Review

Digital Twin and Artificial Intelligence in Machining: A Bibliometric Analysis

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ABSTRACT: The past decade has witnessed an exodus toward smart and lean manufacturing methods. The trend includes integrating intelligent methods into sustainable manufacturing systems purposely to improve the machining efficiency, reduce waste and also optimize productivity. Manufacturing systems have seen transformations from conventional methods, leaning towards smart manufacturing in line with the industrial revolution 4.0. Since the manufacturing process encompasses a wide range of human development capacity, it is essential to analyze its developmental trends, thereby preparing us for future uncertainties. In this work, we have used a Bibliometric analysis technique to study the developmental trends relating to machining, digital twins and artificial intelligence techniques. The review comprises the current activities in relation to the development to this area. The article comprises a Bibliometric analysis of 464 articles that were acquired from the Web of Science database, with a search period until November 2024. The method of obtaining the data includes retrieval from the database, qualitative analysis and interpreting the data via visual representation. The raw data obtained were redrawn using the origin software, and their visual interpretations were represented using the VOSviewer software (VOSviewer_1.6.19). The results obtained indicate that the number of publications related to the searched keywords has remarkably increased since the year 2018, achieving a record maximum of over 80 articles in 2024. This is indicative of its increasing popularity. The analysis of the articles was conducted based on the author countries, journal types, journal names, institutions, article types, major and micro research areas. The findings from the analysis are meant to provide a bibliometric explanation of the developmental trends in machining systems towards achieving the IR 4.0 goals. Additionally, the results would be helpful to researchers and industrialists that intend to achieve optimum and sustainable machining using digital twin technologies.

Keywords: Digital twin; Machining; Bibliometric analysis; Artificial Intelligence; Machine learning

1. Introduction

Evaluating the efficiency of a production method is an important aspect of any manufacturing process. Many studies have been done to improve the efficiency and evaluate the performance of manufacturing systems. Recent studies have shown that more works are focused more on optimizing the manufacturing systems with the aim of

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achieving a lower energy consumption and production cycles. It was observed that both the productivity and product quality can be improved by using futuristic AI and digital twin technology. Analysis of the most recent research outputs has shown that there is a higher utilization of the digital twin (DT) technology in various machining systems. It was shown that the DT can be used to evaluate the outcomes of a machining system prior to the machining activity [1]. This is because the optimum combinations of machining variables can be obtained using the DT systems thereby eliminating waste through trials [2]. However, an overall search has shown that there is still limited research work published relating to the bibliometric analysis for DT in machining systems [3,4].

The concept of DT has been successfully introduced into different engineering fields. A DT is a virtual operation of a real system that allows for simulation, analysis, optimization and prediction of various outcomes of real-life systems [5–7]. The DT system involves creating a virtual model of any physical activity in a simulated environment. By so doing, the interaction and characteristics of the system can be studied intently, thereby allowing for in-process adjustments and feedback [1,8–10]. The relationship between the virtual and physical environments is presented in Figure 1, where the overall steps used to obtain an optimized machining process with a DT are illustrated.

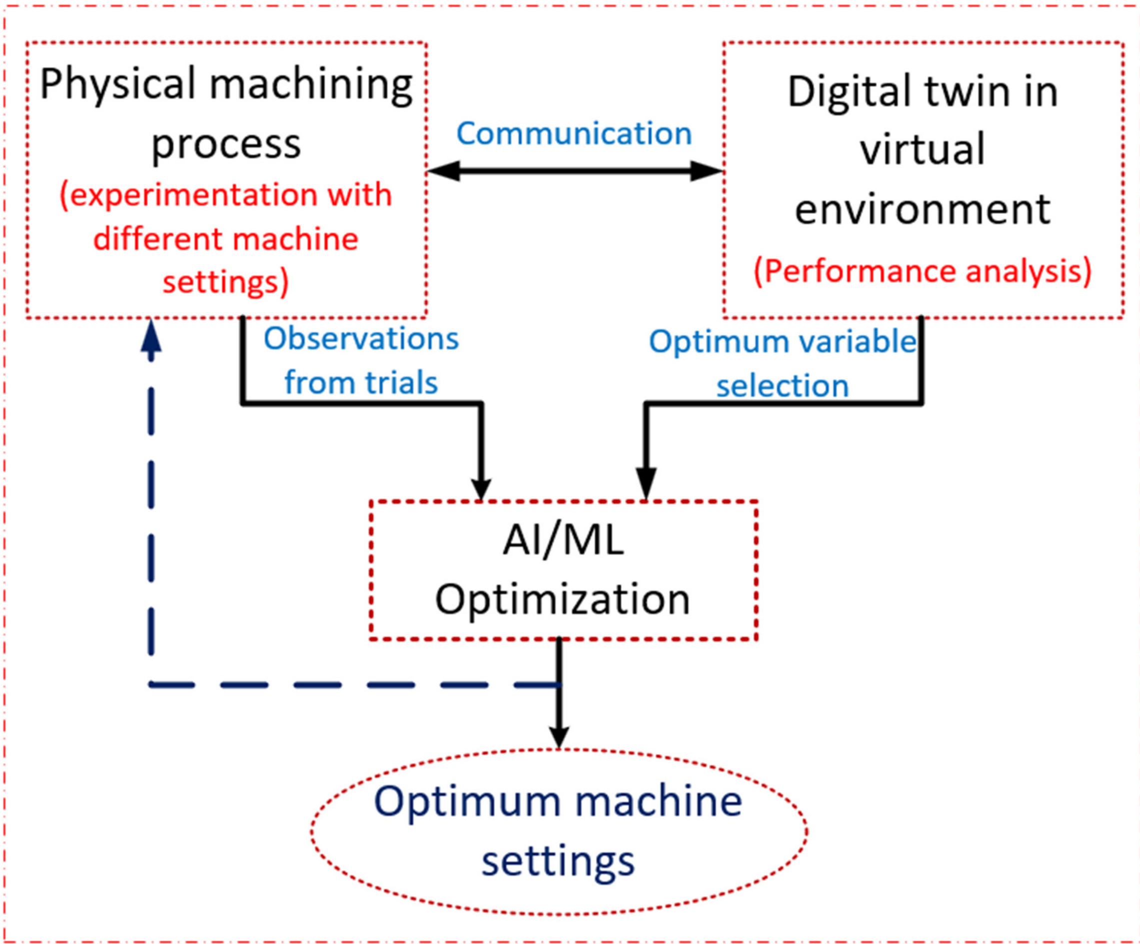

Figure 1. Concept of digital twin in machining systems.

A researcher from Michigan University called Michael Grieves was attested to be the first person who introduced the word DT. He explained the concept of DT as "A Digital Twin is a set of computer-generated datasets that fully defines the operation of a physical manufacturing process at macro and micro geometric levels" [11]. Similarly, Tao et al. [12] explained that DT involves the convergence of physical geometries in computed simulated environments. Many other scientists have given the definition of the DT system, and they mostly relate the concept to mimicking a physical system in a virtual environment.

The concept of DT recently gained substantial popularity in manufacturing systems, principally in the prediction and optimization of machining responses. Here, the DT was presented as a digital depiction of the machining operation, where it executed a "what-if" analysis in the virtual environment. This allows for greater decision-making and optimization of the machining system [13]. More so, Barbara et al. [14] explained that the DT systems can be self-controlled using AI in a virtual environment to optimize the production of any component [15]. This gave rise to a whole dimension in the study of DT systems because the in-process analysis could be controlled by an AI, thereby obtaining an optimized operation for the manufacturing system.

Foremost applications of the DT technology in aerospace studies were first conducted by NASA in the Apollo program. Moreover, recent advances have shown its increased application in different fields such as health, agriculture, sustainable manufacturing, information technology and telecommunications [16].

The application of DT in manufacturing systems specifically relates to preliminary investigation or off-machine monitoring, observing and optimizing of the systems. It also entails the prediction of machining output, improving the designs and better understanding the operations in the manufacturing system [1,17]. In machining systems, recent studies have shown that the DT system can be used to predict many machining responses, *i.e.*, wheel/tool wear, surface integrity, optimum variable settings, MRR and energy consumed in the machining process [18–20]. The findings from these studies indicated how valuable the DT technology is for understanding the operations of a machining system and obtaining an improved efficiency in production [21].

The DT technology has been used to conduct several in-depth investigations on engineering systems in order to fully comprehend their characteristic behavior. The reports presented are mostly indicative of the complexity in the manufacturing systems, whereby different systems exhibit dissimilar performance behaviors. Moreover, recent studies show an increase in the acceptability of DT techniques by scientists and engineers. The findings have shown that the outcomes of any designed virtual system (*i.e.*, DT) often depend on the operator's personality, design procedure, and input commands [7,22].

Many setbacks have been reported by scientists while trying to optimize manufacturing processes using the DT systems. Recently, manufacturing industries in areas of aerospace, automotive, robotics, biomedical, and telecommunications have increased their utilization of DT technology with AI for optimizing the manufacturing process [23–25]. This is because the DT systems utilized in the intelligent manufacturing sector have indicated a positive response towards optimizing highly complex engineering systems [26–28].

Many researchers have embarked on different tasks towards developing a comprehensive review relating to the digital twins for engineering systems. For instance, Jones et al. [29] reviewed 92 articles, whereby they explained that a proper utilization of the DT can greatly improve the overall efficiency in a manufacturing plant. Also, Nan et al. [30] explained that the DT systems can be used to improve the different phases in a production circle, such as conceptualization, designs, production, and post-production processes. However, it was affirmed that the DT technology is still at its infancy stage of development [31].

Many review works have been published pertaining to the application of DT in the manufacturing sector. However, there has not been a bibliometric study on the application of AI and DT in this area. The purpose of conducting this bibliometric review is to obtain deep insights into the development of the DT in machining systems, understand the current trends, and also study how the AI has been incorporated into machining systems and DT [21,32,33]. It has been shown that different fields require a separate approach to developing their digital twins as no one technique fits all [34]. By carefully studying and understanding the different machining systems, optimum DT could be developed based on the peculiar behaviors of the system. Proper designs of DT systems for different machining processes can produce specific optimization methods in these processes [33,35,36].

Recent works have shown an increase in the utilization of artificial intelligence (AI) and/or machine learning (ML) techniques to optimize and predict the outcomes of manufacturing processes [37]. Figure 2 is a flowchart showing how the optimization and prediction in machining can be achieved using the DT systems. The popular optimization systems used to optimize the manufacturing systems include mathematically based algorithms such as cuckoo search algorithms, ant-colony algorithms, genetic algorithms, particle swarm optimization (PSO), *etc.* [38]. Further, outcome predictions in the DT of manufacturing processes have been done using fuzzy logic (FL), artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS), *etc.* [7,39–44].

An in-depth analysis of the recently published papers indicates that there is a rapid increase in the number of articles relating to studying the responses in machining systems using the DT technique. Even though there are quite a number of works presented by previous researchers regarding the development of DT in the manufacturing systems, most of the previous works have been found to be focused on either AI, smart manufacturing, or smart systems [22].

A comprehensive search on the studies relating to the advances of DT in machining systems will, however, return a small or limited number of outcomes. Hence, much work needs to be done to fully understand the performance of the DT technology in machining systems. A representation of the main framework of a DT system involving the process variables, responses, optimization methods, and software used to analyze machining processes is shown in Figure 3.

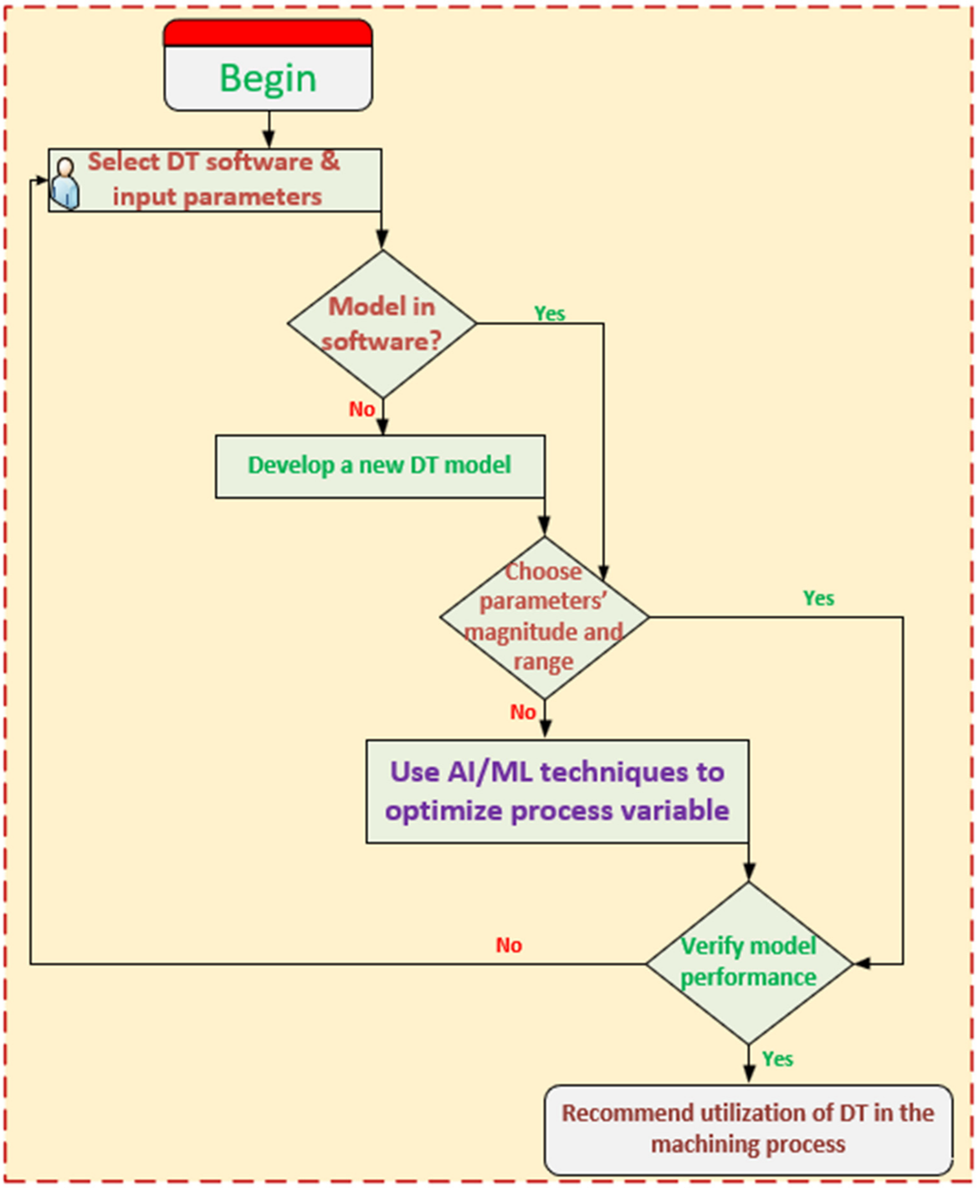

Figure 2. Flowchart for developing a DT for machining systems.

A full search for the keywords "machining", "DT", and "AI" indicates that there has been no bibliometric review work conducted in this area. In this work, we have conducted a full bibliometric analysis of these machining-based keywords that were indexed in the Web of Science database. The overall search goal was meant to obtain the total number of articles related to the searched keywords. Similarly, the prominent authors who have garnered the highest citations and published articles with their affiliations are discussed accordingly.

A comprehensive search on the keywords machining, DT, and AI, indicated that there has been no bibliometric review work conducted in this area. The main objective of this study is to conduct a full bibliometric analysis of the machining-based articles that were indexed in the Web of Science database relating to digital twins and AI. Consequently, the keyword search includes machining, digital twin and AI. The overall search goal was meant to obtain the total number of articles related to the searched keywords. Similarly, the prominent authors with the highest citations and number of published articles in this area, the research-originating institutions and their countries, and finally the classification of the published works.

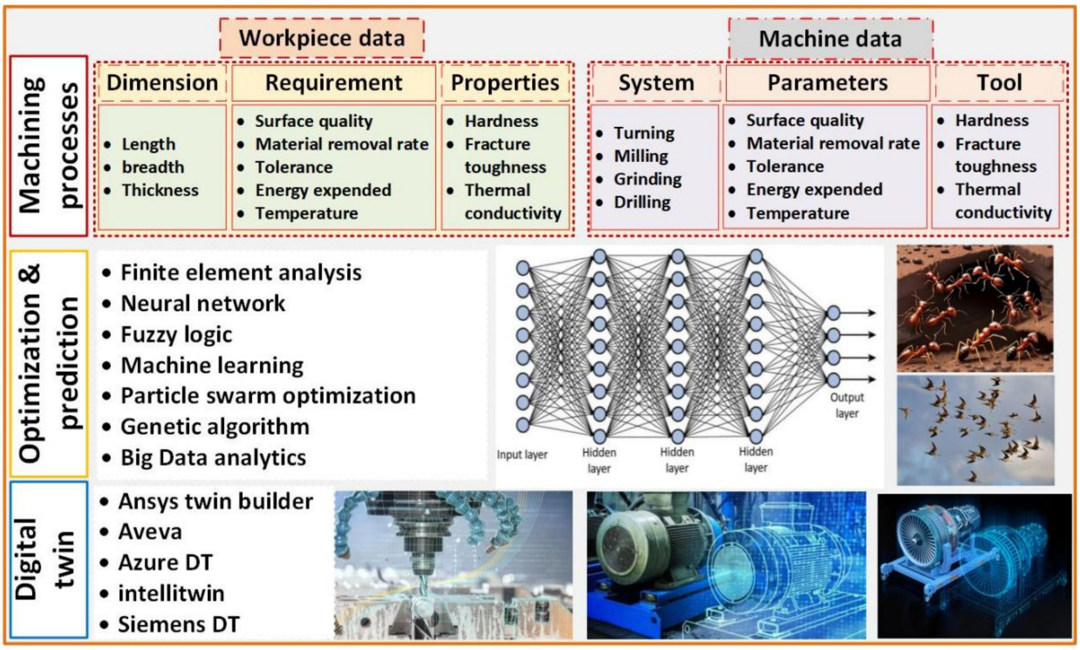

Figure 3. Framework of DT for machining processes.

2. Method of Acquiring Bibliometric Information

The process of acquiring the bibliometric data in this article is explained in this section. The word search was done by searching for a group of keywords on the Web of Science (WoS) database. The main search words used in the Web of Science database to obtain the bibliometric data are machining, artificial intelligence, AI, digital twin, digital twins and DT.

The choice of the WoS database is due to the high number of articles published relating to machining and sustainable manufacturing. Similarly, the high quality of research works and vast amount of knowledge contained in articles that are indexed in the WoS database is a major reason for obtaining data from it.

Bibliometric literature review is among the relevant methods of studying the trends and patterns in a given field/area of study. It involves analyzing the journals, articles, authors, organization/institution, keywords, yearly output, originating countries, and the kind of documents existing in that research area [45–51]. The bibliometric literature analysis includes an overarching portrayal and illustration of the articles found in a research area.

In this work, we have conducted a bibliometric analysis of the published articles focused on the utilization of DT and AI for predicting and optimizing different machining responses. This presents a huge prospect for understanding the role of DT technology and AI in machining processes. This bibliometric analysis was done based on the data available on the Web of Science database up to the year 2024 using the VOSviewer software. The review also gives insight into the prominent authors in this research area and the leading countries. Initial analysis of the results indicates that the researchers come from diverse geographical affiliations. The data obtained indicates the preeminence of researchers from countries such as China, India, USA, UK, Spain, Turkey, Poland, *etc.* as the countries with the highest number of research outputs in this area.

Firstly, the data obtained was classified according to the interconnectivity with various other research fields relating to machining, artificial intelligence, and digital twin technology. Further, the analysis of citations from the published works was done based on the highest cited articles and the most cited authors. Similarly, the amount of interactive author citations was analyzed using the journal co-citation studies with the aid of the VOSviewer software. Co-citations in journals are defined by the amount of joint citation existing between two or more authors in different articles. Analyzing the co-citation allows for identification of linkages between the authors and keywords. Finally, the co-citation analysis was conducted in order to map out the interactions between the authors and published articles. This was done so as to obtain patterns in the keyword search and the interconnectivity between the searched results. The composition of the search words ("syntax") utilized in this study is given in Table 1.

Table 1. Search word used to obtain bibliometric data.

WoS Search	Syntax Used
Search words	((“Artificial intelligence” OR “AI” OR “Machine learning” OR “Prediction”) AND (“Intelligent Manufacturing” OR “Sustainable Manufacturing”) AND/OR (“Machining” OR “Grinding” OR “Milling” OR “Turning” OR “Drilling”) AND (“Digital twin” OR “Digital twins”) AND LIMIT-TO (LANGUAGE, “English”)).

The bibliometric data was obtained on Wednesday, 13 November 2024, at about 9.00 a.m. (GMT). The searched keywords were found to be present in either the title, abstracts, or keywords section of the articles. The searching was done in batches using a combination of each keyword. Further, different responses were obtained each time from the WoS database search when a different keyword combination was inserted. For each keyword search conducted, the results of the number of articles found in the WoS string search are presented in Table 2. At the end of the WoS database search, the search string “6” of Table 2 was chosen and utilized for the bibliometric analysis in this work.

Table 2. Results of WoS string search.

S/N	Search String	Number of Articles Found
1	(“Artificial intelligence” OR “AI” OR “Machine learning” OR “Prediction”) AND (“Digital twin” OR “Digital Twins”)	3437
2	(“Digital twin” OR “Digital Twins”) AND (“Machining” OR “Intelligent Manufacturing” OR “Sustainable Manufacturing”)	484
3	(“Digital twin” OR “Digital Twins”) AND (“Grinding” OR “Milling” OR “Turning” OR “Drilling” OR “Machining”) AND (“Artificial intelligence” OR “AI” OR “Machine learning”)	40
4	(“Digital twin” OR “Digital Twins”) AND (“Machining” OR “Grinding” OR “Milling” OR “Turning” OR “Drilling”)	337
5	(“Artificial intelligence” OR “AI” OR “Machine learning” OR “Prediction”) AND (“Sustainable machining” OR “Intelligent Manufacturing” OR “Sustainable Manufacturing”)	1971
6	((“Artificial intelligence” OR “AI” OR “Machine learning” OR “Prediction”) AND (“Sustainable Machining” OR “Intelligent Manufacturing” OR “Sustainable Manufacturing”) AND (“Grinding” OR “Milling” OR “Turning” OR “Drilling”) AND/OR (“Digital twin” OR “Digital Twins”))	464

Method of Analyzing Bibliometric Data

Bibliometric analysis is an appropriate method of conducting a statistical and quantitative technique of explaining the spread, evolutionary development, and trend of the particular topic. Studies relating to bibliometric analysis are often referred to as bibliometrics. First published by Broadus in 1987 [52], bibliometrics have been observed to be an important and genuine method of making an extensive overview of any field as compared to other reviewing techniques [53].

In its early stage of usage for conducting reviews, the bibliometrics was solely used to analyze the number of articles and their citations. However, recent developments have seen a more thorough evaluation of the trends in a given field of study. With the advent of analysis-based softwares such as RStudio (Rstudio_4.4.2) and VOSviewer, the scientific representations in bibliometrics have seen significant improvements. Using these softwares, the related keywords, institution, authors, countries of originating research work, co-authors and citation analyses could be effectively mapped out.

This study reviewed the articles and advancements in DT technology and AI in machining systems that have been published until 2024. Our keyword on the WoS database returned about 464 relevant articles. Most of the published articles were presented by multiple authors in the same paper. Single-authored articles were not found among the search results.

Finally, the search results were directly obtained and saved from the WoS database in the form of Excel and text files. The Excel file from the search results in the WoS database was then used to conduct the bibliometric analysis.

3. Discussion of Results

A total of 464 articles were returned from the search string. The articles were published by authors from different institutions in about 50 countries. The bibliometrics in this study were presented based on the annual publication output, prominent co-authors, journals, organizational affiliations, affiliated countries of the research works and the citations analysis. The analysis of the results obtained will be discussed further in this section.

3.1. Journals

Table 3 presents the search results of the most prominent journals whereby the articles published on DT technology and AI in machining systems were obtained. Similarly, the number of citations acquired by each journal and its indexing database were all provided. The results were limited to only journals that consist of at least 6 articles published in them. Moreover, details such as the Web of Science sub-category, citescore, and percentage of the total number of articles were also included. Lastly, it was found that the leading journals include the Journal of Manufacturing Systems, International Journal of Advanced Manufacturing Technology, Journal of Intelligent Manufacturing, Robotics and Computer-Integrated Manufacturing, Advanced Engineering Informatics, IEEE Access, Structural and Multidisciplinary Optimization, International Journal of Precision Engineering and Manufacturing, Proceedings of the Institution of Mechanical Engineers Part B-Journal of Engineering Manufacture, Machines, and also Robotics and Computer-Integrated Manufacturing journal.

Table 3. Analysis of prominent journals (≥5 papers).

S/N	Journal Name	Number of Articles	Percentage (%)	Cites Score	Category/Quartile	Publisher
1	JOURNAL OF INTELLIGENT MANUFACTURING	168	36.207	19.3	Computer Science-Artificial Intelligence/Q1	Springer Nature
2	INTERNATIONAL JOURNAL OF ADVANCED MANUFACTURING TECHNOLOGY	52	11.207	5.7	Engineering-Manufacturing/Q2	Springer Nature
3	JOURNAL OF CLEANER PRODUCTION	14	3.017	20.7	Engineering Industrial and Manufacturing/(Q1)	Elsevier
4	ROBOTICS AND COMPUTER INTEGRATED MANUFACTURING	14	3.017	24.1	Engineering Industrial and Manufacturing/(Q1)	Elsevier
5	MEASUREMENT	13	2.802	10.2	ENGINEERING/Q1	Elsevier
6	PROCEEDINGS OF THE INSTITUTION OF MECHANICAL ENGINEERS PART B JOURNAL OF ENGINEERING MANUFACTURE	10	2.155	2.7	Engineering Mechanical/Q2	SAGE Publications Inc
7	JOURNAL OF MANUFACTURING PROCESSES	9	1.94	7.6	Engineering Mechanical/Q2	Elsevier
8	JOURNAL OF MANUFACTURING SYSTEMS	9	1.94	23.3	Engineering Industrial and Manufacturing/Q1	Elsevier
9	ADVANCED ENGINEERING INFORMATICS	8	1.724	12.4	Computer Science - Artificial Intelligence/Q1	Elsevier
10	MECHANICAL SYSTEMS AND SIGNAL PROCESSING	7	1.509	14.8	Engineering Mechanical/Q1	Elsevier
11	IEEE ACCESS	6	1.293	9.8	Engineering (miscellaneous)/Q1	Institute of Electrical and Electronics Engineers Inc.
12	ADVANCES IN MANUFACTURING	5	1.078	5.9	Engineering -Mechanical Engineering/Q1	Springer Nature
13	INTERNATIONAL JOURNAL OF PRECISION ENGINEERING AND MANUFACTURING GREEN TECHNOLOGY	5	1.078	8.5	Engineering -Mechanical Engineering/Q1	Springer Nature
14	JOURNAL OF MANUFACTURING SCIENCE AND ENGINEERING TRANSACTIONS OF THE ASME	5	1.078	6.8	Engineering-Mechanical Engineering/Q1	American Society of Mechanical Engineers (ASME)
15	SCIENTIFIC REPORTS	5	1.078	7.5	Multidisciplinary/Q1	Springer Nature

3.2. Research Area

In terms of the Web of Science publication categories, it can be seen in Figure 4 that about 343 of the articles were indexed under the engineering manufacturing section. Further, 14 articles were classified under the "Friction & Vibration" section, 12 in "Supply Chain & Logistics", and seven articles in Metallurgical Engineering. More so, the subject categories of "Nanofibers, Scaffolds & Fabrication", "Laser Science", and "Artificial Intelligence & Machine Learning" were observed to have five articles each.

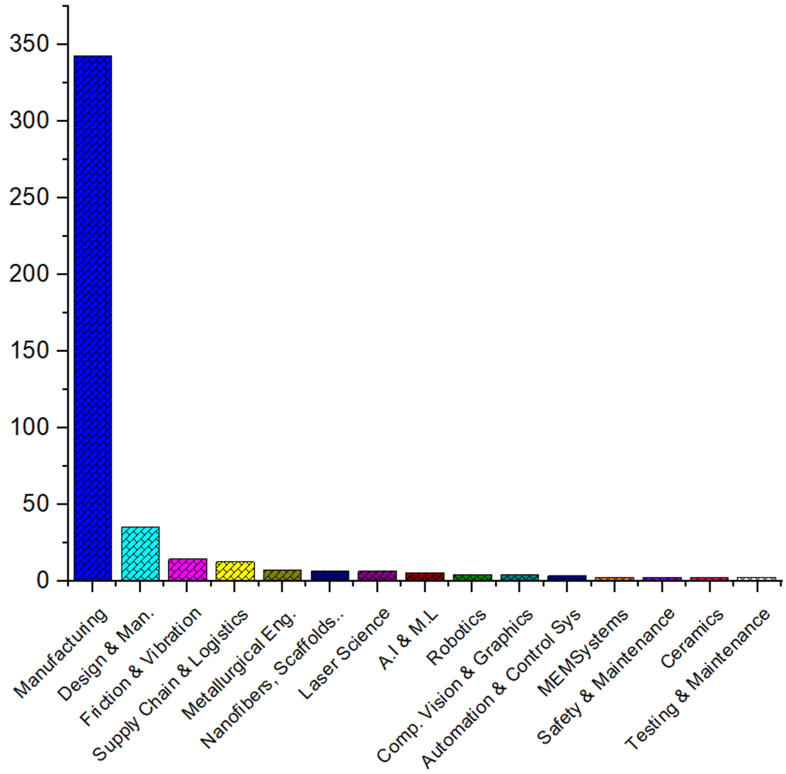

Figure 4. Major subject classification of the articles.

The articles were also observed to be classified based on micro-subject fields. Most of the studies were found to be related to the analysis or optimization of the machining processes towards the reduction of tool wear. About 70% of all the articles (*i.e.*, 326 articles) were observed to be based on the study of tool wear and process optimizations in machining systems (See Figure 5). This is an indication that the main application of the DT in the machining process is on extending the life span of tools/wheels.

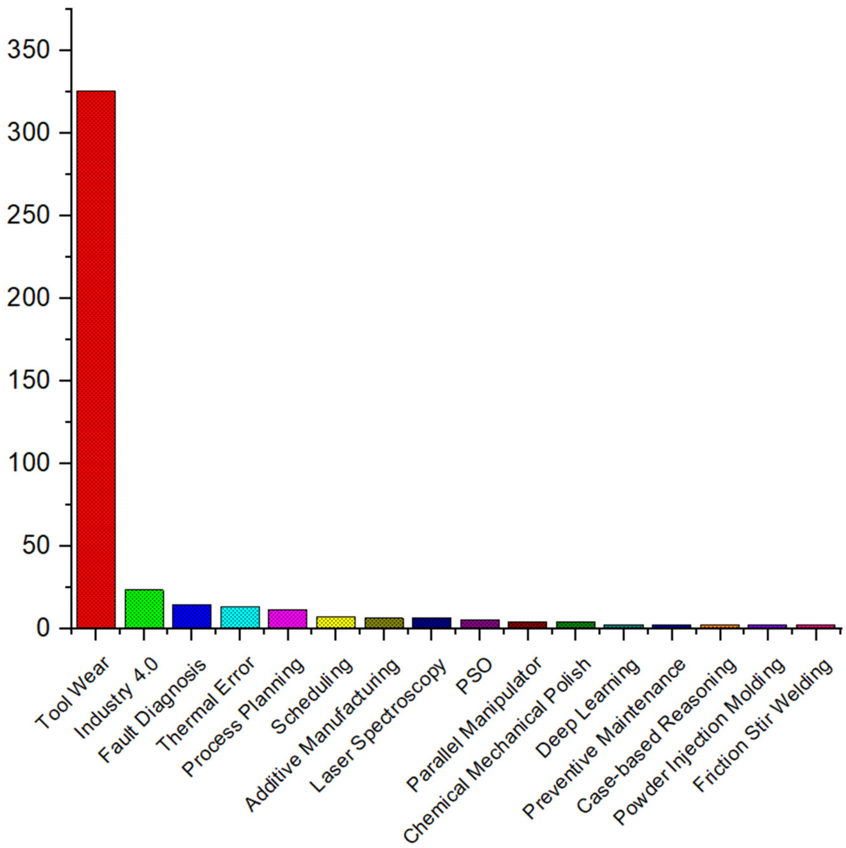

Figure 5. Micro research areas (Areas with more than one published article).

3.3. Author Affiliation

The keyword search in the WoS database also returned the organization/institution where the articles were published. It can be seen that more than 100 institutions/organizations were actively involved in this field of study. Similarly, about 14 institutions were realized to have published more than ten articles in this field of study (chart presented in Figure 6). The top three most active organizations/institutions in this research area in ascending order are Nanjing University of Aeronautics & Astronautics, Huazhong University of Science Technology, and Shandong University with “22”, “21”, and “17” articles, respectively. A summary of the results from the search string in terms of the originating organizations/institutions pertaining to research on DT, AI, and machining is tabulated in Table 4.

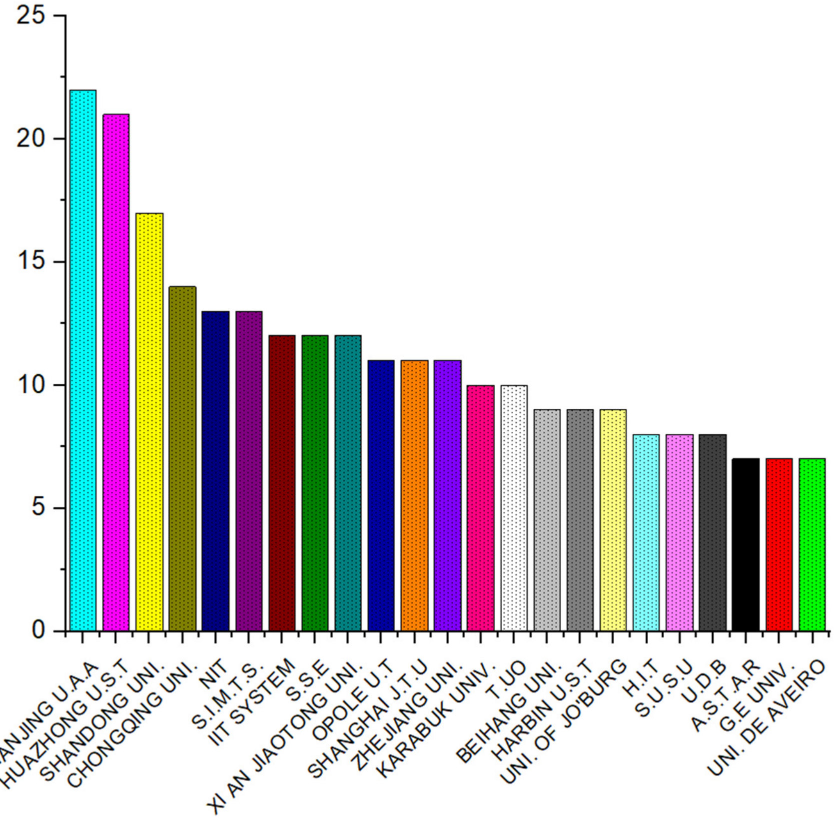

Figure 6. List of institutions with the highest number of articles (≥7 articles).

Table 4. Analysis of Organizations/institution of published articles (≥10 papers).

S/N	Organizations/Institutions	Number of Articles Published	Percentage (%)	Institution Country
1	NANJING UNIVERSITY OF AERONAUTICS & ASTRONAUTICS	22	4.741	China
2	HUAZHONG UNIVERSITY OF SCIENCE TECHNOLOGY	21	4.526	China
3	SHANDONG UNIVERSITY	17	3.664	China
4	CHONGQING UNIVERSITY	14	3.017	China
5	NATIONAL INSTITUTE OF TECHNOLOGY NIT SYSTEM	13	2.802	India
6	SAVEETHA INSTITUTE OF MEDICAL TECHNICAL SCIENCE	13	2.802	India
7	INDIAN INSTITUTE OF TECHNOLOGY SYSTEM IIT SYSTEM	12	2.586	India
8	SAVEETHA SCHOOL OF ENGINEERING	12	2.586	India
9	XI AN JIAOTONG UNIVERSITY	12	2.586	China
10	OPOLE UNIVERSITY OF TECHNOLOGY	11	2.371	Poland
11	SHANGHAI JIAO TONG UNIVERSITY	11	2.371	China
12	ZHEJIANG UNIVERSITY	11	2.371	China
13	KARABUK UNIVERSITY	10	2.155	Turkey
14	TECHNICAL UNIVERSITY OF OSTRAVA	10	2.155	Czech public

The information of the leading authors from the institutions is given in Figure 7. As seen, Gupta MK et al. [54] has the highest number of articles in this field with a total of 14 publications in the WoS database. Moreover, Bustillo et al. [55] was observed to have published about 9 articles in this area. Other prominent authors that have published at least

8 articles include Cep et al. [56], Korkmaz et al. [57], Pimenov et al. [58], and Ross et al. [59]. Furthermore, Jamil [60], Li L et al. [61], Li G et al. [62], and Davim et al. [63] were found to publish about 4 articles each.

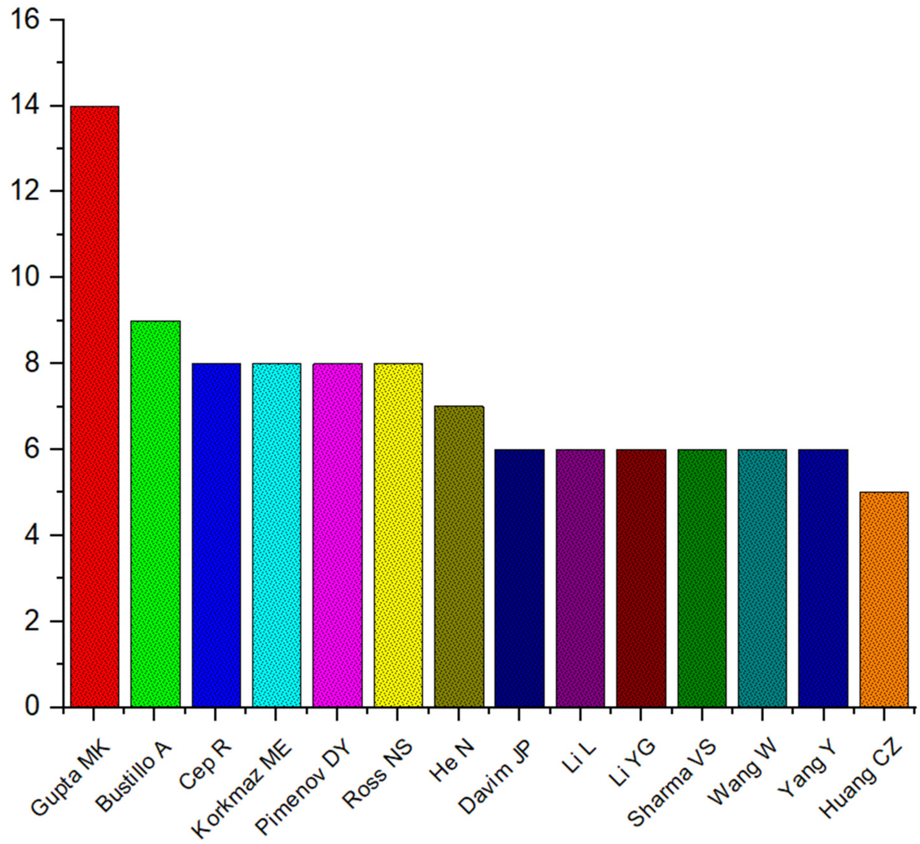

Figure 7. Authors with at least 5 published articles.

Besides, the details of the leading authors in this area of research, their affiliations, and the number of articles they have published are provided in Table 5. Among all the authors, the articles published by Benkedjouh et al. [64] and Zhu L et al. [65], have the highest number of WoS citations, *i.e.*, 267 and 216, respectively. These two authors were found to have the highest number of citations per article and are the only ones to have garnered more than 200 WoS citations. However, many other authors have accumulated more citations but in multiple articles.

Table 5. Details of the authors with highest WoS citations (≥145 WoS citations).

S/N	Author	Paper Title	Journal Name	Number of Citations	Institution/Country of First Author
1	Benkedjouh, et al. [64]	Health assessment and life prediction of cutting tools based on support vector regression	JOURNAL OF INTELLIGENT MANUFACTURING	267	EMP, Bordj El Bahri—Algeria
2	Zhu, L. et al. [65]	Recent progress of chatter prediction, detection and suppression in milling	MECHANICAL SYSTEMS AND SIGNAL PROCESSING	216	Northeastern University—China
3	Wu, D. et al. [66]	A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing	JOURNAL OF MANUFACTURING SYSTEMS	194	Pennsylvania State University—United States
4	Zhao, G. et al. [67]	Energy consumption in machining: Classification, prediction, and reduction strategy	ENERGY	178	Shandong University of Technology—China
5	Li, L. et al. [61]	Energy requirements evaluation of milling machines based on thermal equilibrium and empirical modelling	JOURNAL OF CLEANER PRODUCTION	172	Harbin Institute of Technology—China
6	Huang, Z. et al. [68]	Tool wear predicting based on multi-domain feature fusion by deep convolutional neural network in milling operations	JOURNAL OF INTELLIGENT MANUFACTURING	160	Shanghai University of Science & Technology—China
7	Pimenov D.Y. et al. [58]	Artificial intelligence systems for tool condition monitoring in	JOURNAL OF INTELLIGENT MANUFACTURING	150	South state Ural University-Russia

		machining: analysis and critical review			
8	Cai, W. et al. [69]	A hybrid information model based on long short-term memory network for tool condition monitoring	JOURNAL OF INTELLIGENT MANUFACTURING	146	Shanghai Jiao Tong University—China
9	Pimenov, D. Y. et al. [70]	Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth	JOURNAL OF INTELLIGENT MANUFACTURING	145	South Ural State University—Russia

3.4. Publishers

The analysis of the results from the WoS search indicates that these articles have been published by different publishers. Springer Nature was observed to contain 241 of the articles (accounting for about 52% of all the articles). Similarly, 24% of the articles were published in the Elsevier database. Furthermore, about 6.7%, 4.5% & 3% of the articles were found to be published in the MDPI, Sage, and IEEE databases, respectively. Also, a total of 9% of the articles were found to be published in 22 other databases. Figure 8 illustrates the number of articles published in the searched field in major databases.

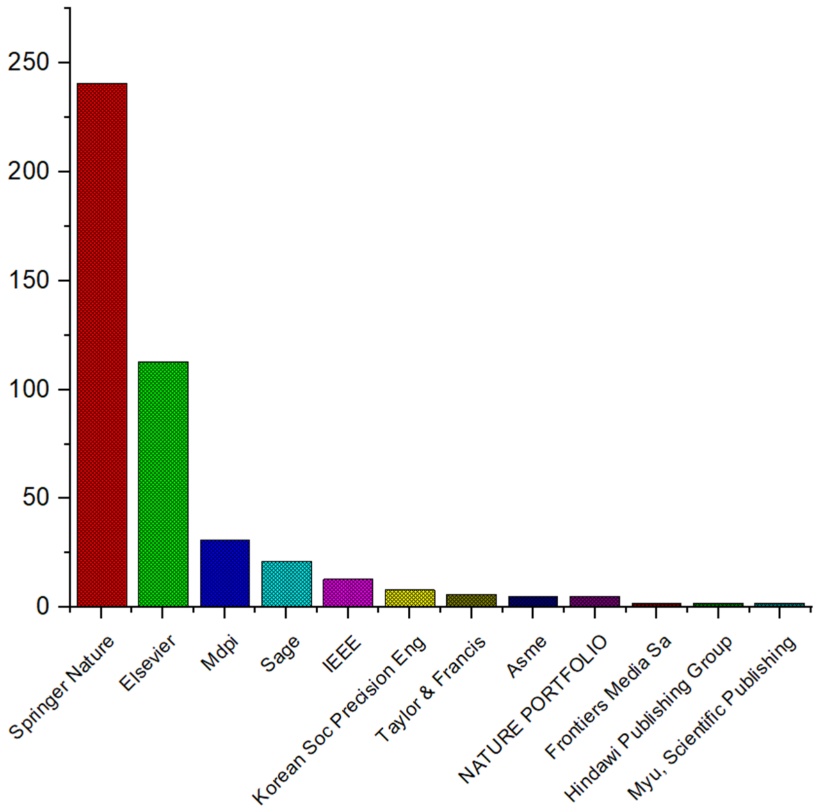

Figure 8. Number of articles published by publishers (≥2 articles).

3.5. Countries

Further analysis of the originating country of each research item indicates that many countries are actively involved in this research area. In particular, Table 6 gives the countries that have published the highest number of articles. In order to limit the number of occurrences, the table presents countries that have at least ten published articles in this research area. China has shown dominance in this research area by having the highest number of published articles in digital twin and machining systems (see Figure 9 for illustration).

Table 6 shows the search results, which indicate that about 231 articles were published by China, followed by India with 67, then the United States with 47 and the United Kingdom with a total of 28 articles. Moreover, 15 other countries were observed to have at least ten articles published in this research area so far. This indicates that there is an increased popularity of the research area around the world.

Based on the contents of the originating research works, the WoS search results indicate that Asia has a total of 373 articles. Similarly, 156 articles were affiliated with European institutions, 60 articles were affiliated to the American continent, and 58 were affiliated to Middle-Eastern-based institutions. Furthermore, institutions affiliated with Africa, the Australian subcontinent, and South America were found to have published 28, 16, and 13 articles, respectively. A noteworthy observation is that most of the published articles are characterized by multi-geographical authorships.

Table 6. Countries with at least 10 articles published under DT, AI and Machining.

S/N	Country	No. of Docs	Percentage (%)
1	PEOPLE REPUBLIC CHINA	231	49.784
2	INDIA	67	14.44
3	USA	47	10.129
4	ENGLAND	28	6.034
5	SPAIN	21	4.526
6	POLAND	20	4.31
7	TURKIYE	18	3.879
8	SOUTH AFRICA	15	3.233
9	TAIWAN	15	3.233
10	MALAYSIA	14	3.017
11	SOUTH KOREA	14	3.017
12	TURKEY	14	3.017
13	CANADA	13	2.802
14	CZECH REPUBLIC	12	2.586
15	SINGAPORE	12	2.586
16	AUSTRALIA	11	2.371
17	SAUDI ARABIA	11	2.371
18	BRAZIL	10	2.155
19	PORTUGAL	10	2.155

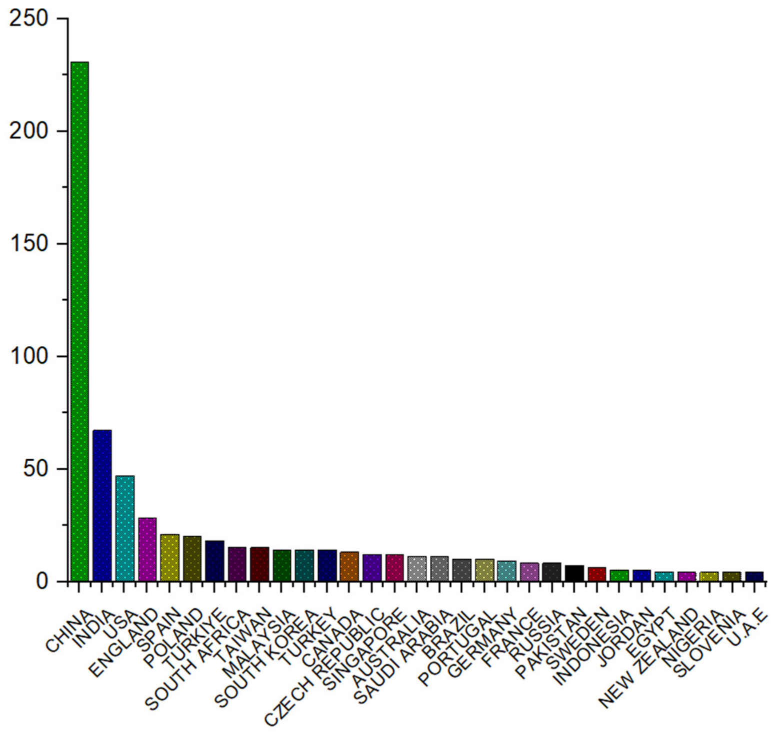

Figure 9. First author country (countries with more than 3 articles).

3.6. Type of Publication

The WoS search result was also used to classify the type of publications in the field of DT, AI and machining systems. It was found that about 437 of the total number of publications were articles, nine of which were indexed from conference proceedings, and 37 articles are early access papers (see Table 7). Furthermore, 27 articles were observed to be review papers. Since the search results were limited to articles and conferences only, there were no book chapters, letters or editorials found in the WoS result. Figure 10 presents the WoS classification of the articles obtained in the WoS search.

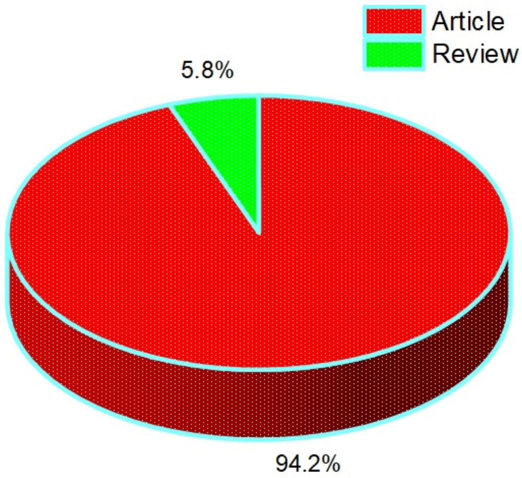

Figure 10. Classification based on the types of published documents.

Table 7. Type of publication.

S/N	Document Types	Number of Articles	Percentage (%)
1	**Article**	437	94.18
	i. Early Access	36	7.76
	ii. Proceeding Paper	9	1.94
2	Review Article	27	5.82

3.7. Annual Research Output

The analysis of annual publications in relation to DT, AI, and machining across the world is presented in Figure 11. The results as obtained from the WoS database indicate the number of articles published in each year. The results indicate that about 464 articles were published in English language from 2018 to date. It can be seen that since 2018, there has been a gradual annual increase in the number of published papers in this field, with the highest numbers recorded in 2024 (*i.e.*, 80 papers). Since 2016, there has a steady rise in the number of articles published in this field. The number of published articles rose from 7 in 2016 to more than 60 in the year 2020. However, it can be seen that there was a drop in the number of published works in 2021 to less than 50 papers. The decline in the number of articles published in 2021 can be attributed to the ripple effects of the COVID-19 lockdowns in the year 2020. Furthermore, since 2022, there has been a gradual increase in the number of articles published in this field. The incremental trajectory exhibited by the number of published works shows that this area is an active one and would likely have a higher number of published articles in the future. More so, it can be hypothesized that as the AI systems become smarter, a higher number of publications relating to AI in manufacturing processes are expected to increase exponentially from the improved optimizations.

Additionally, the overall number of citations has increased significantly over the years. In Figure 11, it can be seen that since 2018, there has been an exponential rise in the citations recorded, from less than 600 citations in 2018 to over 1900 citations in the year 2020. However, there was a slight reduction in the recorded the number of citations in 2021, which was attributed to the research related inactivity due to COVID-19 lockdowns in 2020. However, since 2022, the number of citations has greatly increased in the study area, reaching an all-time high of over 2400 in the year 2024. In addition, the overall citations related to the searched field were found to have garnered 10,657 and 11,226 citations, respectively, for “WoS” and “all other databases” citations.

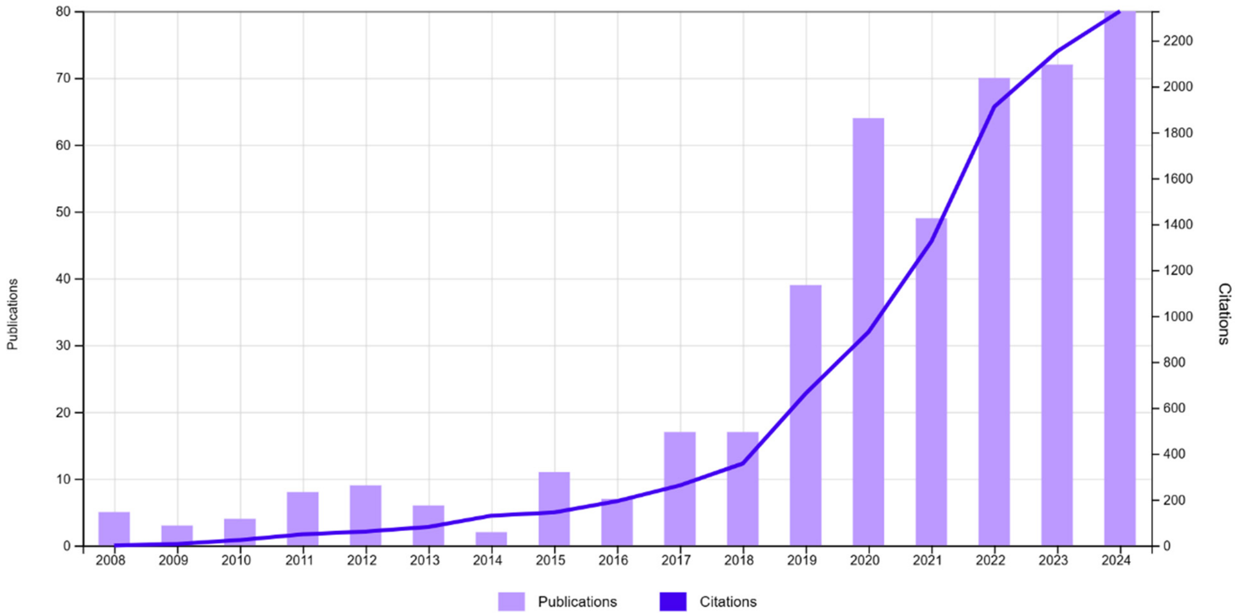

Figure 11. Annual publication output as obtained from the WoS database.

3.8. Keyword Cluster Analysis

Analyzing the keyword cluster is a tool used to understand the interactions between different terms in a data analysis. The most influential term (author or article) can be seen from the networks in a cluster analysis. Collaborative research works and co-citations can also be studied using cluster analysis in a given field of study. The data obtained from the WoS search using the search strings was analyzed using the VOSviewer software.

The interactions between the searched keywords were analyzed on the VOSviewer interface. A large circular dot denotes the main keywords; contrastingly, the related keywords were represented with a smaller shaped dot (see Figure 12). Moreover, the interactions and connectivity of the keywords were done using a set of connecting lines. The thick dashed lines represent strong interconnectivity, whereas the faint lines represent a small correlation between the searched words.

The keyword co-occurrence map enables an understanding of the main research topics in this field (Figure 12). The map forms four main clusters, each with high-frequency keywords. The main keywords in each cluster category were closely related as presented in Table 8. It can be seen that the first cluster centers on analyses of "tool wear" and some predictive analysis based on neural networks and machine learning. Cluster 2 focuses on optimization problems in mechanical processing, focusing on cutting variables and improving the process efficiency. Among them, "optimization" and "parameters" were the most occurring keywords. The main keywords in Cluster 3 are "prediction" and "surface roughness", and the research area was observed to be closely involved around this keyword. This made articles in this cluster have the highest link strengths. In addition, the studies related to "prediction" were observed to be scattered in all the clusters, whereas Cluster 3 mainly focuses on issues related to predicting the outcomes of surface roughness. Cluster 4 was found to be centered on "model" and modeling designs of machining systems. It can be seen that Cluster 4 strictly deals with articles on digital twins and Industry 4.0.

Figure 13 presents the overlay visualization of keyword co-occurrence. The color of the nodes in the figure indicates the novelty of the keywords. The keywords represented with yellow nodes were found to be used more frequently by the authors in recent years. The most used keywords related to intelligent manufacturing and smart manufacturing are presented in Table 9. They include words such as machine learning, deep learning, tool condition monitoring, chatter detection, flank wear prediction, digital twin, and compensation, *etc.*, which have been used at a high frequency since 2022, reflecting that scholars have paid increased attention to research in these fields in recent years. Moreover, due to the high occurrence frequency of some words over time, they tend to overshadow the latest trending words in the overlay description.

Table 8. Keywords found in each cluster.

S/N	Category	The Main Keywords (No. of Occurrence)
1	Cluster 1: Tool wear monitoring and prediction based on neural network	Tool Wear (66); Neural Network (51); Machine Learning (46); Wear (45); System (44); Intelligent Manufacturing (29); Deep Learning (26); Artificial Intelligence (22); Tool Condition Monitoring (22); Machine (18); Selection (17); Signal (17); Support Vector Machine (16); Classification (15); Fault-Diagnosis (15); Regression (15); Flank Wear (13); Tool Wear Prediction (13); Transfer Learning (13); Machining Parameters (12); Feature Extraction (11); Tool Wear Monitoring (11); Vibration (11); Acoustic-Emission (10); Convolutional Neural Network (10); Surface Roughness Prediction (10)
2	Cluster 2: Optimization of machining variables	Optimization (94); Parameters (56); Cutting Force (40); Sustainable Manufacturing (37); Efficiency (31); Cutting Parameters (26); Energy Consumption (26); Tool (25); Machine Tool (24); Sustainable Machining (21); Consumption (20); Machining (18); Power Consumption (18); Energy Efficiency (14); Steel (14); Quality (12); Surface Integrity (12); Systems (12); MQL (10); Sustainability (10); Titanium-Alloy (10)
3	Cluster 3: Prediction of machining responses	Prediction (153); Surface Roughness (101); Algorithm (34); Performance (31); Multi-objective Optimization (28); Force (27); Artificial Neural Network (26); Genetic Algorithm (17); Roughness (16); Material Removal Rate (13); Temperature (13); Response Surface Methodology (12); Turning (11)
4	Cluster 4: System modelling using digital twin	Model (74); Design (34); Digital Twin (20); Milling (18); Identification (17); Machining Process (17); Compensation (15); Simulation (12); Chatter (11); Industry 4.0 (10); Network (10); Stability (10)

Table 9. Frequently used keywords.

Time Frame	Popular Keyword
Since 2022	machine learning; deep learning; tool condition monitoring; digital twin; compensation; energy efficiency; transfer learning; tool wear prediction; tool wear monitoring; industry 4.0; stability; convolutional neural network

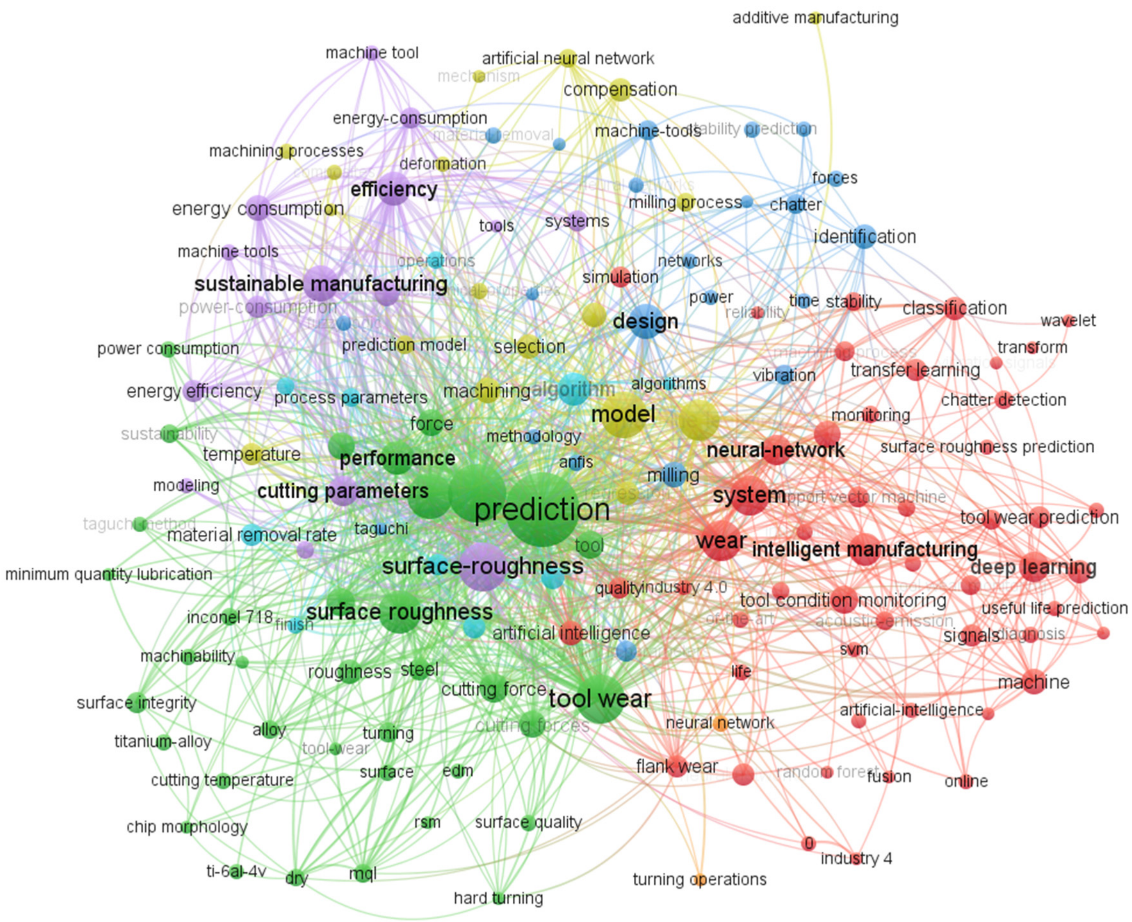

Figure 12. Keywords in each cluster.

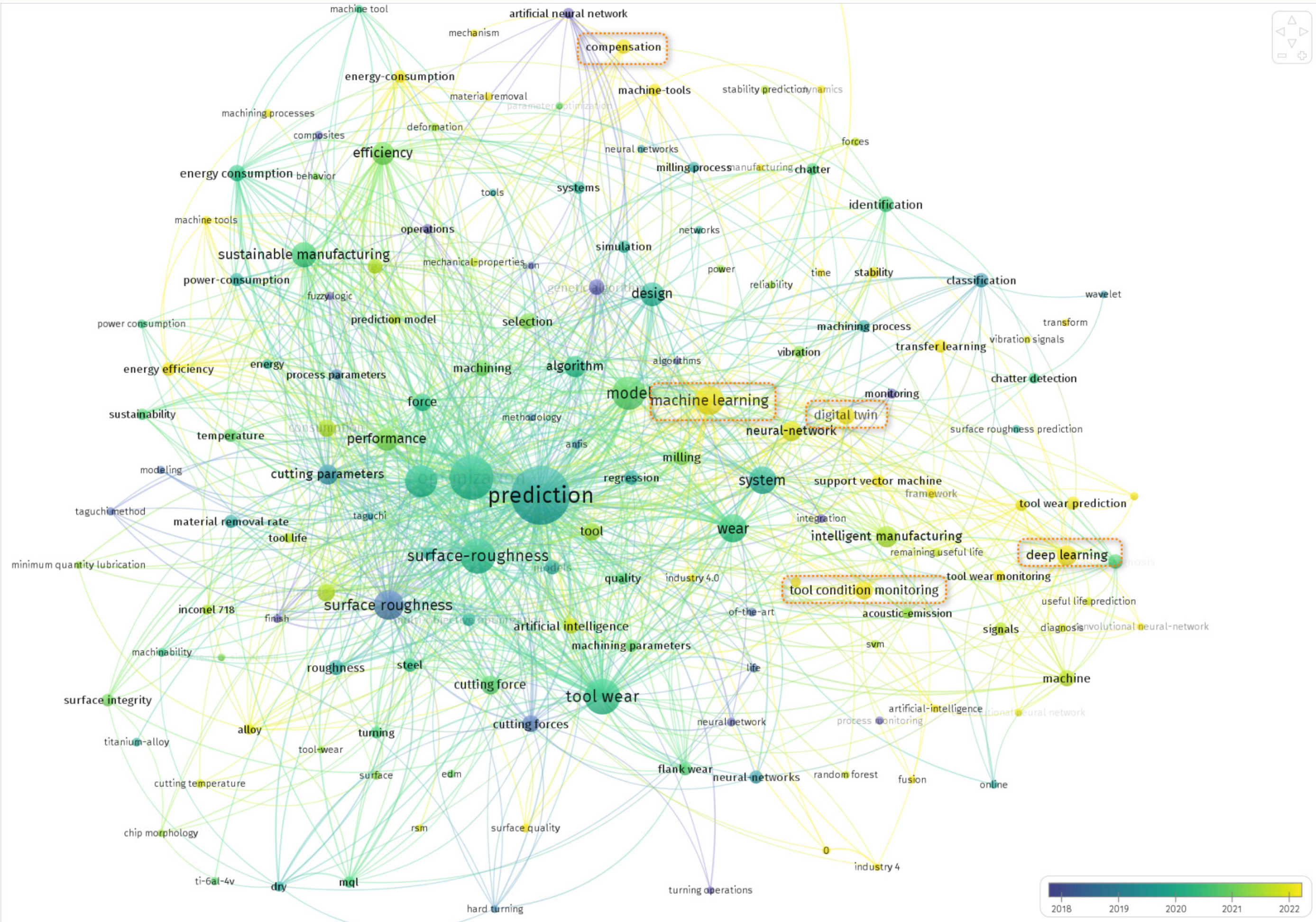

Figure 13. Overlay visualization of keyword co-occurrence.

3.9. Citation Analysis

In terms of the connections between these published articles, the interactions between the authors and citations in each cluster were presented based on the analysis from the VOSviewer visualization software. Citation analysis gives a proper awareness of the interrelationships existing between the different articles. Although the idea of DT is still in its infancy, it has been used in many different processes to achieve pre-fabrication analysis and virtual process optimizations. By scrutinizing the related articles of DT, AI, and machining, researchers can be able to identify the emerging trends in this field. The citation analysis based on the article can help to map out the different publication patterns regarding the DT technology.

Figure 14 shows the visualization network of the cited authors in this research area. As seen, Benkedjouh T. et al. [64] are presented as the most cited authors in this area. Among the 464 articles from the WoS search results, a threshold of a minimum of 5 citations between articles was used in the analysis. Moreover, the overall citations and interconnections existing between the articles were presented in the form of a network map in Figure 14. In addition, the size of the nodes on the network map indicates the number of times the paper has been cited, and the number of connections in each node expresses the closeness of that article to the other connected articles. The citation analysis presented on the network map indicated that there are 104 clusters of the articles. However, only 28 clusters were found to contain more than two articles in them. Besides, 14 clusters were observed to contain more than 10 articles, and 9 other clusters were seen to consist of between three and nine articles. However, the remaining clusters were treated as "noise", because they do not provide relevant information about citation interconnectivity between the articles. Therefore, based on the relevance of the articles to the subject matter, few of the clusters within the given sub-topics were selected for the citation analysis. Lastly, the most cited articles in the first five clusters are presented in Table 10.

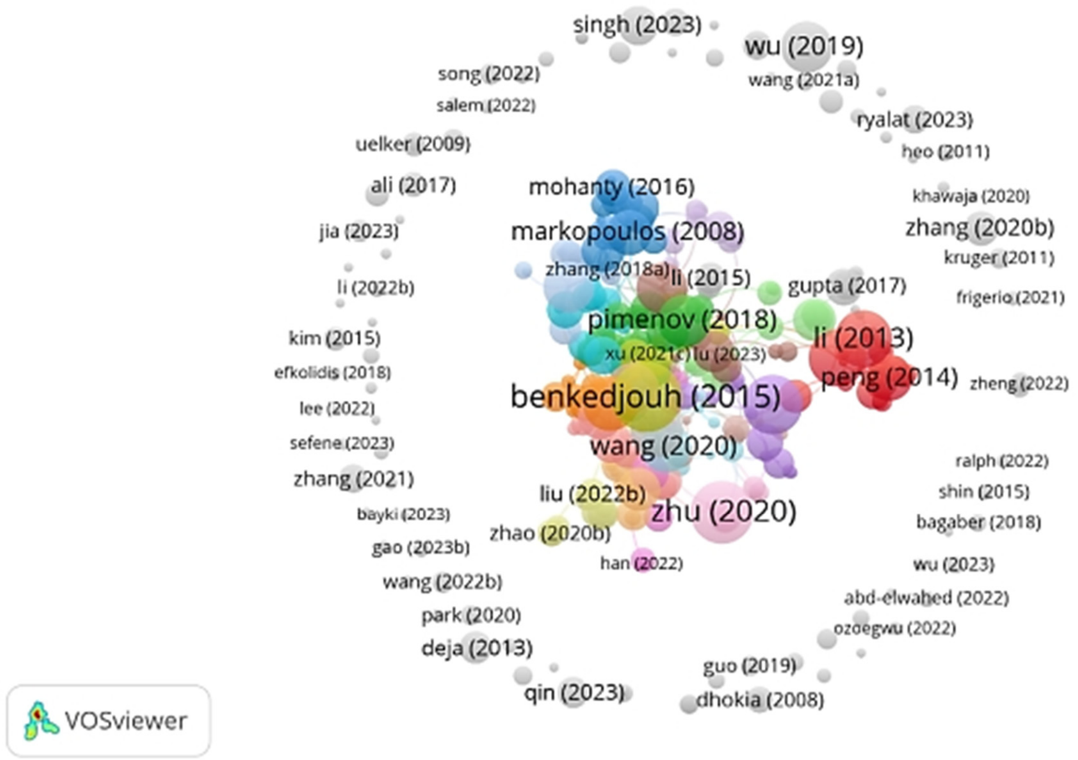

Figure 14. Network visualization of citation and document correlation.

Table 10. List of core articles.

S/N	Cluster	Cluster Topic	Core Article (Author-Year)	Title	Journal	Citations (WoS)
1	1	Energy consumption	Zhao G.Y. et al. [67]	Energy consumption in machining: Classification, prediction, and reduction strategy	Energy	178
2	1		Li L. et al. [61]	Energy requirements evaluation of milling machines based on thermal equilibrium and empirical modelling	Journal of Cleaner Production	172
3	1		Peng T. et al. [71]	Energy-efficient machining systems: a critical review	The International Journal of Advanced Manufacturing Technology	115
4	2	Surface roughness prediction	Pimenov D.Y. et al. [70]	Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth	Journal of Intelligent Manufacturing	145
5	2		Kovac P. et al. [72]	Application of fuzzy logic and regression analysis for modeling surface roughness in face milliing	Journal of Intelligent Manufacturing	99
6	2		Quintana G. et al. [73]	Surface roughness monitoring application based on artificial neural networks for ball-end milling operations	Journal of Intelligent Manufacturing	76
7	3	Multi-objective optimization algorithm	Markopoulos A.P. et al. [74]	Artificial neural network models for the prediction of surface roughness in electrical discharge machining	Journal of Intelligent Manufacturing	110
8	3		Rao R.V. et al. [75]	A multi-objective algorithm for optimization of modern machining processes	Engineering Applications of Artificial Intelligence	
9	3		Rao K.V. et al. [76].	Modeling and optimization of tool vibration and surface roughness in boring of steel using RSM, ANN and SVM	Journal of Intelligent Manufacturing	98
10	4	Tool Wear Prediction	Benkedjouh T. et al. [64]	Health assessment and life prediction of cutting tools based on support vector regression	Journal of Intelligent Manufacturing	267
11	4		Lee W.J et al. [77]	Monitoring of a machining process using kernel principal component analysis and kernel density estimation	Journal of Intelligent Manufacturing	65

12	5	Machine tool status monitoring	Wu D. et al. [66]	A fog computing-based framework for process monitoring and prognosis in cyber-manufacturing	Journal of Manufacturing Systems	194
13	5		Wang Y. et al. [78]	A kMap optimized VMD-SVM model for milling chatter detection with an industrial robot	Journal of Intelligent Manufacturing	75
14	5		Xu Z. et al. [79]	State identification of a 5-axis ultra-precision CNC machine tool using energy consumption data assisted by multi-output densely connected 1D-CNN model	Journal of Intelligent Manufacturing	11

Additionally, the citation analysis was conducted using the number of links, link strength, and citations accumulated by the articles. The link strength between the articles is calculated such that if article A cites article B, then a strength of 1 is established between A & B, indicating that there is a connection between these articles. This is done such that the relationships between the core articles and authors in any given cluster can be quantitatively identified.

Regarding the cluster analysis, the core articles in cluster 1 are Zhao et al. [67], Li et al. [61], and Peng A et al. [71]. The three articles studied issues related to energy consumption. Among them, the article "Energy consumption in machining: Classification, prediction, and reduction strategy" can be seen to be a review article. This paper provides a critical assessment of the energy consumed in a machining system.

In Cluster 2, the core articles were found to be Pimenov DY et al. [70], Kovac P et al. [72], and Quintana et al. [73]. The articles study issues related to surface roughness, including using AI methods to predict the deviation of surface roughness in real-time and modeling surface roughness using AI tools. Among the listed articles, the article by Pimenov DY et al. [70] is the most cited in this field.

In Cluster 3, the core articles were observed to be Markopoulos AP et al. [74], Rao RV et al. [75], and Rao KV et al. [76]. The articles were found to be related to studies on multi-objective optimization algorithms used in the manufacturing process.

In Cluster 4, the most cited article is Benkedjouh T. et al. [64], which has received the most WoS-based citations and has a high frequency of connection to other articles and clusters. This article proposed a method for tool condition assessment and life prediction based on nonlinear feature reduction and support vector regression. The second core article was published by Lee WJ et al. [77], which discusses a method based on KPCA that can be used to effectively monitor tool wear. Most of the articles in this cluster were found to be involved with the topic's evolution process. They were found to propose different tool wear prediction methods, using mathematical, ML, and hybrid optimization such as multi-information fusion and Gaussian process regression (GPR) optimized with a genetic algorithm (GA). Hence, it can be considered that the articles in this cluster mainly focus on the prediction of tool wear.

In the fifth cluster, Wu D. et al. [66] was found to be a prominent source of research data for other articles due to its high number of citations and correlation with other articles. Their work is among the pioneers of IoT-based studies whereby a new computing framework is introduced into remote real-time sensing, monitoring, and high-end computing in manufacturing systems. The computing framework utilizes a network of wireless sensors, cloud computations, and machine learning to conduct real-time cyber-manufacturing. In addition, the authors developed a conceptual prototype to demonstrate how computing frameworks can be used by manufacturers to monitor the reliability of a machine and to predict its performance. Similarly, Wang J. et al. [80] established a variable mode decomposition support vector machine (VMD-SVM) model based on the equilibrium data of the tools to detect wear and also chatter in milling. Also, Xu et al. [79] published a recent article that is closely related to the other articles in this cluster. They proposed the use of a 1-dimensional convolutional neural network (1DCNN-LSTM) to predict real-time power profiles of a 5-axis ultra-precision machine tool (UPMT). This article provided the advances in the studies of ultra-precision machine tool technology towards achieving Industry 4.0. The authors proposed the utilization of an intelligent monitoring system that uses the power consumption data of a device to evaluate and determine the state of health of the device. A densely connected convolutional neural network with multiple outputs was developed to simultaneously identify machine states and also predict optimum feed rates. The articles in this cluster can be seen to be based on applications of AI in manufacturing processes. Likewise, the fifth cluster contains articles classified under cyber-manufacturing and IoT in manufacturing systems.

According to the citation analysis, based on the area of study, the articles can be subdivided into major and minor clusters. Based on the clustered classifications, it was found that the most studied research directions are studies on energy consumption in machining, multi-objective optimization algorithms, prediction of machining outcomes (tool wear, surface roughness, *etc.*), and real-time monitoring of machine conditions.

The details of the most cited articles in each cluster are provided in Table 10, whereby the articles were classified in the VosViewer author citation analysis according to the major topic of their cluster and the total citations garnered.

It should be noted that the analysis we conducted above is at the article level, aiming to identify the most influential articles among these 464 articles and the research topics represented by these articles. However, having a good influence of an article does not necessarily mean that the author of this paper has a very high influence in the whole field, because this author may have published fewer articles than others. Therefore, to understand the most influential scholars in this research field, we often conduct an analysis of author collaboration and author citation relationships at the author level.

Furthermore, we analyzed the author collaborations among the 464 articles. In our analysis, we set the threshold to scholars who have published at least 3 articles in the research field. It was found that about 100 scholars met this minimum threshold requirement, and a network map of the authors was created as shown in Figure 15.

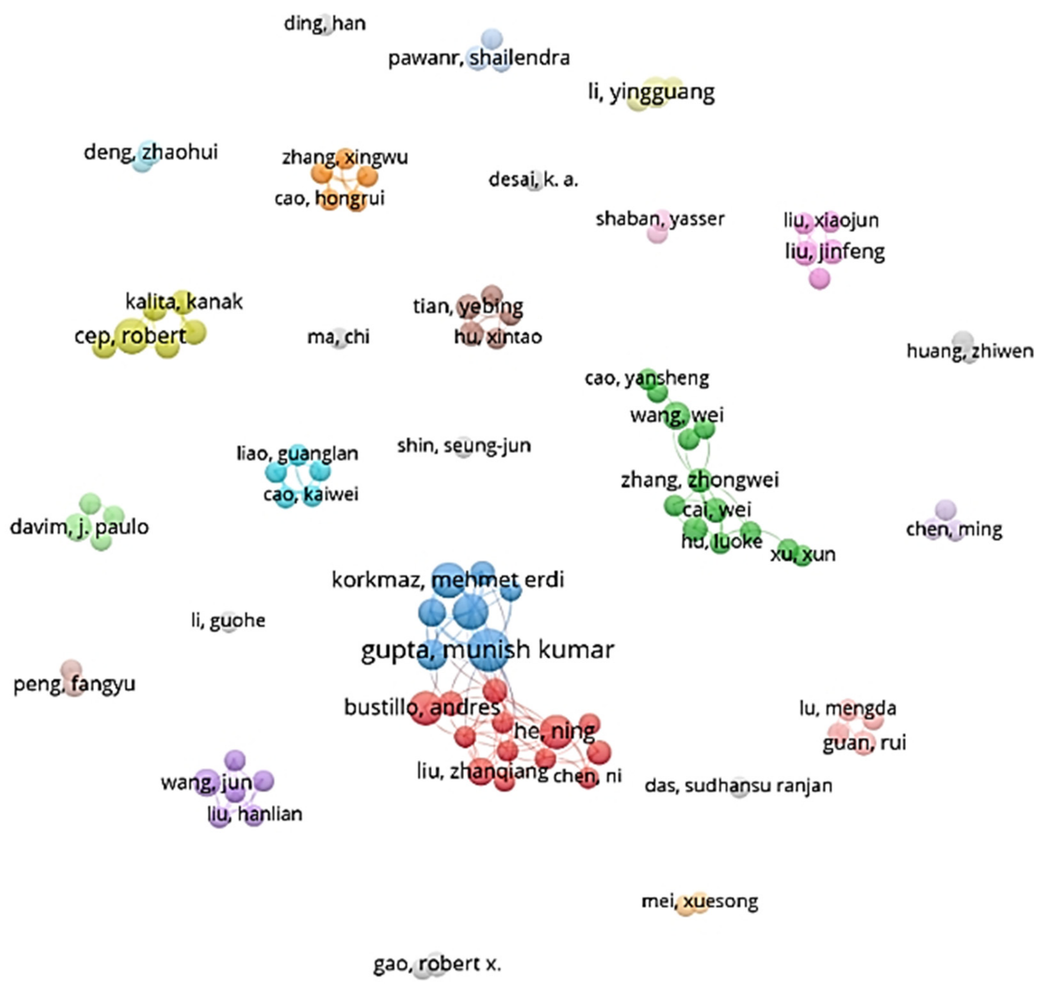

Figure 15. Visualization of authors co-occurrence mapping.

We can observe that the authors of the 464 papers are scattered into several unrelated networks. This suggests that different scholars have formed their own collaborative groups due to differences in their research contents. For the purpose of clarity and coherence, we only focused on the larger research group clusters. For instance, in Figure 16, the largest collaborative group of authors was presented. It can be seen to consist of two major teams. In Table 11 the group of the most prominent authors is presented, which includes the author Gupta MK et al. [54]. This author was found to have the best connectivity in this group and is also the author who has published the most number of articles. He serves as the intermediate node for the cooperation between the two teams. The scholar Gupta MK et al. [54] has a rich research foundation in the field of tool wear analysis and a few studies in the field of additive manufacturing. Further, in the same cluster, Jamil M et al. [60] was found to have published 4 articles but have a superior established cooperative relationship with 14 scholars, thereby indicating a relatively high cooperation capacity with other authors. Additionally, Bustillo A et al. [55] and Sharma VS et al. [81] were observed to have good citation frequencies, with their articles frequently cited in this research area.

Table 11. Collaborations among prominent authors (first group).

S/N	Author	Citation Frequency (1 Article)	The Number of Collaborators	Number of Articles
1	Gupta M.K. et al. [54]	300	15	12
2	Jamil M. et al. [60]	161	14	4
3	Bustillo A. et al. [55]	424	3	7
4	Sharma V.S. et al. [81]	390	8	6

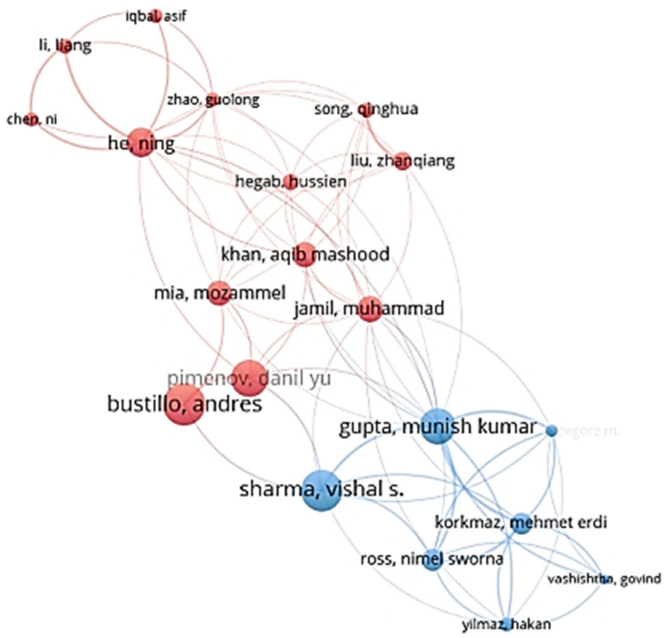

Figure 16. Connections between prominent authors in the first group.

Figure 17 presents another collaborative group comprising two teams. Among them, the author Zhang, Z. et al. [82] played a crucial role in the formation of this group and established the interconnection of the entire group through papers. He is from Henan University of Technology and is engaged in research on intelligent manufacturing. Tool wear is one of his research directions. The author Xu, Xun et al. [83] has the highest citation frequency. However, it was observed that he only has an established network connection in their group with Peng T. et al. [84]. This scholar can be seen to be from the University of Auckland, and he is a recipient of the highly cited award. His research focuses on Industry 4.0 and also involves additive manufacturing. The three papers retrieved this time by him, namely "A Framework for machining optimization based on STEP-NC", "An interoperable energy consumption analysis system for CNC Machining", and "Energy-efficient machining systems: a critical review", have all received relatively high citations. See Table 12 for the total indices archived by these authors.

Table 12. Collaborations among prominent authors (second group).

S/N	Author	Citation Frequency (1 Article)	The Number of Collaborators	The Number of Papers
1	Xu X. et al. [83]	197	1	3
2	Peng T. et al. [84]	155	2	3
3	Yang Y. et al. [85]	101	3	3
4	Cai W. et al. [86]	63	5	4
5	Jia, S. et al. [87]	63	5	4
6	Zheng J. et al. [88]	62	3	3
7	Wang W. et al. [89]	59	4	5
8	Zhang Z. et al. [82]	59	8	4
9	Hu L. et al. [90]	52	4	3
10	Lv J. et al. [91]	35	5	3
11	Cao Y. et al. [92]	32	1	3
12	Zheng L. et al. [93]	7	2	3

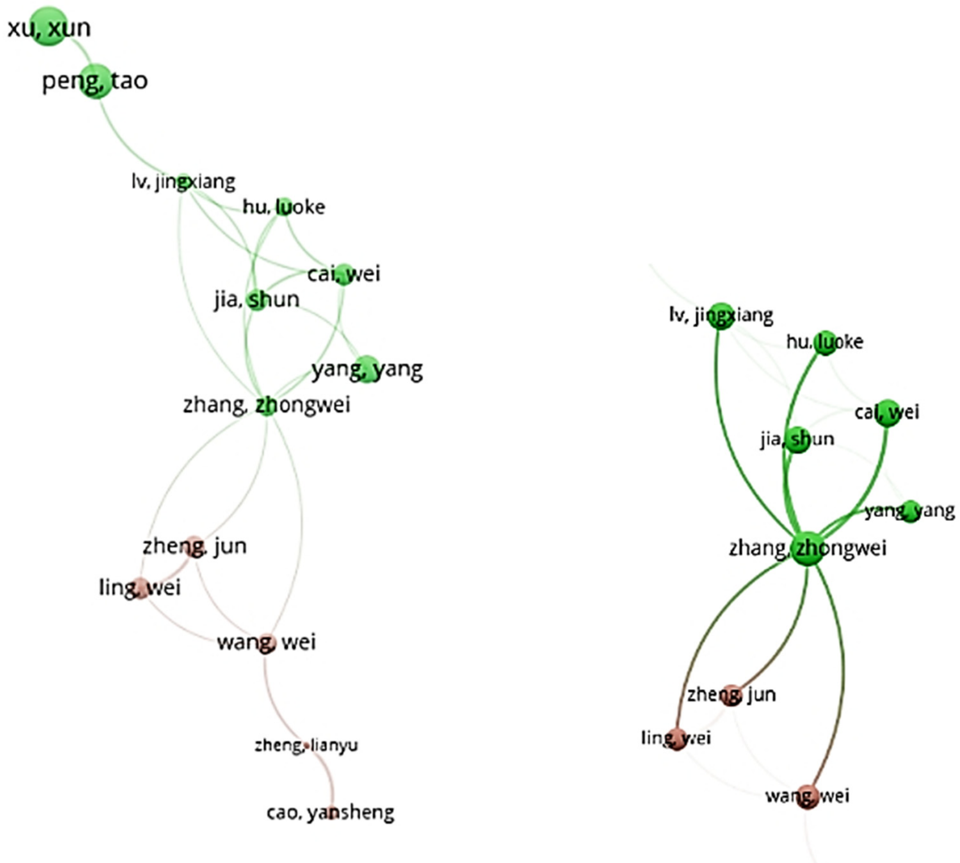

Figure 17. Third clustered collaboration group for prominent authors.

In addition to these two major collaborative groups, there are also some scholars who, despite not having formed numerous collaborations with other scholars in this field, possess relatively high individual influences in this research field. Among them are Gao R.X. et al. [94] and Wang, J. et al. [80] are the most prominent authors'. These authors were found to have collaborated and published articles together, thereby forming a relatively close cooperative relationship. The citation indices are shown in Table 13, and their research topics were observed to be focused on tool wear predictions.

Table 13. Micro-collaboration by prominent authors.

S/N	Author	Number of Citations (All Articles)	Author Collaborations	Number of Articles
1	Gao R.X. et al. [94]	489	1	4
2	Wang J. et al. [81]	295	1	3

Finally, based on the clustered classifications of these articles, it can be seen that the most studied research directions are studies on energy consumption in machining, multi-objective optimization algorithms, prediction of machining outcomes (tool wear, surface roughness, *etc.*), and real-time monitoring of machine conditions. Likewise, it was found that there are a total of 1723 links between the articles with a total link strength of 10,844.

4. Recent Advances/Emerging Technologies in Machining Processes

In recent times, there has been an integration of many kinds of emerging technologies in the machining system. Emerging technologies have been applied to both additive and subtractive manufacturing processes. This has led to the development of intelligent machining, which has produced tremendous improvements in the machining process through the application of generative AI, immersive technology, IoT online machine monitoring, nanotechnology, and intelligent advanced manufacturing. The use of artificial intelligence in machining has brought about great enhancement in temperature controls, tooling technology, material removal process, *etc.* [95].

Intelligent machining has been found to outperform its traditional counterpart in terms of process efficiency and machining outcomes. Recent studies have shown that intelligent machining process incorporates electronic tooling, IoT based sensors [96], smart controllers [97], big data [98] *etc.* Similarly, many researchers have indicated that by optimizing the machining variables, the productivity of machining system can be enhanced greatly [99]. This idea is what led to the development and utilization of DT to enhance the efficiency of machining processes.

Recent studies have proposed the utilization of AI to control and optimize the machining process. The success of the AI in machining has grown tremendously with the use of big data analytics. The use of big data and different other AI platforms was observed to also improve the lifespan of the tools and improve the efficiency of the machining process. Figure 18 illustrates the process control of the machining system using DT and AI to achieve optimum process efficiency.

Recent advances in intelligent machining signal the need for appropriate selection of machining variables. The correct selection of process variables will lead to maximization of productivity and reduction time and material exhausted during the machining process. Furthermore, the lifespan of the machining tools can also be greatly increased by proper selection of the process variables. Consequently, it is vital to obtain optimum machining variable settings in order to enhance the productivity of the machining operations. Several intelligent prediction and optimization methods have been implemented in machining systems to improve efficiency. They include Taguchi ANOVA analysis, fuzzy logic prediction, artificial neural networks, cuckoo search algorithm, genetic algorithm, particle swarm optimization, *etc.* [100].

There has been the use of AI/ML techniques to achieve multi-objective prediction and optimization of machining outcomes. For instance, Dambatta et al. [41] used fuzzy logic to predict the grinding power, force ratios and surface roughness during the grinding of Al_2O_3 ceramic with CNT nanofluid in an MQL system. Similarly, Nguyen et al. [101] used a genetic algorithm to achieve multi-objective optimization of the turning process. Also, Behera et al. [102] used ML techniques (ANN and Taguchi/grey relational analysis) to predict and optimize machining variables during milling of an aluminum composite. More so, Ranjan et al. [103] utilized multi-objective AI optimization to optimize the variables during micro-drilling of holes in austenitic stainless steels. The results obtained from these investigations indicate the effectiveness of AI in predicting different machining outcomes.

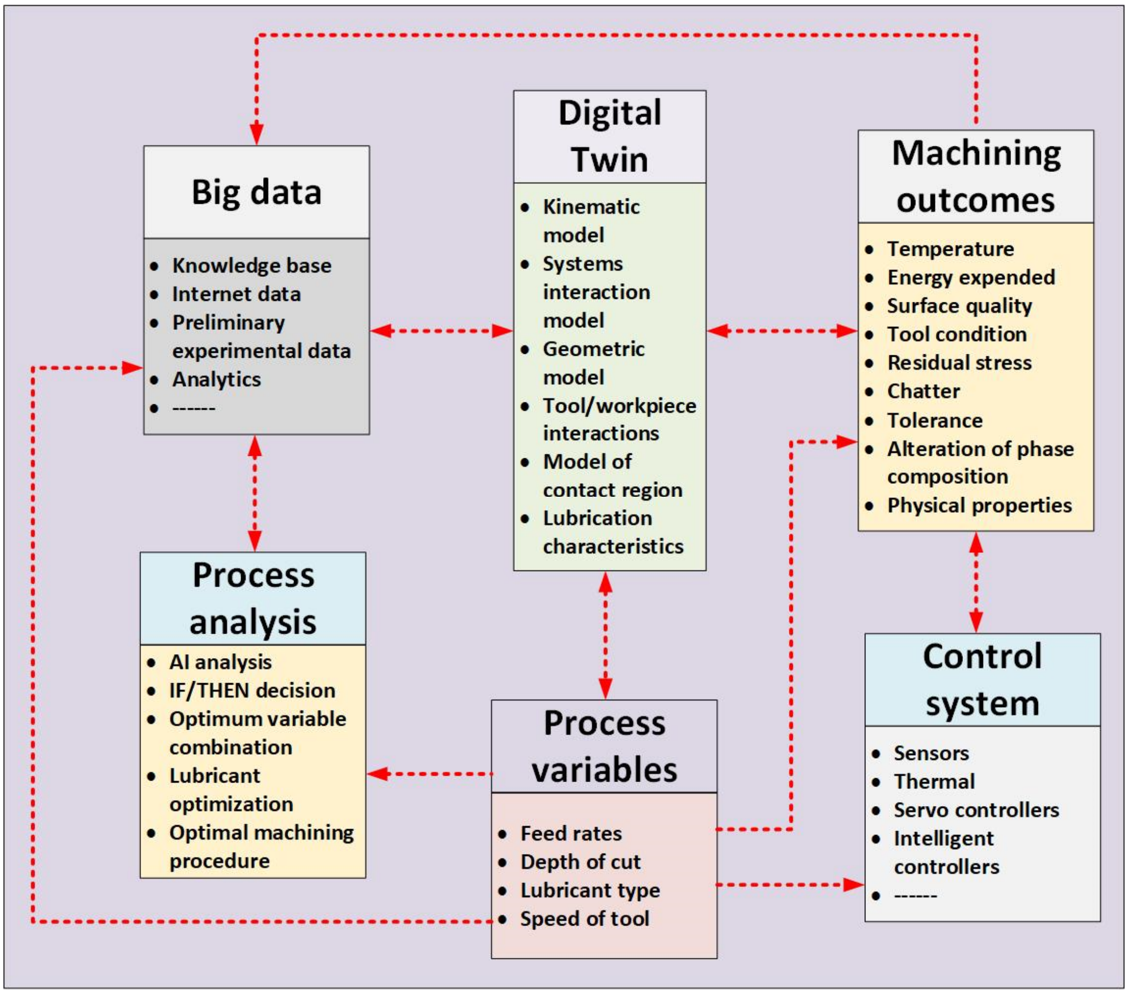

Figure 18. Machining control using AI and DT.

Additionally, the utilization of DT for predicting and acquiring real-time machining data is also becoming popular in manufacturing systems. The DT allows for real-time understanding, prediction, and optimization of different process outcomes such as surface roughness, energy, wear, temperature, *etc.*, thereby eliminating any irregularity in the machining process [100]. For instance, Liu et al. [104] studied the effects of milling variables (*i.e.*, speed, feed, and depth) on the tool wear and surface roughness of a machined component. They developed an improved particle swarm optimization-generalized regression neural network model using the existing experimental data. It was found that the feed rate has the highest effect on the surface roughness compared to the other process variables. Similarly, Zhang et al. [105] developed a DT for milling of thin-walled aerospace components. In their work, they studied the effect of different milling parameters in the DT system based on responses from IoT devices connected in the virtual environment. It was found that the DT machining prototype is highly feasible and effective towards predicting the machining conditions and responses.

Hence, the recent trend towards incorporating the machining systems with real time DT, AI, and IoT based sensors was confirmed as an effective technique for achieving lean manufacturing, thereby reducing machining waste and improving the overall process efficiency. Some of the works by different authors who have used DT systems and AI in different machining systems are presented in Table 14.

Table 14. Selected studies on the application of DT in different machining systems.

S/N	Author	Machining Process	Remarks
1	Zhang et al. [105]	Milling	The MPDT prototype is capable of effectively simulating, monitoring & predicting the machining outcomes and is recommended for industrial implementations.
2	Jauhari et al. [106]	Milling	The findings show that the DT models can predict machining responses with an accuracy of about 94.04%.
3	Qiao et al. [107]	Milling	Confirms that Deep Stacked GRU can be used to effectively identify & predict machining outcomes *i.e.*, tool wear.
4	Hanel et al. [36]	Milling	It is possible to develop a DT for milling that exhibits similar kinematic system using the process variables of a milling process for the manufacture of aerospace components.
5	Liu et al. [21]	Milling	Develop a DT by mimicking biological systems that adapts to multi-physics behavior of the machining operation.
6	Wang et al. [108]	Die cutting	Proposed an economical DT structure for traditional machining based on IoT linking of the process variables.
7	Zhuang et al. [109]	Turning	Proposed a structural analysis technique for monitoring and predicting the tool wear based on DT.
8	Ward et al. [110]	Turning	Developed a DT to study chatter and residual stresses with an effective autonomous feedback control system based on real time machining data.
9	Lu et al. [111]	Turning	Developed an DT based on analytical model which is capable of predicting and auto-correct chatter and dimensional error during machining.
10	Liu et al. [104]	Turning	Proposed a DT for predicting the surface roughness and tool wear in machining systems. Their model incorporates an AI for this purpose named Improved Particle Swarm Optimization-Generalized Regression Neural Networks (IPSO-GRNN).
11	Luo et al. [112]	Turning	Developed an AI controlled DT system for controlling dynamic errors and improving machining accuracies. The AI based control system was found to improve the machining accuracy by 87%, and efficiency by eight times.
12	Bolyn et al. [113]	Turning	Aggregated two different kinds of DT *i.e.*, one for tool operations and another for the lathe machine in order to determine the nonconformity along the tool's trajectory so as to effectively predict and compensate for tool wear during machining.
13	Kannan et al. [114]	Grinding	The findings indicate that the utilization of DT for analyzing the operations of grinding wheels can increase its efficiency by about 14.4%.
14	Tong et al. [115]	Grinding/CNC machining	Studied a five-axis CNC tool grinder thereby ascertaining its viability towards improving the interaction workpiece/tool interactions. It was found that the DT prototype can be effectively used to model and monitor the operations of a CNC machine.
15	Shen et al. [116]	Grinding	Developed a DT capable of obtaining an optimized machining path and duration using genetic algorithm.
16	Qi et al. [117]	Grinding	Proposed a technique of predicting grinding forces using IoT based experimental data from an actual grinding machine.
17	Heininen et al. [118]	Grinding	Developed a novel DT system for simulating and controlling an asymmetric tooth surface grinding process. The model was found to be capable of improving the accuracy of the tooth's edge geometry during real-time operations.
18	Chen et al. [119]	Drilling	Developed a DT system capable of predicting dimensional error and tool wear during simultaneous drilling of 100 holes.

5. Future Direction

There are many key research directions that could be explored relating to conventional machining. The main focus has often been to reduce the carbon footprints and improve the machining efficiency for different engineering materials. The recent use of DT and AI in conventional machining systems has opened newer ways of further improving the performance in machining processes. Moreover, this created many research gaps waiting to be explored. Some proposed research directions in this area include:

1. Many researchers have recently been exploring different types of lubrication systems for use in the conventional machining process. From the utilization of ecofriendly fluids to achieving lean manufacturing through the use of nanofluids in minimum quantity lubrication systems, many interesting researches have been explored by scientists. It is expected that future works would be able to develop a DT that fully mimics the behavior and interaction of lubricants during the machining operation, such that the lubrication efficiency can be considerably improved.
2. The use of cryogenic gases with different eco-friendly lubricants for modern lubrication techniques needs to be studied extensively in order to further develop the lubrication performances. Future studies should focus on using DT to achieve the optimization of process variables of the lubrication systems for the machining operations.
3. The hybridization of different techniques in machining operations can also help to improve the machinability of certain types of "difficult-to-cut" materials. For instance, laser/thermal assisted machining can be hybridized with the conventional machining process such that the work material is pre-heated prior to contact with the tool. The elevated workpiece temperature can cause a loosened macro-bonding in the work material's microstructure, thereby lowering the amount of energy required to remove a unit material from the workpiece. This process of hybrid machining is gaining popularity in subtractive machining technology and it is expected that in the future, an AI-optimized DT twin system can be used to further develop it for effective material removal.
4. Future studies should endeavor to integrate IoT-based technology in the machining systems, which is fully controlled by AI and the output of a DT system. This would allow for real-time correction and adaptation of the machining systems, thereby allowing for the attainment of a premeditated outcome from the machining process. The AI-controlled DT systems can create an IoT system that can be used to perform predictive data analysis such as predictive maintenance, fault prediction and dimensional accuracy.

6. Conclusions

This work presents a bibliometric review of articles, which is expected to help future works in understanding the developmental trends in machining and DT technology. Due to the growing importance of DT in engineering systems, it is vital to understand the developmental trend of the utilization of this technology in manufacturing processes such as machining. The rapid technological evolution of different manufacturing systems makes the study of DT an essential tool towards achieving IR 4.0, smart systems, and intelligent manufacturing. In addition, this study explores the trend and leading research activity of using DT and AI to improve machining systems as observed in the articles published on the Web of Science database. Summarily, the discussion presented can help prospective researchers to fully understand the leading research topics, highly cited articles, trends, and the prominent authors in this area of study. It also gives the information of the major sponsoring countries in the field of digital twin research. China was found to produce the highest number of articles in this field, with the National Natural Science Foundation of China observed to be the leading sponsor for the research. Further, the result discussion would be of potential help to prospective researchers towards having a proper understanding of the field, thereby helping to propose future hotspots via identification of various research gaps and limitations.

Finally, the findings from this work can be summarized as follows:

(a) It was found that the publishers "Springer Nature" have the highest number of publications in the studied area.
(b) The Journal of Intelligent Manufacturing was observed to have the highest number of articles relating to the keywords digital twin, machining, and AI.
(c) 64% of the total articles published in this field were focused on manufacturing processes, especially smart manufacturing.
(d) In terms of subject area, the published articles were also found to be focused on tool wear analysis and prediction of tool wear in machining.
(e) The institution with the highest number of published articles in this field is Nanging University of Aeronautics and Astronautics in China.

(f) The author with the highest WoS based citation in a single article was found to be Benkedjouh et al. [64], whereas Gupta M.K [54] was found to be the author with the most published articles.
(g) It was found that 65% of the total number of articles were published in India and China, where both countries respectively contributed 15% and 50% of the total number of published papers.
(h) Lastly, among the types of publications, it was found that 94% of the published papers were articles, whereas about 6% were review papers.

Author Contributions

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Not applicable.

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Not applicable.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Abbreviations

IR 4.0: Industrial revolution 4.0, IoT: Internet of things, WoS: Web of science, ANOVA: Analysis of variance, DT: Digital twin, CNT: Carbon nanotubes, NASA: National aeronautics and space administration, ANN: Artificial neural network, MRR: Material removal rates, GRU: Gated recurrent unit, AI: Artificial intelligence, MQL: Minimum quantity lubrication, ML: Machine learning, CNC: Computer numerical control, EDM: Electric discharge machining, FL: Fuzzy logic.

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