictive maintenance, mass customization, and on-demand production. The rise of hybrid manufacturing, combining AM with traditional methods, further enhanced material properties and design complexity [57,67,68].

Industry 4.0, also known as the Fourth Industrial Revolution, integrates digital technologies such as cyber-physical systems, IoT, AI, and big data into manufacturing processes, creating more efficient, accurate, and customized production systems [69–71]. By 2013, Industry 4.0 had revolutionized global manufacturing, improving efficiency and supply chain management. The emergence of Industry 5.0 in the late 2010s addressed the limitations of automation by focusing on human-machine collaboration, sustainability, and resilience. Industry 5.0 advocates for the symbiosis of human creativity and machine precision, ensuring that technology complements rather than replaces human capabilities [28,33,57,72,73]. This shift aims to create sustainable manufacturing systems that reduce waste, enhance energy efficiency, and adapt to changing market demands. AM plays a pivotal role in the opportunities offered by both Industry 4.0 and 5.0, aligning with their core principles [27,41,42,53,55,74,75].

Additive manufacturing (AM) has significant potential for integration with Industry 4.0 and 5.0 [41,52,53,76]. The integration of AM with Industry 4.0 supports real-time monitoring, predictive maintenance, and mass customization, while Industry 5.0 enhances these capabilities by prioritizing human-machine collaboration and sustainable manufacturing practices. However, to fully realize the synergies between AM, Industry 4.0, and 5.0, further interdisciplinary research is needed to drive innovative, human-centric manufacturing solutions. As AM continues to evolve, its integration with these industrial paradigms will propel transformative advancements, leading to a more sustainable, efficient, and personalized manufacturing future.

2. Materials and Methods

2.1. Data Processing

A research study was conducted on AM and Industry 4.0 and 5.0 articles published from 2005 to 2024. The two largest web bibliometric databases, WOS and Scopus, were used for this research. To identify relevant studies, a variety of terms, outlined below, were used interchangeably for Industry 4.0 or as a component of it while performing searches in WOS and Scopus.

TITLE-ABS-KEY (((“industry 4.0” OR “industry 5.0” OR “Fourth Industrial Revolution” OR “five Industrial Revolution” OR “smart factory” OR “smart factories” OR “smart technology” OR “smart technologies” OR “smart manufacturing” OR “smarter manufacturing” OR “intelligent factory” OR “intelligent factories” OR “intelligent manufacturing” OR “internet of things” OR “cyber-physical system” OR “ubiquitous factories” OR “real-time factories” OR “ubiquitous manufacturing” OR “real-time manufacturing” OR “factory-of-things”) AND (“Additive manufacture” OR “3D printing” OR “3-D printing” OR “rapid prototyping and/or manufacturing”))) AND (LIMIT-TO (DOCTYPE, “ar”) OR LIMIT-TO (DOCTYPE, “cp”) OR LIMIT-TO (DOCTYPE, “re”) OR LIMIT-TO (DOCTYPE, “cr”)) AND (LIMIT-TO (LANGUAGE, “English”)).

2.2. Analysis Procedure and Software

To conduct a bibliometric analysis, we followed the steps of Zupic and Čater (2015) [77]. This methodology has been used by several scholars (e.g., Köseoglu et al., 2019) [78] and

consists of five steps: (1) study or research design, (2) data collection, (3) data analysis, (4) data visualization, and (5) result interpretation.

In this study, we used the evaluative approach as well as the relational approach to assess the intellectual and conceptual structures of AM in the era of Industry 4.0 and 5.0. The evaluative approach explores the authors, papers, journals, institutions, and countries with the greatest influence in conceptual research on AM in the era of Industry 4.0 and 5.0. This study only uses common analysis in the descriptive analysis of the selected database. We established the intellectual structure using co-citation analysis. This method assesses the similarity between authors, journals, or articles [77]. For example, author co-citations refer to the phenomenon in which two authors are cited jointly in one article. This study uses the author's keyword frequency and co-occurrence to assess the conceptual structure. Co-occurrence, also labeled co-word analysis, reveals the closest keywords or topics through clusters in a field [79].

To analyze and visualize our data, we used multiple methods and three software applications. The descriptive analysis, including the most productive authors and other indicators, was performed by using Notepad ++ (8.5.5) and the Bibliometrix package of R software (4.0.0) [80]. To accomplish the co-citation analysis, we used the VOSviewer software (1.6.18) [81]. This popular software for network mapping is largely used in bibliometric analysis. To deeply analyze the conceptual structure of the FL concept in the B2B literature, we also performed a multidimensional analysis in the Bibliometrix package of R software.

3. Results

Table 1 presents general information about the total number of publications, the type of articles, the number of articles after considering the filter for article type before and after removing duplicates, and the total number of publications in SCOPUS and WOS. As can be observed, the selected articles are research articles, proceedings papers, conference papers, and review papers. It is also illustrated that the number of publications in the SCOPUS database is greater than in the WOS database.

Table 1. General information about publication selection.

Number	SCOPUS	WOS
	2496	1954
Type	Article, proceedings paper, conference paper, review	
Number, after filtering by type (Before removing duplication)	2124	1903
Number, after filtering by type (After removing duplication)	1485	1366
In total, after filtering by type	2851	

As can be observed from Table 2, the timespan for this work is from 2005 to 2024. Overall, 1290 and 2851 sources (journals, etc.) and other documents were obtained, respectively. Within this period, the annual growth rate of publication number was 31.58%. This means that this area became more interesting for researchers year on year, from 2005 to month 4 of 2024. Another important parameter, presented in Table 2, is the document's average age, which is 3.21. This parameter shows that the publications in this area were mostly published recently, and it confirms that this topic is interesting for researchers. Moreover, it is presented that the parameter of the average citation per document is about 15.6, which

means that significant attention has been paid by other researchers to works published in this area. The last parameter presented in Table 1 is the number of references, which is 117,470. This is very high and indicates interest. From the data presented in this table, it can be seen that, with the approaches of Industry 4.0 and 5.0, the field of AM has become very interesting, and since Industry 5.0 is a new area, there is great potential to research this topic. Analyzing both Author Keywords and Keywords Plus allows researchers to gain a comprehensive view of the research landscape. Author Keywords provide a focused view of the specific research topics and trends perceived by the researchers. On the other hand, Keyword Plus offers a broader, context-rich perspective, highlighting related fields and broader themes. By combining the analysis of both, researchers can reveal the alignment or discrepancies between their intended focus and the broader contextual themes, providing a deeper understanding of the impact of the research and its interdisciplinary connections. A higher average number of authors per paper often indicates a trend towards collaborative research. This can reflect the interdisciplinary nature of the field, where diverse expertise is required to address complex problems. On the other hand, a higher proportion of single-authored documents might suggest that the field supports or necessitates individual research efforts. It may also reflect the presence of highly specialized subfields where individual expertise predominates. In this case, the many differences between these parameters clearly show that this area has a significant potential for collaboration between a wide range of researchers with different backgrounds. In the following, the author's collaboration section also confirms the potential of this topic for promoting collaboration among different researchers.

Table 2. Main information for AM and Industry 4.0 and 5.0 from SCOPUS and WOS databases.

Description	Results
Timespan	2005:2024
Sources (journals, books, etc.)	1290
Documents	2851
Annual growth rate %	31.58
Document average age	3.21
Average citations per doc	15.57
References	117,470
Document contents	Results
Keywords plus (ID)	9531
Author's keywords (DE)	6860
Authors	Results
Authors	8246
Authors of single-authored docs	178
Authors collaboration	Results
Single-authored docs	197
Co-authors per doc	4.06
International co-authorships %	11.36

Figure 4 presents the trend for the number of annual publications from 2005 to month 4 of 2024. In the initial decade, the number of articles remained relatively stable, with only slight increases. This suggests a period of steady-state or minimal growth in article production. This could be due to consistent demand and supply factors, technological stability, or market saturation. The trend in this graph can be divided into three milestones, which are rapid growth (2015–2021), continued growth (2021–2023), and stabilization (2023–2025). Post-2015, there was a steep increase in the number of articles. This steep rise

could indicate several factors, such as increased demand for information, technological advancements in publishing, or a significant event driving the need for more articles. The peak around 2021 suggests a climax in these factors. From 2021 to 2023, the number of articles continued to increase, maintaining the growth trend observed earlier. This period showed a continued upward trajectory, consistent with the growth function model used to forecast 2023–2025. The red grape trendline indicates that the increase in articles is likely to persist, driven by factors such as technological developments, research advancements, or growing industry demand for publications. The trendline could have various implications, including technological impact, market dynamics, and economic and political factors. The rapid growth phase might suggest that the adoption of new technologies made article production easier or more necessary. In addition, the sharp upward trend confirms the interest in smart AM for researchers and industries' demands in this area. On the contrary, the primary cause for the decline, starting in 2023, may be rectified with data collected from 2005 through April 2024.

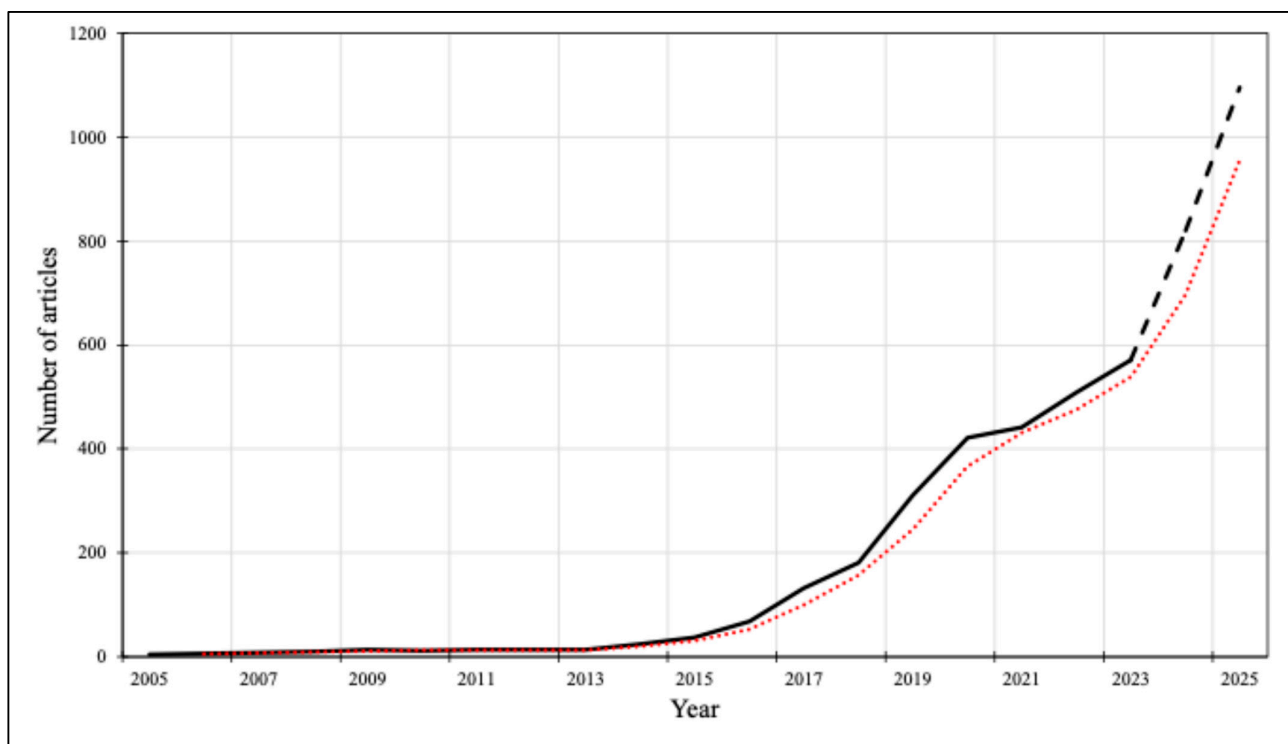


Figure 4. Annual publication trend for Industry 4.0 and 5.0 in AM technology; retrieved from SCOPUS and WOS.

Table 3 shows the most productive authors in the fields of AM and Industry 4.0 and 5.0, as determined by various bibliometric indices. The authors are ranked based on their productivity and the citation impact of their published work.

The h-index measures both the productivity and citation impact of the publications by a scholar. Specifically, a researcher has an index of h if they have h papers, each of which has been cited at least h times. For example, an h-index of 20 means the researcher has 20 papers that have each been cited at least 20 times. This metric helps to evaluate the consistency of the impact of an author's work, rather than just counting their highest number of citations.

The g-index is an enhancement of the h-index, aimed at giving more weight to highly cited articles. A scientist has a g-index of g if g of their articles has together received at least g^2 citations. This index improves on the h-index by recognizing that one highly

influential paper can accumulate many more citations than other papers by the same author. It provides a more sensitive measure of a researcher's output impact.

Table 3. Most productive authors in AM and Industry 4.0 and 5.0.

Authors	Affiliation	h_Index	g_Index	TC	NP	PY_Start
Tentzeris MM	Georgia Institute of Technology, USA	13	22	501	23	2015
Kumar S	Symbiosis Institute of Technology, India	12	16	670	16	2018
Zhang Y	University of Zhengzhou, China	12	22	636	22	2017
Haleem A	National Islamic University, India	11	19	638	19	2019
Bahr R	Georgia Institute of Technology, USA	10	14	397	14	2015
Javid M	National Islamic University, India	10	16	510	16	2019
Li Y	University of Liaoning, Shenyang, China	10	14	232	28	2017
Basit Aw	University of UCL, UK	9	14	542	14	2021
Chhetri SR	Palo Alto Networks, Santa Clara, CA, USA	9	10	344	10	2016
Demir AG	University Politecnico di Milano, Italy	9	16	275	20	2020
Gaisford S	University of UCL, UK	8	10	390	10	2021
Kim N	University of Seoul, Republic of Korea	8	12	343	12	2018
Kumar A	University of London Metropolitan, UK	8	10	252	10	2017
Liu C	University of Aston, UK	8	12	150	16	2019
Liu Y	University of Cardiff, UK	8	18	408	18	2016
Zhang L	University of Finance and Economics, China	8	11	245	11	2016
Zhang Z	University of Tennessee Tech, USA	8	16	372	16	2017
Al Faruque MA	University of California Irvine, USA	7	8	301	8	2016
Beretta S	University Politecnico di Milano, Italy	7	9	281	9	2020
Chen Y	University of Technology South China, Guangzhou, China	7	9	100	14	2016

Tentzeris MM, at the top of the list, boasts an h-index of 13, indicating that he has at least 13 publications which have each been cited at least 13 times. His g-index of 22 further underscores the high citation volume of his most impactful papers. Kumar S and Zhang Y also show remarkable performances, with both maintaining an h-index of 12 and a g-index of 16 and 22, respectively. This highlights their significant contributions and the strong influence their work has in the field. The total citations (TC) column reveals the overall citation impact of the authors' work, with Kumar S leading at 670 citations, followed closely by Haleem A and Zhang Y. This indicates the broader recognition and application of their research in the field. The number of publications (NP) demonstrates the authors' research output, with Li Y leading at 28 publications. This indicates his extensive involvement in research activities and his consistent contribution to the field. The publication year start (PY_start) offers insights into the duration of the authors' active periods in this specific field. For instance, Tentzeris MM began his contributions in 2015 and has since emerged as a leading figure in a relatively short time span. This metric helps in understanding the rapid progress and impact of new entrants in the field, such as Basit Aw and Gaisford S, who only started publishing in 2021 but have already made significant impacts. This analysis highlights the prolific nature and citation impact of the authors. It also points out the dynamic evolution of the field through the contributions of both established and new researchers. These insights are critical for anyone seeking to understand the landscape of AM and Industry 4.0 and 5.0. They are important for citing influential work, seeking collaboration opportunities, or identifying focus areas and gaps in the current research. This nuanced understanding is essential for situating further studies within the ongoing scholarly conversation, thereby enhancing the relevance and contribution of subsequent research endeavors in these technologically advanced domains.

While Table 3 presents detailed information about the most productive authors in the field of additive manufacturing (AM) and Industry 4.0 and 5.0, Figure 5 visually represents the h-index values of these authors, providing a clearer understanding of their relative

impact within the field. The h-index is a key metric that quantifies both productivity and citation impact, with higher values indicating that an author has multiple highly cited publications. This graphical representation allows for a quick visual comparison of the authors' influence, highlighting the leading researchers, such as Tentzeris MM and Kumar S, whose work has achieved widespread recognition. The figure further enhances the table's data by offering a visual insight into the tiered distribution of h-index values, showing the disparities in the academic influence of these authors. This visual format is particularly helpful for readers who prefer quick, comparative assessments of the research landscape in AM and Industry 4.0 and 5.0, thus complementing the detailed information in the table.

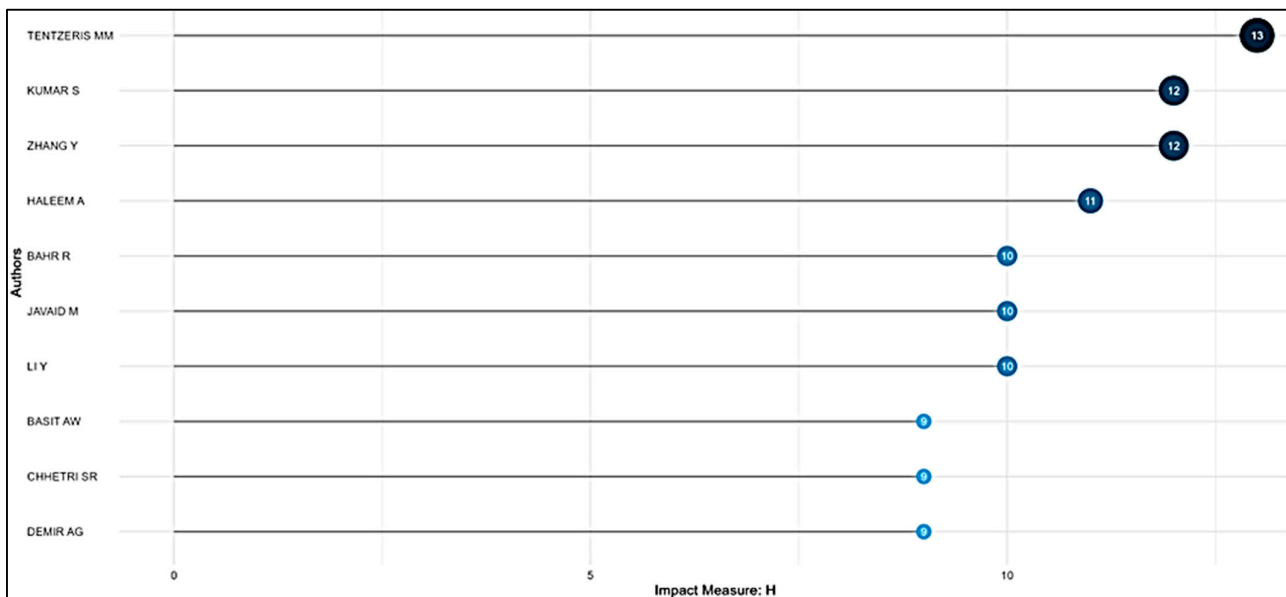


Figure 5. Authors' impact by h-index; retrieved from SCOPUS and WOS.

Figure 6 presents a timeline analysis of publication and citation activity for key authors in AM and Industry 4.0/5.0. Each author's annual publication output is shown by circles, where size indicates the number of articles published and color intensity reflects the total citations. Li Y stands out as a consistently productive author, with notable publication and citation peaks in 2021. Kumar S also saw significant activity in 2021, with multiple impactful papers and high citation impact, suggesting strong academic resonance. Tentzeris MM demonstrates steady publication, with high citation impact, especially in 2016 and 2017, indicating lasting relevance. Zhang Y's work in 2017 and 2018 shows high publication and citation levels, signaling key contributions to the field. Authors like Demir AG and Haleem A maintain consistent, though smaller, outputs, indicating ongoing research efforts. This visualization highlights shifts in publication and citation trends, offering insights for stakeholders in AM to make informed decisions on research, collaboration, and funding.

Table 4 presents a detailed analysis of academic documents, highlighting their local and global citations, along with normalized citation values. Local citations indicate how often a document is cited within a specific dataset, while global citations represent its total international impact. For instance, Al Faruque MA's 2016 document received 6 local citations and 105 global citations, showing wide recognition. Normalized citations adjust for factors like publication age and citation practices, offering a more balanced comparison across disciplines. Despite just 1 citation, Liang S's 2021 publication scored highly on the normalized local citation scale at 145.67, indicating a strong local impact. These data help researchers to identify influential works and emerging trends, with high citation counts and normalized scores highlighting key works shaping the field. The continued relevance

of older publications, like Al Faruque MA's, demonstrates their lasting influence. Overall, analyzing citation data is vital for understanding scholarly impact and helps researchers to position their work strategically within the literature.

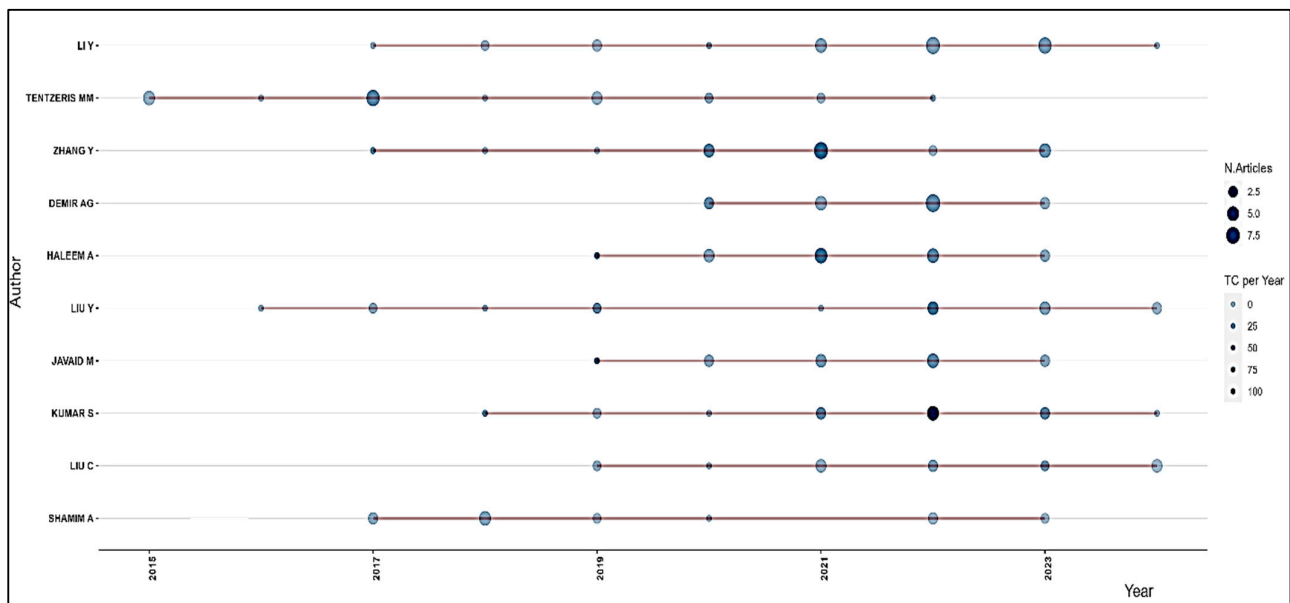


Figure 6. Key authors' production over time; retrieved from SCOPUS and WOS.

Table 4. Most cited documents in AM and Industry 4.0 and 5.0.

DOI	Year	Local Citations	Global Citations	Normalized Local Citations	Normalized Global Citations
[82]	2016	6	105	25.71	4.97
[83]	2016	5	77	21.43	3.64
[84]	2017	1	3	64.00	0.11
[85]	2019	1	2	45.14	0.08
[86]	2019	1	5	45.14	0.20
[87]	2019	1	5	45.14	0.20
[88]	2019	1	34	45.14	1.35
[89]	2021	1	1	145.67	0.06
[90]	2016	1	22	4.29	1.04
[91]	2018	1	7	58.67	0.18
[92]	2018	1	3	58.67	0.08
[93]	2020	1	4	104.75	0.19
[94]	2018	1	2	58.67	0.05
[95]	2019	1	4	45.14	0.16
[96]	2017	1	30	64.00	1.10
[97]	2020	1	7	104.75	0.33
[98]	2019	1	8	45.14	0.32
[99]	2021	1	5	145.67	0.32
[100]	2020	1	6	104.75	0.28
[101]	2020	1	2	104.75	0.09

Table 5 lists the sources of scholarly articles on manufacturing and technology, detailing the number of articles published by each source. These data help to identify the most active and influential journals and conferences in intelligent manufacturing and advanced manufacturing technologies. The *Journal of Intelligent Manufacturing* leads with 118 articles, reflecting its significant impact in the field. Next, *Lecture Notes in Mechanical Engineering* and the *International Journal of Advanced Manufacturing Technology* contribute 56 and 49 articles, respectively, focusing on mechanical engineering and manufacturing technology. Procedia

CIRP and AM, with 33 and 32 articles, highlight the importance of emerging manufacturing processes, particularly in additive manufacturing (AM). Conference proceedings like the *Proceedings of the International Conference on Physical Micromechanics* and the *30th International Conference on Flexible Automation and Intelligent Manufacturing* contribute 30 and 22 articles, emphasizing the value of conferences as platforms for innovative research. Journals like *IEEE Access* and *Sensors* reflect the interdisciplinary nature of manufacturing research, integrating electrical engineering and sensor technology. The distribution of articles across these sources showcases the diverse nature of manufacturing research, from traditional mechanical engineering to modern digital and AM techniques, positioning these journals and conferences as key resources for researchers and practitioners in the field.

Table 5. Source’s production in AM and Industry 4.0 and 5.0.

Sources	Articles
<i>Journal of Intelligent Manufacturing</i>	118
<i>Lecture Notes in Mechanical Engineering</i>	56
<i>International Journal of Advanced Manufacturing Technology</i>	49
<i>Procedia CIRP</i>	33
AM	32
<i>IEEE Access</i>	30
<i>Proceedings of the International Conference on Physical Micromechanics</i>	
<i>Materials With Multilevel Hierarchical Structure and Intelligent Manufacturing Technology</i>	30
IFAC Papers Online	28
<i>Sensors</i>	28
<i>Lecture Notes in Networks and Systems</i>	23
<i>30th International Conference on Flexible Automation and Intelligent Manufacturing</i> (Faim, 2021)	22
<i>Rapid Prototyping Journal</i>	20
<i>Polymers</i>	19
<i>Applied Sciences—Basel</i>	18
<i>Journal of Manufacturing Systems</i>	18
<i>Materials Today: Proceedings</i>	18
<i>Materials</i>	17
<i>Sustainability</i>	17
<i>Applied Sciences</i> (Switzerland)	16
<i>IOP Conference Series: Materials Science and Engineering</i>	16

Figure 7 illustrates the cumulative publication occurrences from five key journals on manufacturing and engineering from 2005 to April 2024, showing growth patterns and shifts in research focus. The graph reveals significant exponential growth in the journal AM, which began around 2016 and continued sharply through 2024, reflecting the increasing relevance of additive manufacturing (AM) in industrial applications. The *Journal of Intelligent Manufacturing* also shows a steady upward trend, starting in 2005, indicating sustained interest in intelligent manufacturing systems that incorporate AI, machine learning, and IoT. The *International Journal of Advanced Manufacturing Technology* and *Lecture Notes in Mechanical Engineering* display moderate, consistent growth, signaling ongoing contributions in mechanical engineering and manufacturing technologies. *Procedia CIRP* started later but saw rapid growth from 2012 onwards, highlighting its emerging importance in disseminating research and conference proceedings. Overall, the trends emphasize the rising significance of AM and intelligent systems, driven by technological advancements and the industrial demand for more efficient, flexible, and innovative solutions. These data provide valuable insights for researchers and practitioners in strategic decision-making for future research and technology development.

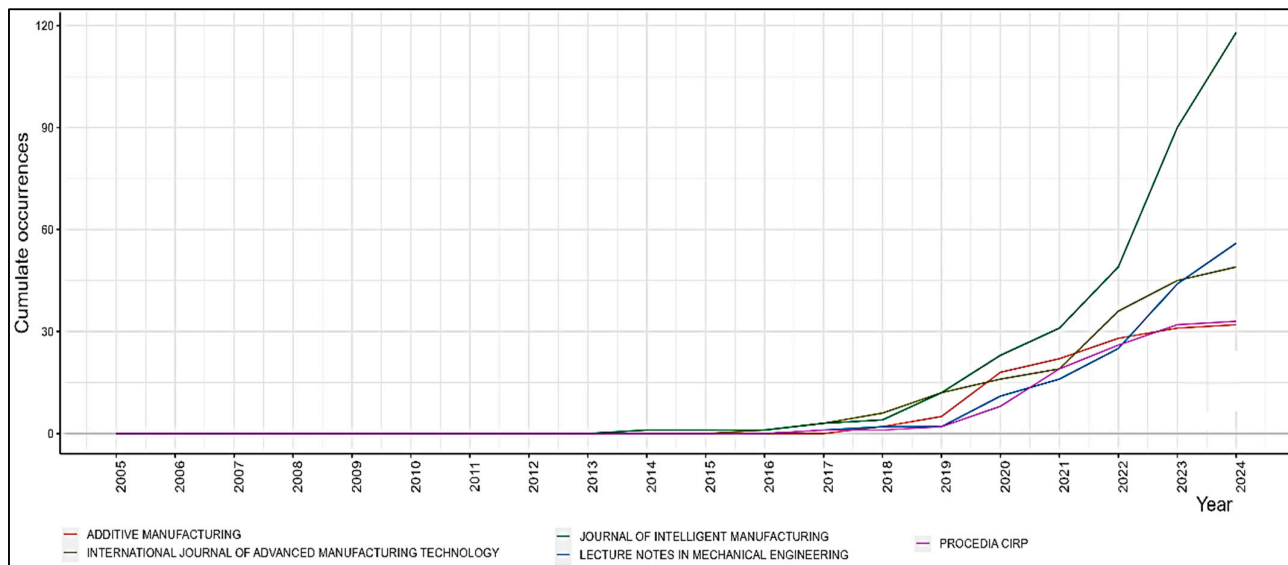


Figure 7. Key source's production over time; retrieved from SCOPUS and WOS.

Table 6 provides detailed bibliometric analysis of various journals and conferences that are influential in the field of manufacturing and technology. This analysis includes several metrics such as the h-index, g-index, total citations (TC), the number of publications (NP), and the year publication started (PY_start) for each listed source. These metrics are crucial for assessing the impact, influence, and productivity of these sources within the academic community. The *Journal of Intelligent Manufacturing* leads with the highest h-index of 26, indicating that at least 26 of its articles have been cited at least 26 times. This is complemented by a g-index of 55, suggesting that the most cited articles from this journal have received a significant number of citations, highlighting its substantial influence and established credibility in the field. AM shows a remarkable presence with an h-index of 20 and a g-index of 32, despite the fact it only started publishing more recently in 2018. Its 1299 total citations from just 32 publications indicate high citation rates per article, reflecting the current interest and rapid development within the AM sector. The *International Journal of Advanced Manufacturing Technology* also demonstrates considerable impact, with an h-index of 17 and a g-index of 29, as corroborated by 909 total citations. Starting in 2016, it has quickly become a pivotal platform for disseminating advanced manufacturing technologies. Other notable publications include *IEEE Access* and *Materials*, which, although they have lower h-indexes of 10 and 9, respectively, show significant global outreach and citation impact, as evidenced by their g-index score and total citations. *IEEE Access* demonstrates a broad interdisciplinary appeal with 387 total citations from 30 publications since 2019. *Procedia CIRP* and the *Rapid Prototyping Journal* represent specialized sources with focused contributions to their respective areas, as seen in their consistent publication and citation metrics. This specialized focus is often essential for advancing aspects of manufacturing technologies. Journals such as *Sensors* and *Sustainability* (Switzerland), with h-indexes of 8, illustrate the interdisciplinary nature of manufacturing research that intersects with environmental and technological developments in sensors and sustainable practices. This table measures the scholarly impact of journals and conferences in manufacturing and technology. It shows the dynamic nature of the field and helps to identify leading sources of knowledge and trends for researchers, academicians, and practitioners.

Table 6. Sources' impact in AM and Industry 4.0 and 5.0.

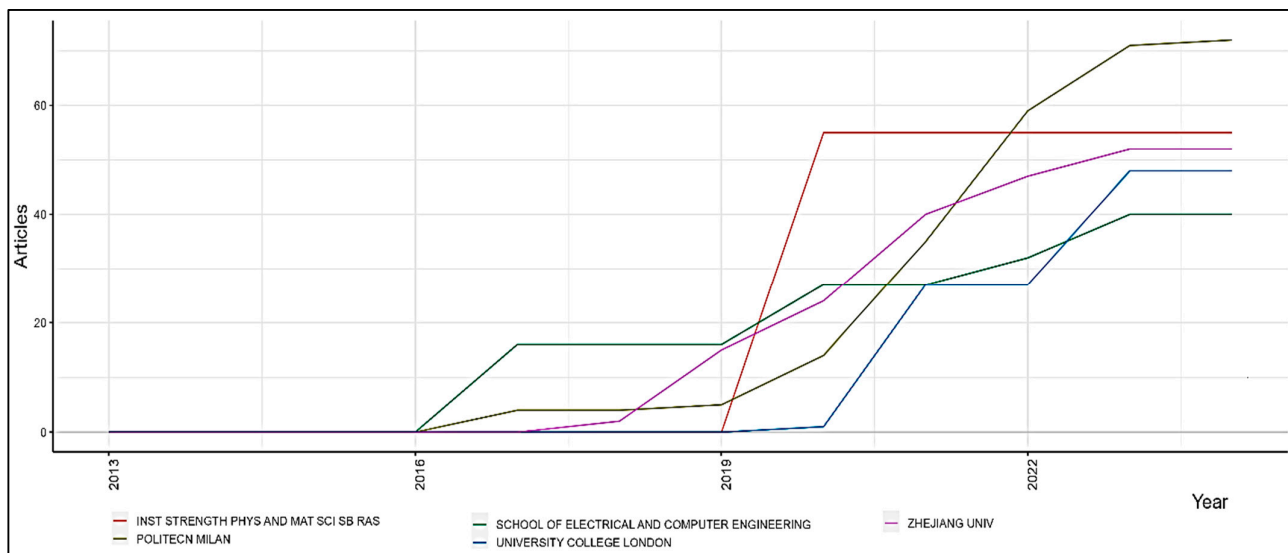
Element	h_Index	g_Index	TC	NP	PY_Start
<i>Journal of Intelligent Manufacturing</i>	26	55	3256	118	2014
<i>AM</i>	20	32	1299	32	2018
<i>International Journal of Advanced Manufacturing Technology</i>	17	29	909	49	2016
<i>Journal of Manufacturing Systems</i>	13	18	643	18	2017
<i>IEEE Access</i>	10	19	387	30	2019
<i>Materials</i>	9	17	406	17	2018
<i>Polymers</i>	9	12	172	19	2021
<i>Procedia CIRP</i>	9	16	305	33	2017
<i>Rapid Prototyping Journal</i>	9	15	238	20	2014
<i>Robotics And Computer-Integrated Manufacturing</i>	9	9	323	9	2017
<i>Applied Sciences (Switzerland)</i>	8	16	519	16	2019
<i>IFAC Papers Online</i>	8	13	211	28	2016
<i>International Journal of Production Research</i>	8	11	1583	11	2018
<i>Journal of Manufacturing Technology Management</i>	8	10	622	10	2018
<i>Materials Today: Proceedings</i>	8	18	354	18	2021
<i>Procedia Manufacturing</i>	8	11	142	13	2018
<i>Sensors</i>	8	20	429	28	2017
<i>Sustainability (Switzerland)</i>	8	14	513	14	2018
<i>30th International Conference on Flexible Automation and Intelligent Manufacturing (Faim, 2021)</i>	7	11	141	22	2020
<i>Applied Sciences—Basel</i>	7	14	210	18	2018

Table 7 lists various academic institutions and the number of articles they have contributed to a specific field, typically within the context of advanced manufacturing or a related technological domain. These data are crucial for understanding which universities and research institutes are leading in research output in these specialized areas. The University of Milan leads the list with the highest number of publications, totaling 72 articles. This high output suggests that the University of Milan is a significant hub for research in this field, potentially due to strong industrial collaborations, substantial research funding, and the many active researchers in the relevant disciplines. Following closely are the Institute of Strength Physics and Materials Science Siberian Branch of the Russian Academy of Sciences (RAS), with 55 articles, and Zhejiang University, with 52 articles. The substantial contributions of these institutions indicate their strong emphasis on advancing research in physical sciences and materials, which are pivotal in developments such as the development of new materials for manufacturing or innovations in physical processes. University College London and the Georgia Institute of Technology, with 48 and 40 articles, respectively, show the involvement of diverse academic departments in contributing to this field, highlighting the interdisciplinary nature of technology and engineering research. The list includes other notable institutions, like Shanghai Jiao Tong University, University of Johannesburg, and National Cheng Kung University, each contributing significant numbers of articles, which underscores their role in fostering research environments that promote substantial scholarly output. The presence of universities from various geographical regions reflects the global nature of research in technology and engineering, with institutions from Europe, Asia, and Africa all making significant contributions. This geographical diversity is crucial as it points to a worldwide collaborative and competitive environment where knowledge creation and innovation transcend national boundaries. Table 7 identifies leading institutions in technological research and indicates the global distribution of academic influence and research capabilities in advanced manufacturing and related technologies. These insights are valuable for prospective students, researchers seeking collaborative opportunities, and policymakers aiming to promote research excellence globally.

Table 7. Affiliations' production in AM and Industry 4.0 and 5.0.

Affiliation	Articles
University of Milan	72
Institute of Strength Physics and Materials Science	55
Siberian Branch of the Russian Academy of Sciences (RAS)	52
Zhejiang University	48
University College London	40
Georgia Institute of Technology	39
Shanghai Jiao Tong University	37
University of Johannesburg	36
National University of Cheng Kung	31
Politecnico Di Torino	29
National University of Singapore	29
University of Johannesburg	25
University of Patras	24
Hong Kong University of Science and Technology	23
Birla Institute of Technology and Science Pilani	23
Nanyang Technology University	23
Northwestern Polytechnical University	23
University of Limerick	23
Politecnico Di Milano	22

Figure 8 presents a trend analysis of scholarly articles published from 2013 to 2022 by five distinguished institutions: the Institute of Strength Physics and Materials Science SB RAS, Politecnico di Milano, the School of Electrical and Computer Engineering, University College London, and Zhejiang University. The plotted trajectories illustrate the annual publication output of each institution, providing insights into their research activity and prominence in the field over the given period.

**Figure 8.** Affiliations' production over time; retrieved from SCOPUS and WOS.

The Institute of Strength Physics and Materials Science SB RAS shows a relatively steady increase in publication output until 2019. This is followed by a dramatic rise, peaking in 2020, and then a high level of output is maintained. This surge suggests a significant expansion in research activities, or an enhanced level of collaboration and funding received during this period. Politecnico di Milano exhibits a consistent growth in publication count throughout the decade, with a notable acceleration starting in 2019. This consistent upward trajectory indicates sustained progress and ongoing enhancement in research capabilities.

The School of Electrical and Computer Engineering demonstrates a more gradual increase with a steadier slope compared to others, suggesting a consistent but more moderate growth in research output. University College London and Zhejiang University both display robust growth with similar patterns. Zhejiang University started with fewer publications in 2013 but experienced rapid growth from 2016 onwards, eventually surpassing other institutions by 2022. This indicates a strong focus on expanding their research impact within the decade. The graph shows the growth patterns of each institution and the competitive global research landscape. These insights are crucial, helping policymakers, researchers, and academics to make strategic decisions. This also sets a benchmark for institutions aiming to enhance their research impact and visibility internationally.

Figure 9 presents a detailed count of academic articles published by various countries, offering insights into the global distribution of research output. The United States leads with 981 publications, reflecting a strong academic environment and substantial investment in research. India follows with 627 publications, highlighting its growing role in global research due to expanding higher education and increased funding. China, with 527 publications, shows significant research capabilities, which are supported by governmental policies aimed at advancing technology and science. Italy and Germany, with 443 and 322 publications, respectively, emphasize Europe's strong academic presence, bolstered by extensive funding and collaboration networks within the EU.

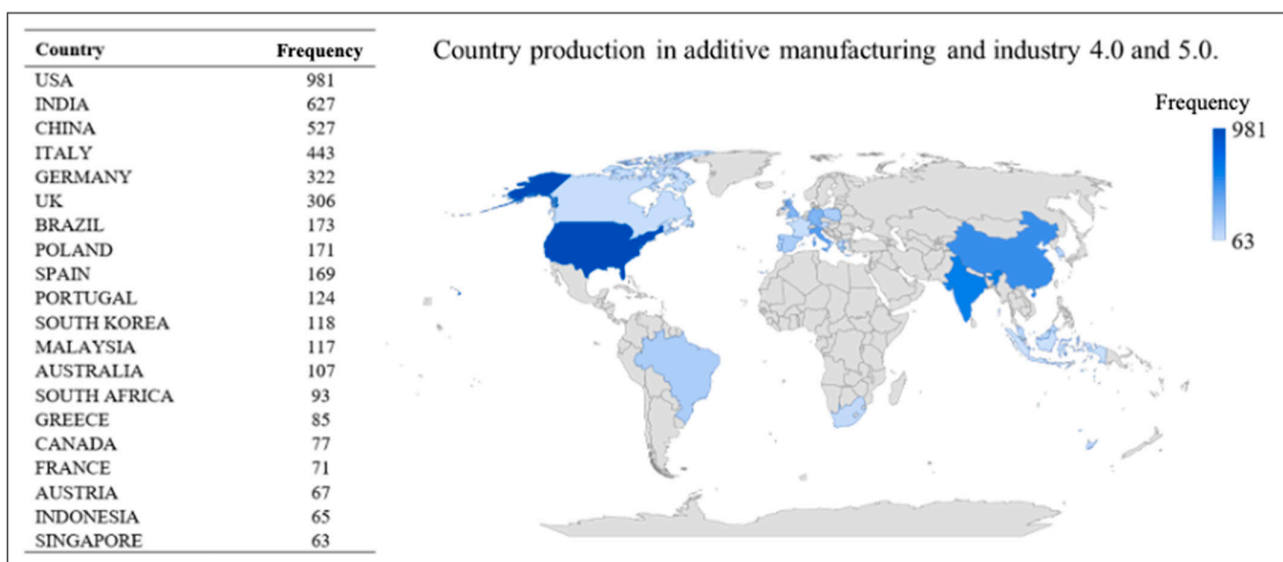


Figure 9. Country production in AM and Industry 4.0 and 5.0.

Further analysis reveals diverse contributions from countries like the United Kingdom, Brazil, Poland, and Spain, demonstrating widespread global research efforts. Smaller countries, such as South Korea, Malaysia, and Singapore, also make notable contributions, driven by targeted investments in education and technology. These data not only reflect the volume of research but also the broader socio-economic factors like government funding, the number of research institutions, and global collaboration patterns. The variation in publication counts highlights challenges and opportunities for smaller nations, which may need to leverage international collaborations to enhance their research footprint.

The distribution of research output is key for understanding how knowledge creation and innovation are dispersed globally. It informs policymakers, educational leaders, and international bodies in crafting strategies for fostering partnerships and enhancing research quality and quantity. Additionally, it aids students and researchers in identifying global leaders in specific fields, guiding their education and collaboration choices. This snapshot

underscores the interconnected nature of modern science, where global contributions drive collective progress and innovation.

Figure 10 indicates the growth in the number of scholarly articles published by researchers in China, India, Germany, Italy, and the USA from 2012 to April 2024. This longitudinal analysis offers a window into the research output dynamics of these countries in the context of a particular academic field, potentially reflecting broader trends in research and development priorities, funding allocations, and the overall health of the academic environment of these nations. Exhibiting a leading edge at the start, the USA showed a gradual increase in publications until about 2019, followed by a sharper rise continuing into 2024. This indicates sustained investment in research, with the acceleration possibly taking place due to increased funding or a strategic emphasis on certain research domains. Starting from a significantly lower point than the USA, China demonstrated a steep and almost exponential growth in publications around 2019, eventually surpassing the USA by 2023. This dramatic rise could be indicative of major governmental investment in research and education, reflecting China's aggressive push to become a global leader in scientific research. India's publication trajectory started lower but showed consistent growth throughout the period. The steady rise suggests the continuous enhancement in research capabilities and, possibly, improvements in higher education and research infrastructure. Germany and Italy show moderate but stable increases in research output over the analyzed period. The growth is less pronounced compared to China and the USA but indicates a solid, ongoing commitment to research within the European context.

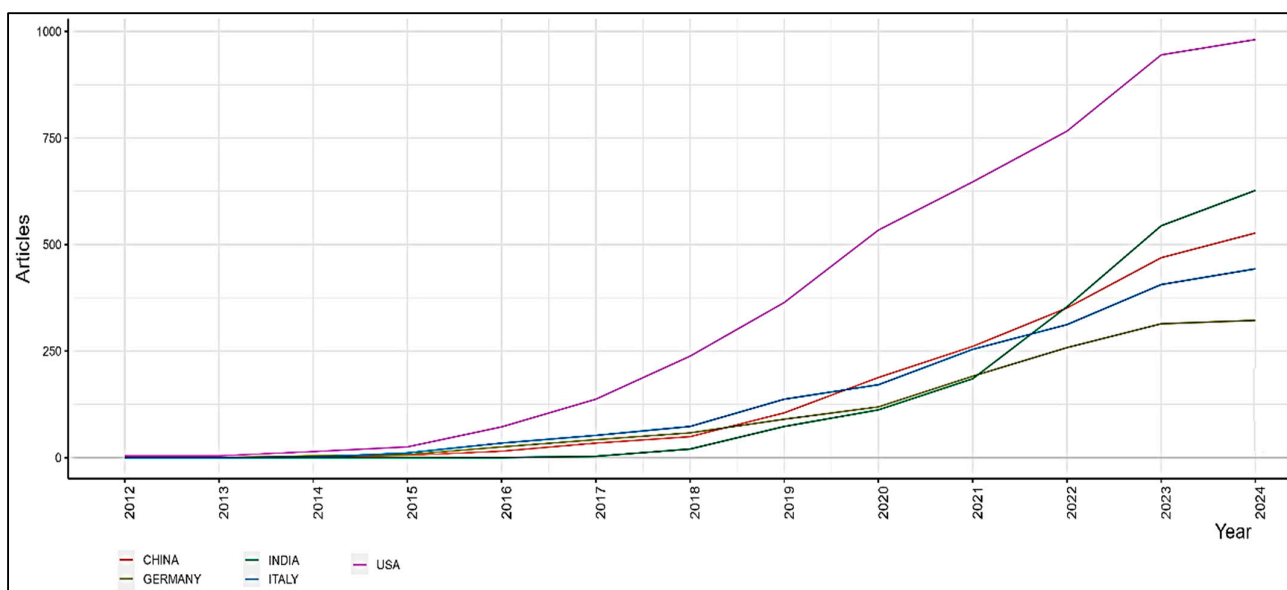


Figure 10. Country-level production over time; retrieved from SCOPUS and WOS.

The graph underlines significant insights into the global distribution of research output, underscoring how geopolitical, economic, and policy dimensions can drive changes in academic productivity. For policymakers, understanding these trends is crucial for crafting responsive strategies that foster research and development. For the academic community, these trends may guide decisions on collaboration, research focus areas, and the geographical distribution of conferences and resources. This analysis, therefore, not only reflects past and present research dynamics, but also helps to anticipate future shifts in the global academic landscape.

Table 8 illustrates the list of various keywords associated with contemporary topics in technology and manufacturing, along with their respective occurrences in the academic literature. This compilation of terms offers a quantitative perspective on research trends and thematic emphases within these fields over a specific period. Dominating the list, ‘AM’ and ‘3d_printing’ are mentioned 993 and 672 times, respectively, illustrating the substantial focus on these technologies within the research community. The prominence of these terms underscores the ongoing revolution in manufacturing processes, where traditional methods are being enhanced or replaced by more flexible, efficient, and sophisticated AM techniques. Industry_4_0’ and ‘IoT’ (Internet of Things) are also frequently cited, with 542 and 347 occurrences, respectively. These topics reflect the significant interest in the Fourth Industrial Revolution, which is characterized by a fusion of technologies, blurring the lines between the physical, digital, and biological spheres, and is heavily reliant on interconnected and autonomous systems. Terms like ‘ai’ (artificial intelligence) and ‘machine_learning’, appearing 136 and 132 times, respectively, point to the critical role of intelligent systems in modern industrial applications. The integration of AI and machine learning algorithms into various sectors is a major subject of research, impacting everything from production optimization to predictive maintenance. Other significant terms include ‘digital_twin’, ‘blockchain’, ‘sensor’, and ‘cybersecurity’. Each of these reflects pivotal areas of development that are likely shaping multiple facets of technology and industry. For instance, digital twins are vital for creating virtual replicas of physical devices to simulate and predict performance, while blockchain is emerging as a crucial technology for enhancing transparency and security in industrial operations. Interestingly, the occurrence of ‘COVID-19’ shows the research community’s response to the pandemic, indicating the existence of investigations into its impacts on various sectors, and perhaps focusing on disruptions and adaptations within manufacturing and supply chain systems.

Table 8. Most cited keywords in AM and Industry 4.0 and 5.0.

Words	Occurrences
additive_manufacturing	993
3d_printing	672
industry_4_0	542
IoT	347
AI	136
machine_learning	132
smart_manufacturing	130
manufacturing	98
CPC	91
digital_twin	79
sustainability	73
selective_laser	64
fused_deposition modeling	59
digitalization	55
big_data	53
robotic	52
blockchain	50
laser powder_bed_fusion	50
technology	48
sensor	45
fourth_industrial_revolution	44
automation	41
deep_learning	41
cloud_computer	40
IoT	40
optimization	38

Table 8. Cont.

Words	Occurrences
cybersecurity	37
covid	36
augmented_reality	34
circular_economy	34
rapid_prototyping	34
digital_manufacturing	33
innovation	33
simulation	33

The detailed examination of these keywords and their occurrences in scholarly articles provides valuable insights into the dynamics of research within the fields of technology and manufacturing. It highlights the areas that are currently receiving the most academic attention and that are likely to influence future technological developments and policy-making. Understanding these trends is crucial for stakeholders across sectors, including researchers, industry practitioners, and policymakers, as they navigate the complexities of innovation and its implications for society. This keyword analysis serves as a barometer for the pulse of research activity and areas of prospective growth within global industries.

Figure 11, depicting the frequency of specific terms across the academic literature from 2014 to 2024, provides a clear narrative about evolving focus areas in manufacturing, technology, and innovation. It captures how certain technologies such as ‘AM’ and ‘3D printing’ have maintained a consistent and growing academic interest, reflecting their continued advancement and broader application across industries. Similarly, the terms ‘industry 4.0’, ‘ai’, and ‘machine learning’ show an upward trend, underscoring the digital transformation sweeping through various sectors, with a growing emphasis on automation and data-driven decision-making. Emerging technologies such as ‘wireless sensor’, ‘smart skins’, and ‘flexible electronic fabrication’ began to appear more prominently towards the latter part of the decade, indicating the transition from nascent stages to more recognized fields of study with tangible applications, particularly in wearable technology and IoT. The specific focus on manufacturing techniques, like ‘wire arc AM’, ‘selective laser’, and ‘laser sintering’, highlights the detailed exploration of niche areas within manufacturing, responding to both technological advances and industry demands. The graph shows that as the decade progressed, the importance and impact of technologies that intersected multiple sectors grew. It also indicates a shift towards more specialized areas. This shift is characterized by the adoption of innovative technologies and their integration into existing industrial practices. This points to a broader trend of technological convergence, where digital fabrication, AI, and advanced materials science come together to create sophisticated solutions. On the other hand, the analysis of term frequencies provides essential insights into technological research trends. This information is crucial for directing future research efforts, informing educational strategies, and guiding policy and investment decisions in technology development and implementation. The graph reflects past, present, and future research dynamics in technology and innovation.

Figure 12 presents a compelling visualization of the cumulative occurrences of various technological and industrial terms from 2005 to 2024, illustrating significant trends in academic and industrial focus areas over nearly two decades. Each line represents a specific term, tracking its trajectory through the academic literature, and offering insights into the evolving priorities and advancements within the fields of manufacturing and technology. Starting from a baseline where most terms showed minimal activity, there was a clear inflection point around the early 2010s when these terms began to show distinct upward trends. This period likely corresponded with technological advancements

and increased investments in research and development, which drove the interest and scholarly output in these areas. The terms ‘3d_printing’ and ‘additive_manufacturing’ led in terms of frequency, with steep ascents beginning around 2016, reflecting the rapid adoption and integration of these technologies into various sectors. This surge in research activity correlated with the broader industrial adoption as these technologies matured and became more accessible. The growth in these terms indicates their central role in driving innovations in manufacturing, creating more efficient, cost-effective, and customizable production methods. The term ‘industry_4_0’, which encapsulates the move towards automation and data exchange in manufacturing technologies, also shows significant growth, especially from 2017 onwards. This growth is paralleled by similar increases in ‘IoT’ (Internet of Things) and ‘AI’ (artificial intelligence), highlighting a broader shift towards smart manufacturing processes that leverage data analytics and machine learning to optimize production and operations. Interestingly, ‘digital_twin’—a technology that pairs the virtual and physical worlds to analyze data and monitor systems—begins to appear later in the timeline but rapidly increases in frequency. This reflects its emerging importance in optimizing the operation and maintenance of physical systems and in predictive analytics. The consistent rise in the occurrences of these terms through 2024 not only suggests robust engagement within these research areas but also indicates the potential for ongoing contributions to technological innovation and development. These trends demonstrate the dynamic nature of technological research, which continues to evolve rapidly in response to new challenges and opportunities. Overall, the graph underlines the shift in academic and industrial landscapes towards more digital, automated, and data-driven environments. Understanding these trends is essential for researchers, policymakers, and industry leaders as they navigate the complexities of modern manufacturing and strive to harness the potential of new technologies to revolutionize production processes and enhance operational efficiencies. The trajectory of these terms offers predictive insights into future research areas that are likely to continue attracting substantial academic and industrial investment.

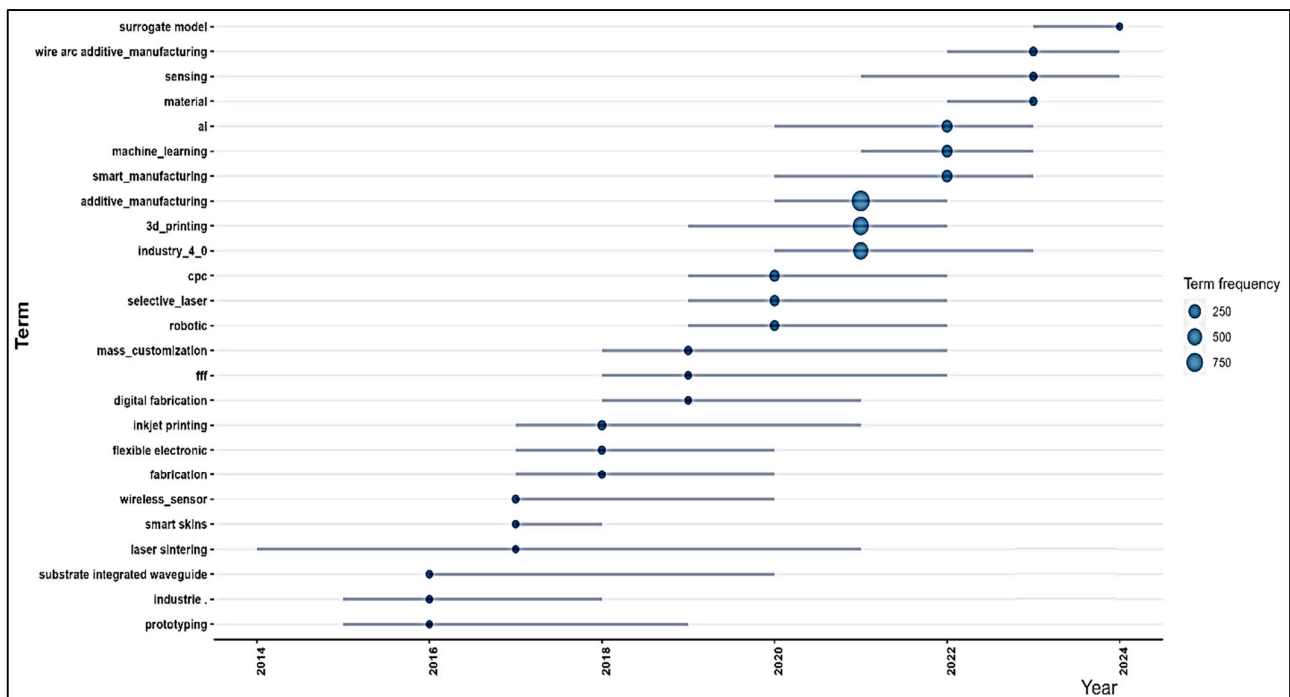


Figure 11. Trend topics over time retrieved from SCOPUS and WOS.

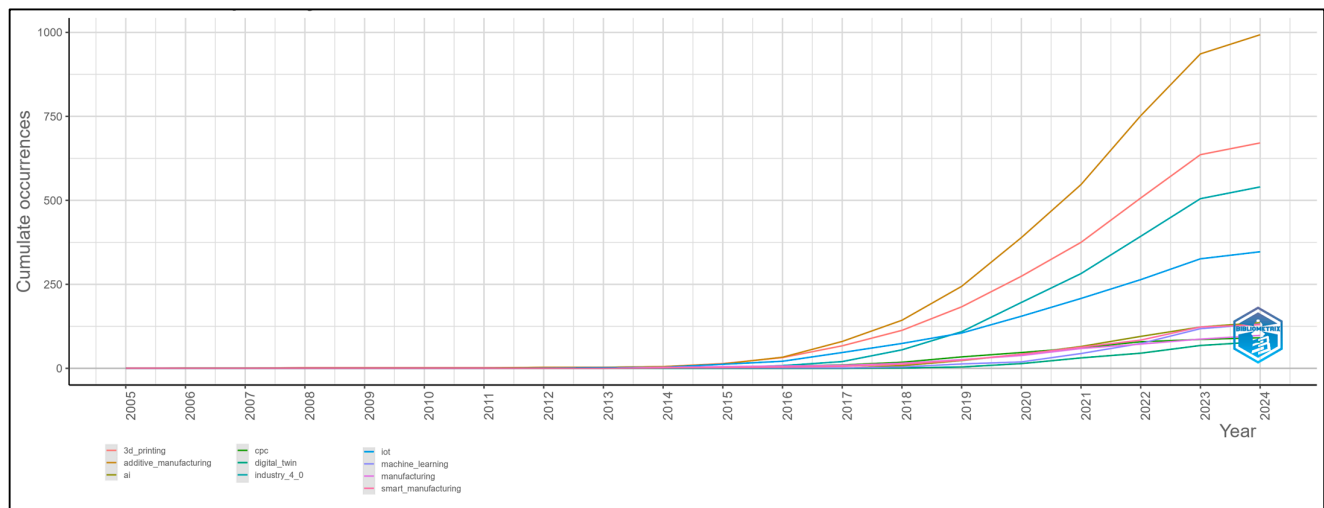


Figure 12. Frequency of words over time; retrieved from SCOPUS and WOS.

The strategic diagram, Figure 13, categorizes key research themes in technology and manufacturing into four quadrants based on their developmental density and centrality within the field, offering insights into their maturity and impact. This visualization aids stakeholders in academia, industry, and policymaking by highlighting foundational areas, potential growth sectors, and emerging or declining topics. Motor themes are characterized by high centrality and high density, indicating well-developed and central research areas that drive multiple agendas across the sector. Themes like '3d_printing', 'industry_4_0', 'IoT', 'AI', and 'smart_manufacturing' dominate this quadrant, reflecting their widespread application and foundational role in advancing manufacturing technologies. Their prominence suggests a broad impact across various sectors, solidifying their position as pivotal elements in the evolution of modern manufacturing. Niche themes, such as 'disruptive_technology', possess high centrality but low density. This positioning suggests significant potential, despite currently limited development. Such themes are likely to transform research directions and applications within the field, marking them as areas ripe for exploration and investment. Emerging or declining themes include 'inkjet_printing' and 'energy_harvesting', which exhibit low centrality and low density. These themes may be in early developmental stages or losing momentum within the research community. Their placement highlights specific, possibly specialized applications that have not yet been achieved or are losing broader prominence within the broader academic and industrial landscapes. Basic themes feature high density but low centrality, representing areas like 'selective_laser', 'laser_powder_bed_fusion', and 'metal_additive_manufacturing'. These well-developed areas may not be at the forefront of current research agendas, but provide essential knowledge and techniques crucial to the field. Their role underpins many of the practical applications in manufacturing, serving as the backbone for more advanced exploration. The diagram serves as a strategic tool for mapping the landscape of research and innovation. It identifies where current research energies are concentrated, indicates potential for future exploration, and points to the foundational technologies that support ongoing advancements. For researchers and strategists, this map is invaluable for making informed decisions on directing research efforts, allocating funding, and establishing collaborations that align with both current needs and future opportunities. This comprehensive approach ensures that all facets of manufacturing technology are explored, from emerging innovations to critical established techniques, shaping a well-rounded and forward-looking research strategy.

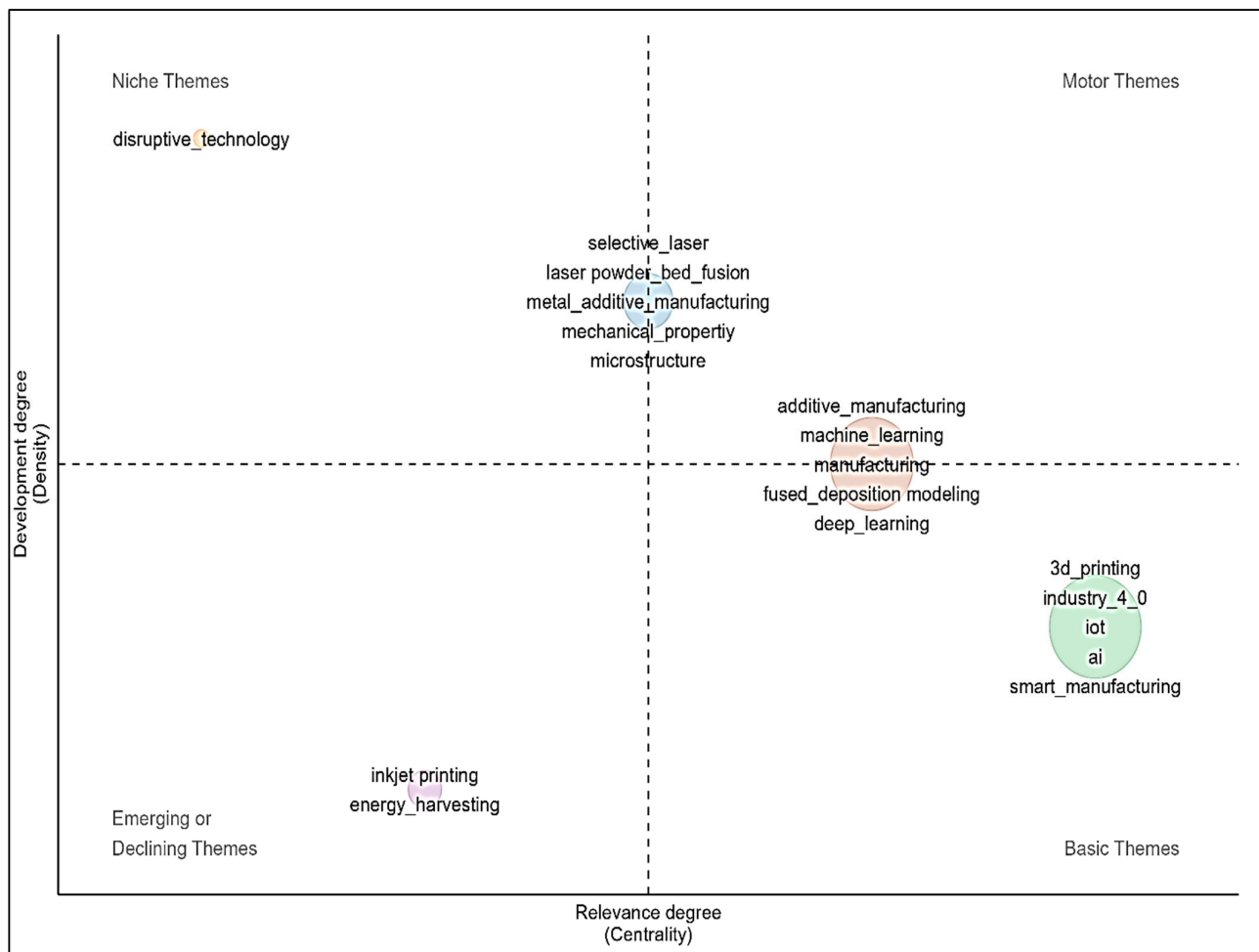


Figure 13. Thematic map for Industry 4.0 and 5.0 in AM technology.

The visual representation, Figure 14, maps a wide array of research terms within the domain of manufacturing and technology, categorized by their connectivity and thematic closeness, using a color gradient from red to green. This color-coded thematic analysis serves to illustrate the interrelationships among various concepts and highlight the centrality of certain themes within the broader research landscape. Terms like ‘sustainable manufacturing’, ‘circular_economy’, and ‘sustainability’ are clustered together at the heart of the diagram in the red zone, signaling a strong focus within the research community on the environmental aspects of manufacturing. This suggests a trend towards integrating sustainability into the core of manufacturing processes, which may be a response to global demands for greener production techniques and the increasing societal awareness of environmental issues. Transitioning to the middle of the spectrum, where the terms turn orange and then yellow, there is a mix of foundational and innovative manufacturing technologies such as ‘3d_printing’, ‘digital_transformation’, ‘industry_4_0’, and ‘smart_manufacturing’. These terms are densely packed, indicating a robust interconnection between traditional manufacturing processes and modern technological advancements. The presence of ‘digital_transformation’ alongside ‘industry_4_0’ highlights the shift towards more integrated, data-driven production environments enhanced by IoT and AI technologies. In the green zone, the terms shift towards cutting-edge technologies and their applications, including ‘blockchain’, ‘IoT’, ‘cybersecurity’, and ‘cloud_computer’. The placement of these terms suggests that they are not only pivotal to the current technological frontier but are also expected to be central to future developments. Their position in the graph reflects the critical role of secure, interconnected, and scalable technologies in the advancement of

modern manufacturing processes. The overarching theme captured by this diagram is the transformative impact of digital technologies across all facets of manufacturing—from the foundational changes in how goods are produced, and services are delivered to the strategic shifts towards sustainable and integrated advanced data analytics. The visualization also underscores the complex and multidisciplinary nature of current research in manufacturing, where technological innovation continually intersects with sustainability goals. In essence, the diagram provides a holistic view of the dynamic and evolving field of manufacturing technology, illustrating how deeply interconnected and multifaceted the research landscape has become. It underscores the importance of synergy between different research areas and highlights how technological advancements are increasingly aligned with sustainable practices. For stakeholders in academia, industry, and policymaking, this mapping offers a strategic overview that can guide decision-making processes, investment strategies, and educational priorities to address both current needs and future challenges in manufacturing and technology.

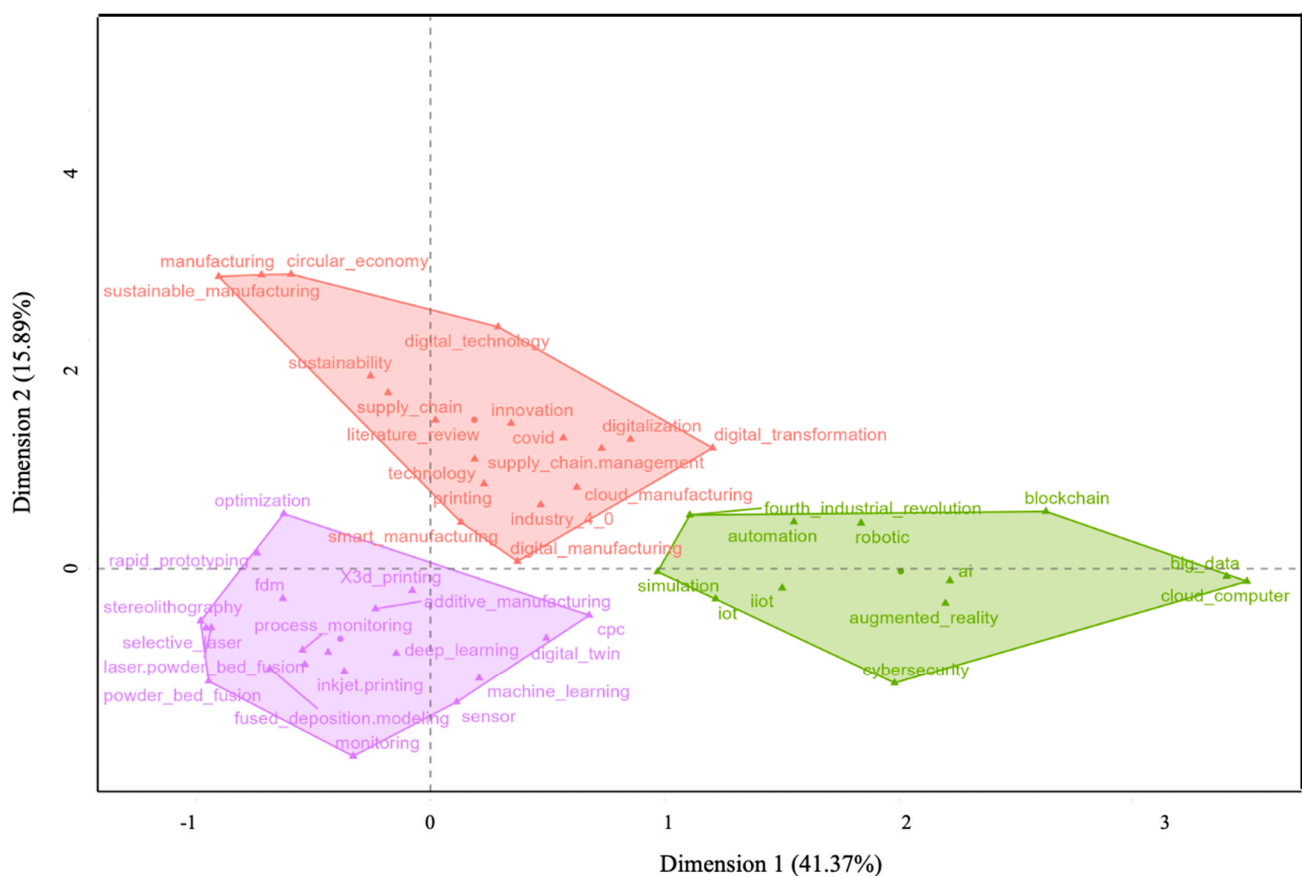


Figure 14. Conceptual structure map (method MCA) for Industry 4.0 and 5.0 in AM technology.

The provided visualization, Figure 15, offers a complex network analysis of various research terms associated with manufacturing and technology, which are mapped according to their interconnections and thematic relevance. The network clusters terms into a vibrant, interconnected web, indicating not only the individual popularity of each term but also their relationships and the frequency of their co-occurrence in academic literature. At the center of this network, 'AM' and 'industry 4.0' emerge as super nodes, signifying their broad influence and central role in current manufacturing research. These terms act as hubs, linking a wide range of associated technologies and concepts, ranging from 'IoT' and 'cybersecurity' to more specific manufacturing processes like 'laser powder bed fusion' and 'metal AM'. The prominence of these central nodes underscores the critical

importance of these areas in driving the capabilities and applications of modern manufacturing techniques forward. Surrounding these central themes are clusters of related terms that define specific subfields within the broader manufacturing landscape. For instance, a cluster focused on ‘sustainability’ and ‘sustainable manufacturing’ highlights the increasing emphasis on environmental considerations within the manufacturing sector. This cluster is closely linked to ‘IoT’ and ‘digital technology’, suggesting a convergence between technological innovation and sustainable practices. Another vibrant cluster revolves around ‘digital twin’ and ‘simulation’ technologies, which are closely related to ‘industry 4.0’ but also connect to ‘ai’ and ‘machine learning’. This indicates the growing research focus on integrating predictive analytics and real-time data monitoring to enhance manufacturing processes. These technologies are depicted as bridging elements that connect traditional manufacturing concerns with cutting-edge computational methods, highlighting their role in advancing intelligent manufacturing solutions. The network also shows emerging terms like ‘blockchain’ and ‘cybersecurity’ positioned near ‘cloud computing’ and ‘big data’, reflecting the critical need for secure data management systems within highly digital and interconnected manufacturing environments. This proximity underscores the interdependence of data security and manufacturing efficiency, aligning with the industry’s movement toward Industry 4.0. Overall, this network diagram provides a dynamic representation of the multifaceted research landscape in manufacturing and technology. It illustrates how foundational technologies such as ‘AM’ and ‘industry 4.0’ serve as cornerstones for a multitude of research areas, influencing a wide array of both established and emerging fields. This visualization not only reflects the current state of manufacturing research but also offers insights into potential future developments, suggesting areas where technology and innovation will likely converge. For researchers, industry practitioners, and policymakers, understanding these connections and the landscape’s complexity is essential for navigating future challenges and harnessing the potential of these transformative technologies.

The visualization provided in Figure 16 is a bibliometric network that maps the interconnections between various scholarly articles, representing a multifaceted view of research impacts and themes within the fields of manufacturing and technology. The network is color-coded, and likely to denote different thematic clusters or the intensity of interconnections among the articles. This visualization highlights several prominent nodes, which are presumably highly cited or foundational papers within the network. Notably, larger nodes, such as those linked to “industry 4.0”, “AM”, and “intelligent manufacturing”, suggest that these topics are central hubs of research activity. These larger nodes are heavily interconnected with numerous other studies, indicating a broad influence on related research areas and a high degree of integration within the field. The red lines and nodes possibly represent a cluster focused on foundational technologies and their evolution. This might include seminal works on specific manufacturing processes or technologies that have shaped current practices. The dense connectivity within this cluster suggests a mature body of research with established methodologies and findings that continue to influence new studies. In contrast, the green cluster appears to include more recent advancements and emerging technologies such as “robotic manufacturing” and “big data in manufacturing”. The placement of these nodes, along with their connections, likely points to dynamic and rapidly evolving areas of research that are building upon the foundational knowledge represented by the red cluster. Some of the specific articles, like “Schwab K.M., 2016, the Fourth”, likely refer to influential publications such as Klaus Schwab’s work on the Fourth Industrial Revolution, which underscores the theoretical and contextual backbone for much of the current research in intelligent and automated manufacturing. Similarly, other highlighted articles in the network might represent key studies that have introduced new concepts or technologies, influenced policy, or redirected

research trajectories in significant ways. This network graph not only serves as a visual representation of how various research topics in manufacturing are interconnected but also highlights the evolutionary path from basic research to innovative applications. The layout and clustering of the network provide insights into which areas are saturated, and which remain on the frontier of research, guiding future studies to either build on established knowledge or explore emerging themes. Overall, network visualization provides a strategic overview of the research landscape, identifying key papers and themes that shape the field of manufacturing and technology. It reveals the complex, interconnected nature of academic research, where each study potentially influences numerous other facets of understanding and application. This type of analysis is crucial, helping academics, industry professionals, and policymakers to understand the depth and breadth of the field, facilitating informed decisions on where to focus future research efforts and resources.

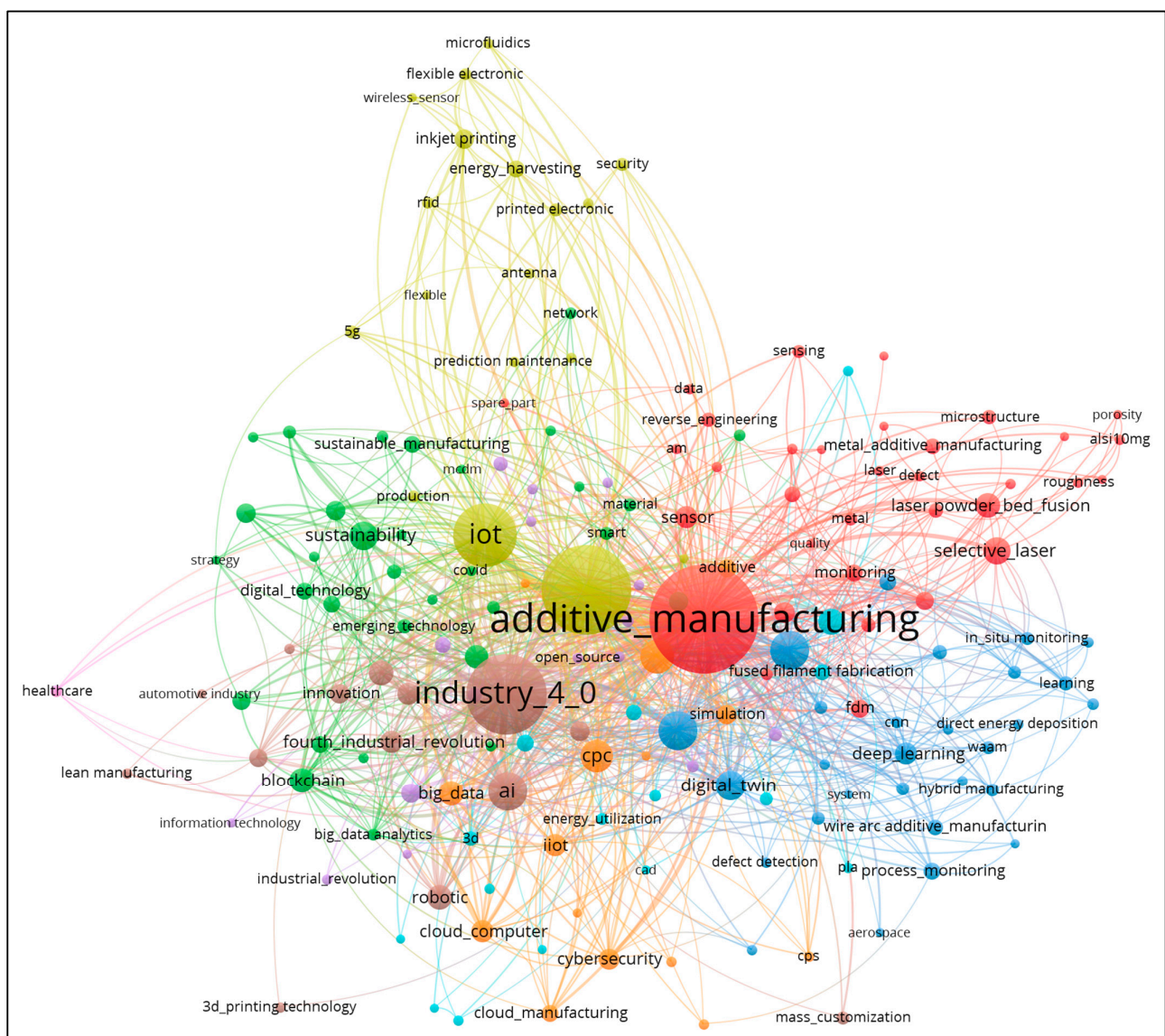


Figure 15. Co-occurrence map for Industry 4.0 and 5.0 in AM technology.

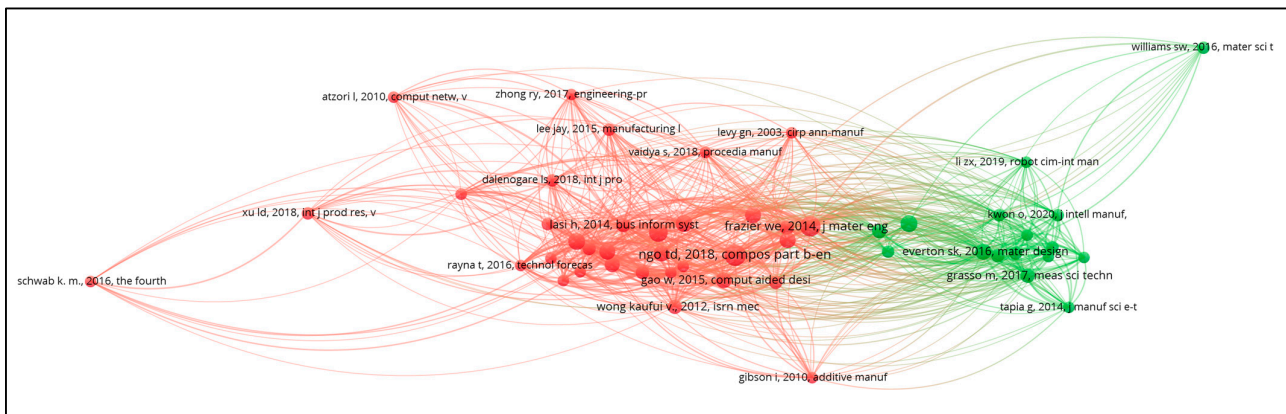


Figure 16. Co-citation cited references for Industry 4.0 and 5.0 in AM technology.

Figure 17 shows a bibliometric network diagram that maps the interconnections among various researchers based on their contributions to specific fields, typically within the realm of technology, manufacturing, or a related discipline. This type of diagram helps in understanding the relationships between key researchers and their central role in advancing certain topics. Researchers such as ‘Zhang Y.’, ‘Gibson I.’, and ‘Schwab K.M.’ appear as central nodes within the network, indicated by their positioning and the number of connections. This suggests that these individuals are influential within their fields, likely due to the production of seminal works or widely cited research contributions. Klaus Schwab, for example, is known for his work on the Fourth Industrial Revolution, which could explain his prominence in a network focused on modern manufacturing and technology paradigms. The diagram shows clusters of researchers, which could indicate collaborative groups or those whose research areas closely align. For instance, the proximity of ‘Lipson H.’ and ‘Gibson I.’ may suggest a shared focus on specific technologies such as 3D printing or digital fabrication, given their known contributions to these fields. Researchers like ‘Murakami Y.’ and ‘Palazzi V.’ are placed on the periphery of the network, suggesting that while they contribute to the field, their impact or degree of centrality to the core research themes might be less pronounced. This can also indicate specialization in niche areas that do not intersect frequently with the main research streams represented by central nodes. The arrangement and connections within this network not only highlight who is leading in these research areas but also imply the thematic structure of the field. Central nodes that connect diverse clusters illustrate topics with broad implications, while tighter, more isolated clusters could represent specialized areas or emerging topics within the broader field. For researchers entering the field or looking to collaborate, understanding this network can provide valuable insights into potential mentors, collaborators, or the key literature that can be used to begin their investigation. For institutions or funding bodies, this visualization aids in identifying thought leaders and determining where to allocate resources to maximize impact based on the centrality and connectivity of researchers. This network diagram serves as a strategic tool for visualizing the landscape of academic research within a particular technological or manufacturing domain. It not only highlights influential researchers and their relationships but also provides a structural overview of how research topics are interconnected, guiding strategic decisions in research direction, collaboration, and resource allocation.

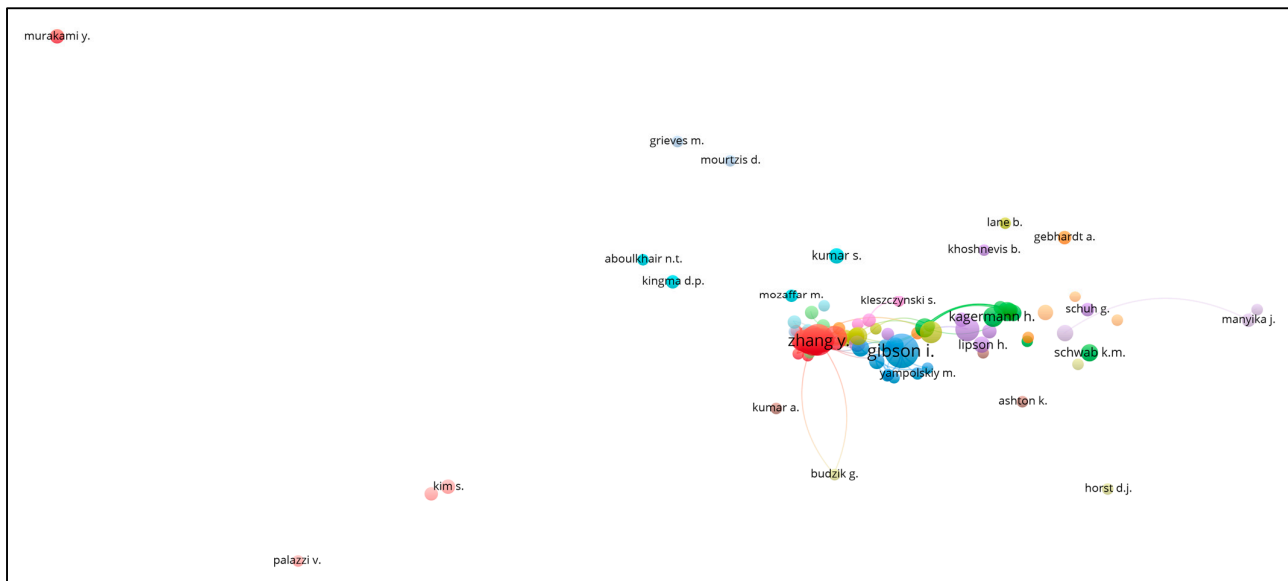


Figure 17. Co-citation cited authors for Industry 4.0 and 5.0 in AM technology.

4. Discussion

To address the main expected contributions of this research, the analysis revealed a rapidly growing interest and significant impact of AM (AM) in Industry 4.0 and 5.0, driven by influential research and collaborative opportunities. This trend underscored the sector's importance and numerous opportunities for future interdisciplinary research and innovation. The yearly publication patterns from 2005 to April 2024 illustrated periods of rapid growth, decline, and stability, reflecting technological advancements, market forces, and external factors such as economic or political influences. By examining publication trends, citation patterns, and keyword clusters, this bibliometric analysis uncovered current research trends and popular topics in AM within the context of Industry 4.0 and 5.0.

Key areas of interest included AM, Industry 4.0, the Internet of Things (IoT), artificial intelligence (AI), and smart manufacturing. This information was crucial for helping researchers, industry experts, and policymakers to stay informed about recent advancements and to highlight important research areas. Bibliometric analysis also revealed collaboration networks among researchers, institutions, and countries involved in AM research. Understanding these networks fostered partnerships, leveraged expertise, and promoted international knowledge exchange.

Leading academic institutions emphasized the interdisciplinary and global aspects of technological research, guiding strategic decisions to enhance research impact. Citation analysis assessed the impact of research publications, identifying highly cited papers, influential authors, and leading journals in the field. This evaluation helped in recognizing seminal works, benchmarking research quality, and measuring the influence of research contributions on the advancement of AM technologies in Industry 4.0 and 5.0. Notable journals and conferences were highlighted for their strong influence and credibility in the field.

Bibliometric analysis also identified emerging technologies and innovative methods in AM that were gaining momentum in Industry 4.0 and 5.0. Prominent areas included digital twins, blockchain, cybersecurity, and smart skins. This information assisted industry stakeholders in investing in promising technologies, predicting market trends, and aligning research with industry demands. The shift towards digital, automated, and data-driven manufacturing emphasized the need for guidance in future research and technological advancements.

While the literature has extensively covered AM's applications within Industry 4.0, there is a noticeable gap in exploring AM's integration into Industry 5.0. Industry 5.0 emphasizes human-centric manufacturing, which seeks to bring the human element back into the production process by fostering human–machine collaboration. Studies such as those by [46,52,58] have shown that collaborative robots (cobots) are a key aspect of Industry 5.0, enabling workers to focus on creative problem-solving while robots handle repetitive tasks. However, the role of AM in supporting this collaboration remains underexplored. This study highlights the opportunity for AM to evolve beyond automation and be integrated into human-centered manufacturing models, where the combination of human creativity and machine precision can drive innovation and efficiency.

In addition to the gap in human–machine collaboration, there is also a need for further exploration into the integration of AM with other emerging technologies like blockchain and advanced AI [102]. Blockchain technology can provide a decentralized system for tracking and ensuring the quality and traceability of AM products, which is particularly important in sectors like aerospace and healthcare [103]. AI-driven design optimization also holds significant promise for enhancing AM processes by reducing material waste, improving design efficiency, and accelerating product development [104]. Despite the advancements made, these technologies are still underexplored in the context of AM, and more research is needed to understand how they can be effectively integrated into AM processes within Industry 4.0 and 5.0 [103–105].

Sustainability remains a critical concern for AM processes. While AM can reduce material waste, the environmental impacts of energy consumption during processes like laser sintering need to be addressed. Kumar and Patel [106] pointed out that the environmental footprint of AM processes has not been sufficiently explored. Future research should assess the lifecycle impacts of AM, from raw material sourcing to end-of-life recycling, to ensure these processes align with the sustainability goals of Industry 5.0.

5. Prospects and Recommendations

Human–machine interactions (HMIs) in AM offer significant potential to enhance productivity, efficiency, and innovation. As AM has evolved, effective HMIs bridge the gap between human abilities and cutting-edge technologies, optimizing production. Real-time data and advanced analytics enable human operators to make informed decisions, address problems quickly, and optimize workflows. Collaborative robots, or cobots, such as those designed by Universal Robots, perform repetitive tasks, freeing humans up for participation in complex problem-solving and innovative work. In aerospace, the use of HMIs in AM creates lightweight, complex parts that improve fuel efficiency. The automotive industry benefits from rapid prototyping and customized parts, reducing the time to market. Healthcare applications include customized medical devices and implants, enhancing patient outcomes. In consumer goods, HMIs enable mass customization, allowing for the efficient production of personalized items. Industrial manufacturing leverages HMIs for high-performance components, with real-time monitoring and predictive maintenance enhancing reliability. The defense sector produces precise parts quickly, ensuring readiness. Education and research institutions benefit from hands-on learning and innovation. The energy sector creates optimized renewable energy components. The fashion and jewelry industries use HMIs for intricate, customized designs. Architecture and construction employ HMIs for complex structural components, optimizing material use and ensuring safety. Overall, the use of HMIs in AM drives innovation and efficiency across diverse industries, from the aerospace and automotive sectors to areas of healthcare, consumer goods, industrial manufacturing, defense, education, energy, fashion, and construction.

Improvements in design and customization are important opportunities. AI-driven and machine learning-based software tools that support the design of complex geometries and personalized products are essential for exploring new options, optimizing material consumption, and creating customer-specific products. HMIs facilitate the real-time monitoring and control of AM processes through which optimized printing parameters are achieved, as well as the instant remedy of any deviations that might occur. This ensures that quality control is enhanced while minimizing wastage and reducing downtime. To prevent production disruption, sensor data analysis-driven predictive maintenance helps in identifying possible equipment failures even before they happen.

Through automated hazardous tasks, HMIs help to improve working conditions, further mitigating the strain on workers' bodies. Cobots and automatic systems take care of dangerous or repetitive operations, leaving humans to supervise or make decisions. Ergonomically designed interfaces and control systems reduce operator fatigue, minimizing injuries. Another benefit is constant learning with skill development. The introduction of advanced training programs through virtual reality (VR) and augmented reality (AR) enables the simulation of AM processes, allowing operators to practice their skills in a controlled setting. This training enhances operator skills, improves process understanding, and ensures better handling of complex manufacturing tasks.

For the complete utilization of HMI potential in AM, manufacturers should invest in advanced technologies like AI-enabled programs, AR/VR training systems, and cobots. This is crucial for improving human–machine interaction and, consequently, productivity and efficiency. User-friendly interfaces and intuitive control systems are vital in ensuring the maximum benefit is received from HMIs. Encouraging collaboration between humans and machines is essential, as it fosters innovation and increases the overall efficiency of manufacturing systems.

Data analytics and AI integration into HMIs can significantly enhance process optimization, quality control, and predictive maintenance. AI algorithms, for instance, can enable real-time decision-making, improving manufacturing efficiency. While many human-centric approaches to HMIs focus on augmenting human capabilities rather than replacing them, manufacturers must design systems that capitalize on human creativity, problem-solving, and decision-making capacity. This approach can further enhance productivity and innovation in AM practices.

In conclusion, there are vast prospects for HMI application in AM, which can significantly enhance productivity, efficiency, and spur innovation. For the successful integration of HMIs into AM practices, manufacturers should focus on investing in modernized technologies, fostering collaboration, providing robust training programs, ensuring ergonomic designs, and integrating data analytics and AI to achieve high-level performances. Promoting a human-centric approach will be key to the successful future of AM in Industry 4.0 and 5.0.

6. Conclusions

This bibliometric analysis provides insights into the integration of additive manufacturing (AM) with Industry 4.0 and 5.0, highlighting trends, opportunities, and challenges. The 31.58% annual growth in publications on AM, Industry 4.0, and 5.0 reflects the increasing interest in these areas. The rapid expansion of research from 2015 to 2024 emphasizes AM's growing role in manufacturing, driven by advancements in digital technologies, machine learning, and real-time production systems. The key themes identified include human–machine collaboration, sustainability in AM, and the role of AI and IoT in optimizing manufacturing. Interdisciplinary collaboration is expanding, with co-authorships across regions and institutions. The average citation per document, around 15.6, highlights

the substantial academic impact of this research, signaling potential breakthroughs. These findings underscore AM's transformative potential in Industry 4.0 and 5.0. The alignment of AM with smart technologies, such as predictive maintenance and real-time monitoring, is set to redefine manufacturing, making it more flexible, efficient, and sustainable.

7. Current Landscape and Challenges

Despite significant advancements, challenges remain in fully realizing AM's potential within Industry 4.0 and 5.0. There are flaws in applying AI to optimize AM processes and in standardizing materials and techniques. Sustainability is a central concern, requiring more research on reducing waste, energy consumption, and improving material efficiency in AM. The automation in Industry 4.0 is balanced by Industry 5.0's human-centric focus on innovation and decision-making. The challenge is to balance automation with meaningful human roles, where cobots can help to achieve human-machine synergy, enhancing productivity and job satisfaction. While AM has revolutionized manufacturing, its full integration with Industry 4.0 and 5.0 is still in the early stages. Further research is needed to synchronize AM with IoT and AI systems, and the lack of universal material standards limits broader adoption.

8. Future Work and Research Directions

Promising research directions include the continued exploration of human-machine collaboration, with cobots enhancing worker productivity and safety. AI-driven design optimization in AM is crucial for advancing rapid prototyping and mass customization. Further interdisciplinary research is needed on integrating blockchain and IoT sensors into AM systems to improve data security, traceability, and real-time process monitoring. The integration of digital twins for real-time optimization and predictive maintenance offers exciting possibilities. Sustainability remains a critical area, with research focusing on the circular economy, recycling strategies, and the development of eco-friendly materials. In conclusion, AM, enhanced by Industry 4.0 and 5.0, has tremendous potential to reshape manufacturing. However, overcoming existing challenges will require continued research and interdisciplinary collaboration.

Author Contributions: Conceptualization, S.D. and N.B.; methodology, S.D., S.S.K. and S.E.; formal analysis, S.D. and S.E.; investigation, S.D.; resources, S.D.; data curation, S.D.; writing—original draft preparation, S.D.; writing—review and editing, S.D. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

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