mathematics

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A Bibliometric Analysis of Digital Twin in the Supply Chain

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Abstract: Digital twin is the digital representation of an entity, and it drives Industry 4.0. This paper presents a bibliometric analysis of digital twin in the supply chain to help researchers, industry practitioners, and academics to understand the trend, development, and focus of the areas of digital twin in the supply chain. This paper found several key clusters of research, including the designing of a digital twin model, integration of a digital twin model, application of digital twin in quality control, and digital twin in digitalization. In the embryonic stage of research, digital twin was tested in the production line with limited optimization. In the development stage, the importance of digital twin in Industry 4.0 was observed, as big data, machine learning, Industrial Internet of Things, blockchain, edge computing, and cloud-based systems complemented digital twin models. Digital twin was applied to improve sustainability in manufacturing and production logistics. In the current prosperity stage with high annual publications, the recent trends of this topic focus on the integration of deep learning, data models, and artificial intelligence for digitalization. This bibliometric analysis also found that the COVID-19 pandemic drove the start of the prosperity stage of digital twin research in the supply chain. Researchers in this field are slowly moving towards applying digital twin for human-centric systems and mass personalization to prepare to transit to Industry 5.0.

Keywords: digital twin; machine learning; Industry 4.0; supply chain; bibliometric analysis; subject area

MSC: 00A06

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Citation: Lam, W.S.; Lam, W.H.; Lee, P.F. A Bibliometric Analysis of Digital Twin in the Supply Chain. *Mathematics* **2023**, *11*, 3350. https://doi.org/10.3390/math11153350

Academic Editors: Aihua Wood and Qun Li

Received: 13 June 2023
Revised: 17 July 2023
Accepted: 24 July 2023
Published: 31 July 2023

1. Introduction

Many industries are red oceans, hypercompetitive, and oversaturated [1,2]. Shorter product lifecycles means that companies are placing more efforts in innovating new ideas for market launch [3]. Consumers have increased purchasing power as they are offered a large pool of product and service choices. Meanwhile, consumers are also given greater empowerment because they can obtain information online easily. Many companies often rely on market research when developing their products or services. However, market research is insufficient to bring success to a company as this process only helps companies to understand consumer demand. To increase sales and revenues, companies have to satisfy the demand by creating the right products and delivering astonishing services. Typically, companies can only test their new or upgraded offerings after creating and displaying them for sampling. This may be a long process as errors and faults could happen during production and the final product may not meet consumer expectations.

Digital twin shows the virtual representation of a physical entity that changes instantaneously with the actual object, process, or system [4,5]. This emerging technology allows companies to create a virtual manufacturing process to identify defects before the actual process is conducted [6]. Digital twin also helps to provide various results concurrently as the inputs are manipulated when testing a product, process, or system [7,8]. Even as the production process is ongoing, the production team can halt the process to perform simulations with various ideas to examine the potential outcomes [9]. This enhances the risk assessment process and development of risk mitigation plan [10]. Moreover, the digital twin allows financial data to be incorporated so that the cost of the entire supply chain can be adjusted from time to time. As such, companies can save time and cost to deliver their products [11].

After obtaining data on consumer demands and expectations, the first step of developing a product is designing. The production trend has changed from make to stock to make to order as consumers are becoming more empowered. Thus, the process of designing is also becoming more complex to match the individual preferences. Digital twin then facilitates the translation of the needs of the customers to the product designs where the parameters, structures, and geometry of the product can be conceptualized in a virtual setting [12]. With constant data generation, the virtual product can be improved and optimized [13]. Zhang et al. [14] proposed a digital twin manufacturing cell framework for smart manufacturing that includes replicas for work in process items, devices, processes, and environments to simulate and optimize production. Cheng et al. [15] explained that the concept of smart manufacturing is data-driven to connect the physical and cyber worlds. Onaji et al. [16] proposed a digital twin framework for manufacturing. This framework consists of the integration of physical assets and virtual models, creating an intelligent layer to allow supportive decision making to take place.

The history of digital twin can be traced back to the 1960s when the National Aeronautics and Space Administration (NASA) created a representation of space vehicles to reflect their performances and identify faults when on a mission [17]. Then, in the early 2000s, Professor Michael Grieves presented the digital twin concept in his course [18]. This means that the research of digital twin in the supply chain only began after Professor Michael Grieves presented the white paper of digital twin in 2002 with the proposal to develop a product lifecycle management center [18,19]. This digital twin concept has three components, namely, the real spaces, virtual spaces, and a linking system to transfer data and information between the real and virtual spaces [20]. This was then called the "Mirrored Spaces Model" [21]. A year later, Kary Främling suggested an architecture where physical items would have a virtual representation for more efficient information flow in manufacturing [22]. In 2006, Hribernik et al. [23] also proposed a similar concept known as "product avatar". In the same year, the initial model of Professor Michael Greives was renamed to the "Information Mirroring Model" to emphasize the importance of two-way information flow and the availability of more than one virtual space for an individual real space [24].

The name "digital twin" was only widely applied from 2010 when NASA introduced digital twin in their roadmap. From the first presentation of a digital twin by Professor Grieves in 2002 until 2010, the application of digital twin was not widely explored as the concept of digital twin was still in its infancy. In 2012, NASA simulated vehicle management systems and maintenance to increase the safety and reliability of transportation [25]. Since then, the aerospace industry has been employing digital twin in research and development. As Industry 4.0 took place, Internet of Things then drove the advancement of digital twin in other fields, as large multinational companies such as IBM, Siemens, and General Electric implemented digital twin for optimization and prediction [4,26–28]. The global market for digital twin is expected to exceed USD 73 billion by 2027, with a compounded annual growth rate of greater than 60% [28]. The rapid growth of the digital twin industry will continue as this industry becomes one of the main drivers for Industry 4.0 [29].

Digital twin was also reflected in the planning, ordering, making, delivering, returning, and enabling in the supply chain operations reference (SCOR) model, which is a supply chain performance measurement model [30]. Planning in the supply chain requires past data for forecasting. Digital twin reduces the time between target setting, data collection from a large pool of sources, big data analytics, data processing, deriving inferences, and taking actions for future planning. Researchers can plan instantaneously by using the synchronized data and making changes in the virtual model with higher accuracy [31]. The longer the digital twin model runs, the more data it collects, the higher the precision of the model. Thus, product designs, inventory management, material usage, transportation, and lead time can be streamlined and optimized with ease and accuracy for profit maximization and cost reduction [32]. In the supply chain, digital twin can be found in the designing, manufacturing, and servicing phases [33]. In designing, digital twin provides information that could be used for decision making in various design processes. Digital twin can be used for geometry assurance in the design process for optimization in manufacturing variation [34]. Each design and dimension will be listed and formed into a locator or datum position. Digital twin can also provide information on the tolerances of each part in the design process before they are moved into production. Tao et al. [12] explained that the virtual model consists of the geometric and physical models of products, consumers, and the environments. This allows the designers to observe the behaviors of products and consumer interactions. After that, data from the behaviors, environmental data, or Internet data can be integrated into the virtual model to be analyzed and visualized using digital twin's cognitive abilities. Then, a simulation can take place to observe how the product would function in the real world. Besides creating a prototype, using virtual reality, consumers or designers can also interact with the virtual product. At the later stage, based on the outcomes of the digital twin model, sensors and actuators will be equipped on the physical item to allow the physical item to adjust itself to changes in the consumers and environment. Finally, networking technologies and cloud computing allow information transfer between the physical and virtual models. In short, product designs with digital twin begin with planning, conceptual designs, embodiment designs, detail designs, and virtual verifications. Digital twin can also be used for risk management to identify areas of hazard using the virtual model, especially for events such as natural disasters during shipping and accidents in ports [35–38].

Zhu et al. [39] reviewed production logistics activities such as transportation, packaging, warehousing, material distribution, and information processing with digital twin. In transportation, past data embedded in the production logistics of digital twin were used to highlight the bottlenecks in the entire transport process [40]. A digital twin model of the transportation system also allows for real-time tracking of the location and condition of cargoes during transit [41]. Pan et al. [42] proposed a digital twin control architecture to simulate, analyze, and optimize the production logistics in industrial parks in China. This digital twin solved the sudden surge in order volume, which could not be handled with the usual transportation and storage in the industrial parks because the digital twin model helped in arranging vehicles with optimal routing at the lowest cost. Wu et al. [43] developed an Industrial Internet of Things and Digital Twin model for finished goods logistics. This model helped to reduce picking time, detect emergency orders, and optimize waiting time in packaging. Marmolejo-Saucedo [44] optimized bin-packing issues with digital twin. This model reduced packaging volumes, lowered operation cost, and minimized servers. Leng et al. [45] used the digital twin system to optimize stacked packing and storage in a warehouse. A prototype was developed and applied in a tobacco warehouse that successfully maximized the utilization and efficiency of automated high-rise warehouse product service systems. Perez and Korth [46] adopted digital twin to establish a database for compliance in the handling and storage of dangerous goods in warehouses. Petković et al. [47] proposed a human intention prediction algorithm to estimate a worker's path in a warehouse. A very important benefit of digital twin is the ability to integrate all the production logistics activities for parallel monitoring [48].

Liu et al. [33] reviewed the applications of digital twin and found that digital twin helps in iterative optimization by integrating past product design with potential improvements for configuration and execution as digital twin could forecast the outcomes of the products and allow designers to take preventive measures [49]. This could also help in careful planning when selecting materials [50]. As virtual prototypes can be created with digital twin, designers are able to test various product designs under different conditions to find the best fit and balance between the expected and real functions. Therefore, digital twin is important to produce an effective product design within a shorter time frame. Currently, monitoring of the manufacturing process is performed in the physical floor. Digital twin allows monitoring with the virtual model as all data are integrated into the virtual model.

It combines past, current, and future data for real-time monitoring and forecasting of the future outcomes for informed decision making [51,52]. The importance of digital twin in manufacturing is the ability to visualize the production process and to compare the physical item with the virtual model to match expectations with realities as personalized production takes over the traditional manufacturing process [53]. Moreover, as unexpected events such as slight discrepancies of raw materials and underperformance of machines might happen, digital twin can adjust the entire manufacturing process quickly to produce similar results [54]. This reduces manufacturing defects and increases quality consistency of the produced items. After manufacturing and upon usage, digital twin can detect faults and perform predictive maintenance for issues that were not identified during the product design phase. For a large and complex product such as a vessel, digital twin can detect performance deviations and predict damages [55].

Digital twin is an important advancement in the supply chain during industrialization and digitalization. Liu et al. [33] reviewed the status, technologies, and application of digital twin. Holler et al. [56] reviewed 38 papers on digital twin until 2016 to clarify the status of digital twin during that time. Negri et al. [57] reviewed the definitions of digital twin and explored smart manufacturing with digital twin. Shekarian et al. [58] reviewed sustainable supply chain management in manufacturing, design, logistics, procurement, management information systems, quality assurance, safety, social responsibility, financial management, structural management, and promotional activities. This current paper aims to present a bibliometric analysis of digital twin in the supply chain. This bibliometric analysis is distinct and differs from past publications in which this analysis considers the application of digital twin in the entire supply chain, including product design, manufacturing, shipping, warehousing, logistics, port, packaging, distribution, and transportation. This bibliometric analysis also studied the impact of digital twin in Industry 4.0 and the future research and application of digital twin in Industry 5.0.

Bibliometric analysis includes performance analysis and science mapping [59]. Performance analysis studies the contributions of each research component such as authorship, publication title, keyword, and region [60,61]. Performance analysis includes performance metrics such as total publication (TP) and citation metrics such as number of cited publications (NCPs), total citations (TCs), average citation per paper (C/P), average citation per cited paper (C/CP), h-index, and g-index [62,63]. Science mapping examines the relationships that exist in each research component such as co-citation, co-occurrence, and co-authorship [64]. Science mapping visualizes the scientific links and systematic patterns within the research area to find connected research themes [65–67]. The main focus of a bibliometric analysis is to identify the scientific research contribution of the authors and countries [68]. This paper also determined the reputable publication titles for digital twin publications. Moreover, this paper underlined the topics of digital twin to uncover the hot topics in this area for potential future studies [69]. Moreover, this paper studied the evolvement of the research on digital twin over the years. This paper can be a reference to help researchers, governments, and industry leaders in developing a proper digitalization framework by including digital twin technology.

Section 2 presents the materials and methods for this bibliometric analysis. Section 3 discusses the findings of this bibliometric analysis. Section 4 concludes the paper with potential future studies.

2. Materials and Methods

This paper aims to present a bibliometric analysis of digital twin in the supply chain. The database used was the Web of Science. Owned by Thomson and Reuters, Web of Science has comprehensive and high-quality multidisciplinary journals and is becoming the most preferred database for bibliometric analysis [70–72]. Figure 1 presents the flowchart of the bibliometric analysis of digital twin in supply chain.

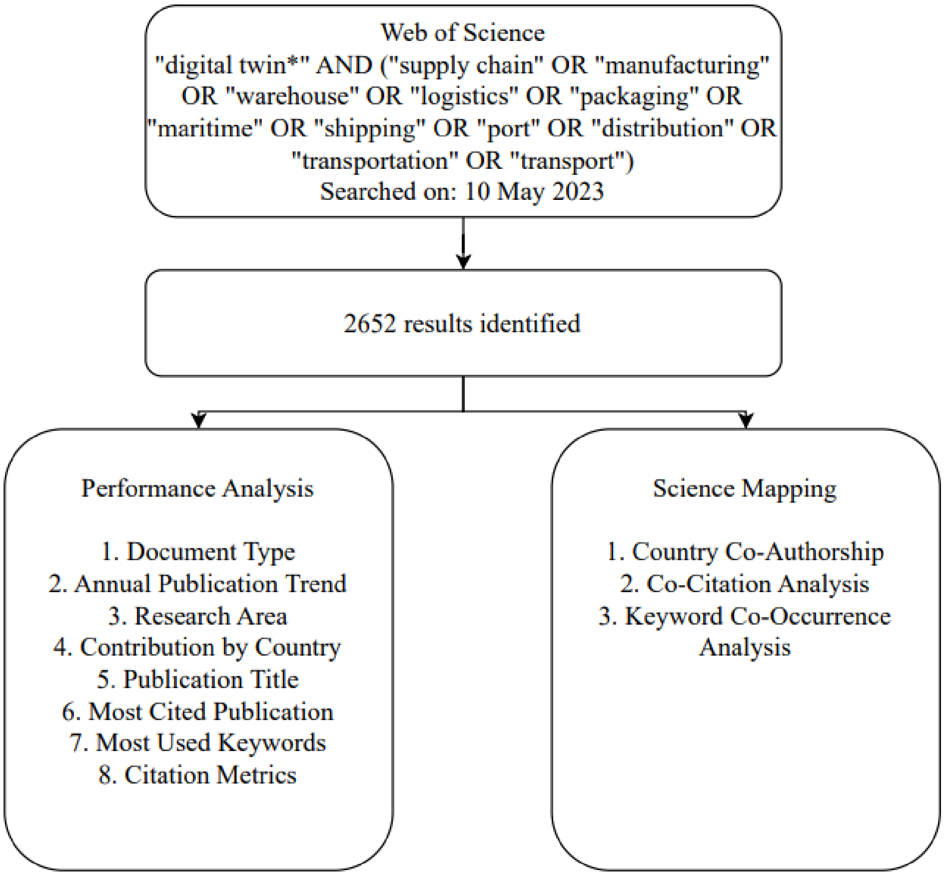

Figure 1. Flowchart of bibliometric analysis of digital twin in the supply chain.

Figure 1 presents the flowchart of the bibliometric analysis of digital twin in the supply chain. After identifying the keywords, the Web of Science database was queried, and 2652 documents were found to match the criteria for bibliometric analysis. The publication period was from 2014 to 2023. The data were exported on 10 May 2023. About 60.98% (or 1708 documents) of the 2652 documents are articles, followed by proceeding papers (29.95%), review articles (7.64%), editorial materials (0.86%), and book chapters (0.57%). The document types are described in Table 1.

Table 1. Document types.

Document Types	Total Publications (TP)	Percentage (%)
Article	1708	60.98
Proceeding paper	839	29.95
Review article	214	7.64
Editorial material	24	0.86
Book chapters	16	0.57

Performance analysis is then performed using Harzing's Publish or Perish 8 [73–75]. This paper then evaluated the contributions by year, research area, country, and publication title while identifying the impacts of the most cited publications. VOSviewer, one of the most popular bibliometric tools, is used to present the visual graphs of the research elements. The country co-authorship analysis was performed to understand the collaboration among researchers across countries. Then, to identify the hotspots and trends of research, the keyword co-authorship diagram was generated. The co-citation analysis was also conducted to identify the classical publication of digital twin in the supply chain [76–78]. Data processing was carried out using Microsoft Excel 365 [79].

3. Results

3.1. Publication Trend Analysis

The trends and growth of digital twin can be observed from the total number of publications (TP) and total citations (TC). From 2014 to 10 May 2023, there was a collection of 2652 documents on digital twin in the supply chain, with 40,768 total citations. Table 2 tabulates the publication trends of digital twin in the supply chain. Figure 2 demonstrates the trends of publication and citation for digital twin in the supply chain.

Table 2. Publication trend.

Year	TP [1]	Percentage (%)	Cumulative Percentage (%)	NCP [2]	TC [3]	C/P [4]	C/CP [5]	*h*-Index	*g*-Index
2014	2	0.08	0.08	2	71	35.50	35.50	2	2
2015	2	0.08	0.15	2	547	273.50	273.50	2	2
2016	6	0.23	0.38	6	393	65.50	65.50	5	6
2017	34	1.28	1.66	31	3555	104.56	114.68	20	34
2018	101	3.81	5.47	95	5652	55.96	59.49	29	74
2019	244	9.20	14.67	227	8561	35.09	37.71	48	86
2020	399	15.05	29.71	357	9349	23.43	26.19	51	83
2021	654	24.66	54.37	556	8614	13.17	15.52	42	68
2022	880	33.18	87.56	539	3683	4.19	6.83	24	40
2023	330	12.44	100.00	94	343	1.04	3.65	9	13

[1] Total publication; [2] number of cited publications; [3] total citations; [4] citations per publication; [5] citations per cited publication.

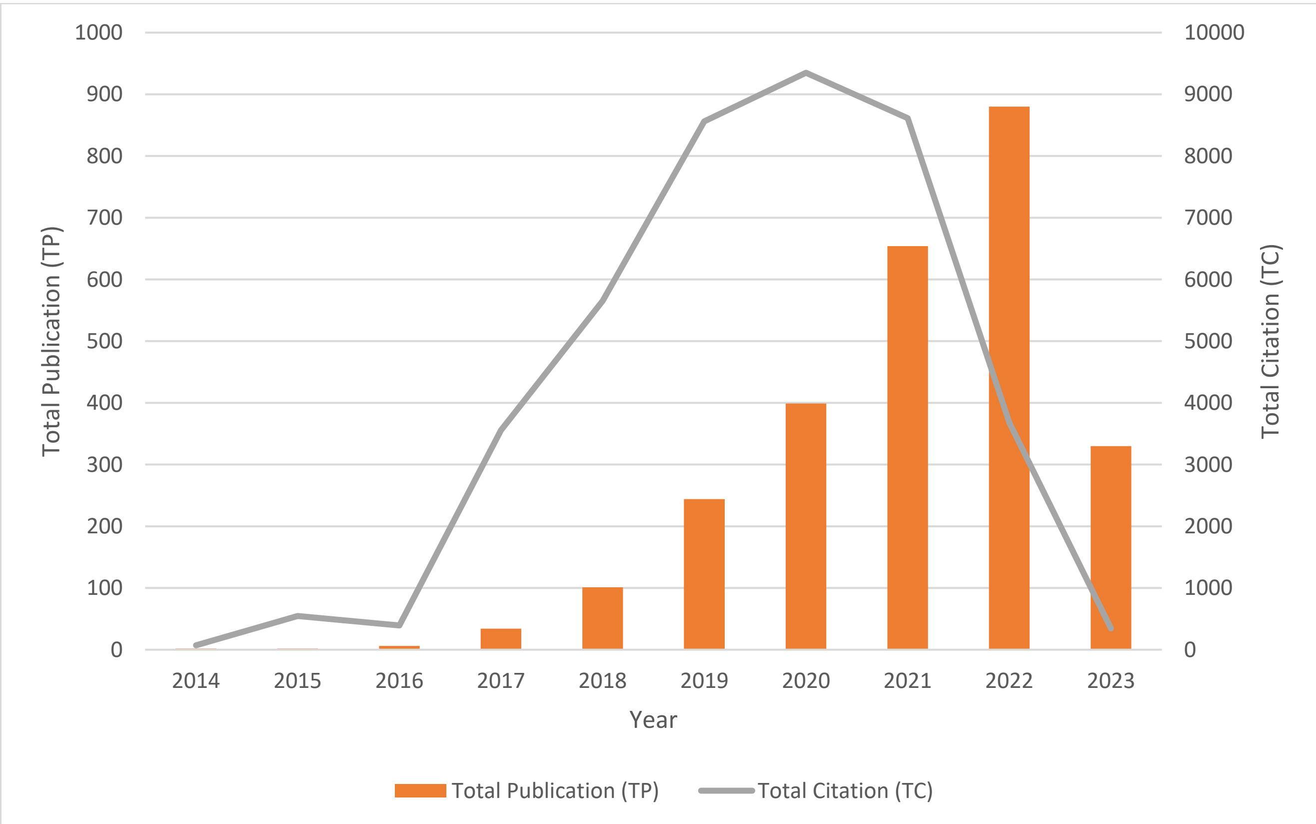

Figure 2. Publication and citation trend.

As shown in Table 2, the first publications listed on the Web of Science database were produced in 2014. One of the papers was published by Cerrone et al. [80], which modelled the as-manufactured component geometry, which is a part of the digital twin. This paper obtained 69 citations. Another paper published in 2014 was by Scott-Emuakpor et al. [81]. This paper received two citations and the discussed process of obtaining part-specific geometry and material performance to create a digital twin model for gas turbine engines. The total number of publications and citations have increased tremendously since 2018. The number of publications exceeded 100 in 2018, up to 880 in 2022. The number of citations also crossed 3000 for the publications in 2017, up to 9349 for the publications in 2020. This indicates that digital twin in the supply chain is becoming more popular.

The highest citation per paper (C/P) and citation per cited paper (C/CP) were recorded in 2015. There were two listed papers with 547 citations in 2015. The paper by Rosen et al. [82] titled "About the importance of autonomy and digital twins for the future of manufacturing" has received 531 citations. This paper then contributed to the high C/P and C/CP over the years. The highest *h*-index of 51 was in 2020. This implies that in 2020, there were 51 publications receiving at least 51 total citations. The highest *g*-index of 86 was in 2019. This implies that 86 documents have received an average of 86^2 or 7396 citations.

3.2. Research Area

There were more than 70 research areas on digital twin in the supply chain. The top 10 research areas were engineering (1681), computer science (847), automation control systems (345), operations research/management science (265), materials science (249), telecommunications (198), chemistry (189), science technology other topics (159), physics (145), and energy fuels (109). Table 3 shows the top 20 research areas on digital twin in the supply chain.

Table 3. Research area.

Research Areas	Total Publication
Engineering	1681
Computer Science	847
Automation Control Systems	345
Operations Research/Management Science	265
Materials Science	249
Telecommunications	198
Chemistry	189
Science Technology Other Topics	159
Physics	145
Energy Fuels	109
Instruments Instrumentation	92
Environmental Sciences Ecology	82
Business Economics	66
Robotics	59
Transportation	59
Mathematics	47
Construction Building Technology	41
Remote Sensing	37
Imaging Science Photographic Technology	25
Metallurgy Metallurgical Engineering	25
Mechanics	23
Thermodynamics	23

3.3. Country Contribution

China had the most publications, with 648 documents on digital twin in the supply chain. China also had 15,058 total citations, 23.24 citations per publication, and 30.92 citations per cited publication. This makes China the most productive and impactful country in terms of digital twin in the supply chain publications. China had a *h*-index of 59 and *g*-index of 110. This implies that 59 documents had at least 59 citations while 110 documents had an average of at least 110^2 or 12,100 citations. Table 4 displays the top 10 countries contributing to digital twin in the supply chain. The top 10 countries contributed more than 87% of the total publications.

Table 4. Top 10 countries contributing to digital twin in the supply chain.

Country	TP [1]	NCP [2]	TC [3]	C/P [4]	C/CP [5]	*h*-Index	*g*-Index
China	648	487	15,058	23.24	30.92	59	110
Germany	384	270	5771	15.03	21.37	29	69
United States	366	272	5822	15.91	21.40	40	66
Italy	220	150	3305	15.02	22.03	27	53
England	198	149	3105	15.68	20.84	27	51
France	114	86	2288	20.07	26.60	21	47
Spain	112	81	940	8.39	11.60	16	28
Sweden	112	95	1884	16.82	19.83	21	41
South Korea	91	67	1045	11.48	15.60	16	30
India	81	59	1418	17.51	24.03	20	36

[1] Total publication; [2] number of cited publications; [3] total citations; [4] citations per publication; [5] citations per cited publication.

Collaboration between countries is important in order to develop a research domain. This is reflected in the country co-authorship diagram generated from VOSviewer. Table 5 presents the top 10 countries with the highest collaboration between countries. China (300) had the highest total link strength, which means that China had the highest collaboration between countries. This was followed by the United States (241), Germany (209), England (186), Italy (173), France (122), Sweden (122), Spain (103), India (77), and Switzerland (75). Figure 3 demonstrates the country co-authorship diagram.

Table 5. Country co-authorship.

Country	Total Publication	Total Link Strength
China	648	300
United States	366	241
Germany	384	209
England	198	286
Italy	220	173
France	114	122
Sweden	112	122
Spain	112	103
India	81	77
Switzerland	64	75

Figure 3 displays the country co-authorship diagram. China has the largest node size because China had the highest number of publications. The line between China and the United States is the thickest, indicating the strongest collaboration between China and the United States, with a link strength of 49. China and Sweden also have a strong collaborative relationship, with a link strength of 33. China and England also work well, with a link strength of 31.

There are six clusters in total. Australia, Bangladesh, Canada, Egypt, India, Iran, Malaysia, New Zealand, Pakistan, China, Saudi Arabia, Singapore, South Korea, Taiwan, United Arab Emirates, and Wales make up the largest cluster in red. The second cluster (green) is formed by Austria, the Czech Republic, Finland, Germany, Japan, Latvia, the Netherlands, Norway, Poland, Romania, Scotland, Slovakia, Sweden, and Ukraine. Argentina, Croatia, Greece, Israel, Italy, Northern Ireland, Serbia, Slovenia, Spain, and Switzerland form the third cluster in blue. The fourth cluster is in yellow and has countries such as England, Estonia, Hungary, Portugal, Russia, the United States, and Vietnam. The fifth cluster is in purple with countries such as Brazil, Columbia, Denmark, France, Luxembourg, and Morocco. The last cluster (light blue) consists of Belgium, Ireland, Mexico, South Africa, and Turkey.

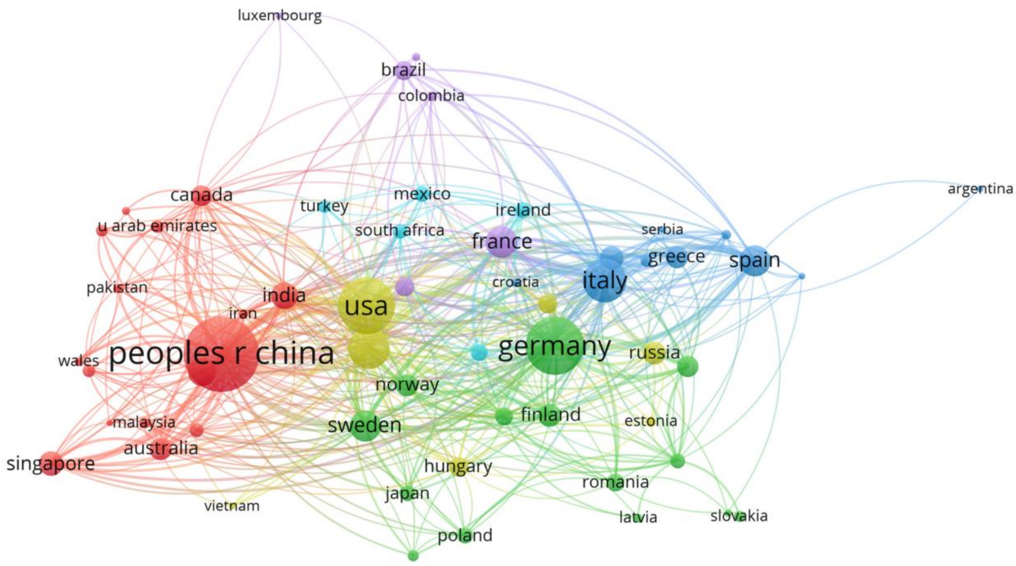

Figure 3. Country co-authorship.

3.4. Publication Title

The top 10 publication titles are listed in Table 6. Applied Science (impact factor, IF = 2.838) was the journal with the highest publication for digital twin in the supply chain, with 100 total publications. IEEE Access (IF = 3.476) was the highest cited publication title, with 2979 total citations. The highest cited publication under IEEE Access was written by Qi and Tao [83], which compared big data and digital twin in Industry 4.0. Journal of Manufacturing Systems (IF = 9.498) and International Journal of Production Research (IF = 9.018) had the highest impact factors among the top 10 publication titles.

3.5. Citation Analysis

Table 7 reveals the top 10 highly cited publications of digital twin in the supply chain. The paper "Digital twin-driven product design, manufacturing and service with big data" published by Tao et al. [13] received 1002 citations since its publication in 2018. This paper investigated the application methods and frameworks of digital-twin-driven product design, manufacturing, and service. It is important to implement the digital twin in the supply chain, particularly in terms of material intelligent tracking and distribution technology. The second most cited paper is titled "Digital twin in industry: state-of-the-art" authored by Tao et al. [84], which received 814 citations. This paper reviewed the development and application of digital twin in industry. In supply chain management, the digital twin provides more accurate planning and efficient dispatching. The scheduling scheme can be analyzed, evaluated, and optimized through self-organizing and self-learning. The third most cited paper by Kritzinger et al. [85] provided a categorical literature review of the digital twin in manufacturing. The authors found that the main focus of digital twin research in the supply chain is dealing with production planning and control. Ivanov [86] studied the impacts of epidemic outbreaks on global supply chain with the example of the coronavirus COVID-19. The study showed that lead time, speed of epidemic propagation, and the upstream and downstream disruption durations in the supply chain were major factors that determined the epidemic outbreak impact on the performance of supply chain based on the simulation results. The next most cited paper by Qi and Tao [83] studied big data and digital twin in manufacturing as well as their applications in product design, production planning, manufacturing, and predictive maintenance. Digital twin could optimize the whole process in the supply chain based on the cyber–physical closed loop system.

Table 6. Publication titles.

Publication Title	TP [1]	Percentage (%)	TC [2]	Publisher	JIF [3]	JCI [4]	Cite Score	SJR [5]	SNIP [6]	*h*-Index
Applied Sciences	100	3.76	1103	MDPI	2.838	0.59	3.7	0.507	1.026	101
IFAC-PapersOnLine	100	3.76	1942	ELSEVIER	N/A	N/A	1.5	0.324	0.442	86
Journal of Manufacturing Systems	76	2.86	2181	ELSEVIER SCI LTD	9.498	1.81	15.0	2.950	3.439	92
International Journal of Advanced Manufacturing Technology	72	2.71	1855	SPRINGER LONDON LTD	3.563	0.67	6.4	0.924	1.368	145
IEEE Access	67	2.52	2979	IEEE-INST ELECTRICAL ELECTRONICS ENGINEERS INC	3.476	0.93	6.7	0.927	1.326	204
Procedia Manufacturing	60	2.26	1640	ELSEVIER	N/A	N/A	N/A	N/A	N/A	69
Sensors	58	2.18	416	MDPI	3.847	0.90	6.4	0.803	1.420	219
International Journal of Production Research	47	1.77	1656	TAYLOR & FRANCIS LTD	9.018	1.51	14.6	2.780	2.901	170
International Journal of Computer Integrated Manufacturing	43	1.62	968	TAYLOR & FRANCIS LTD	4.420	0.81	7.2	1.095	1.409	63
Processes	43	1.62	451	MDPI	3.352	0.48	3.5	0.474	0.889	54

[1] Total publication; [2] total citation; [3] journal impact factor 2021; [4] journal citation indicator 2021; [5] SCImago journal rank 2021; [6] source normalized impact per paper 2021.

Table 7. Most cited publications.

Title	Year	Total Citation	Publication Title
Digital twin-driven product design, manufacturing and service with big data [13]	2018	1002	International Journal of Advanced Manufacturing Technology
Digital Twin in Industry: State-of-the-Art [84]	2019	814	IEEE Transactions on Industrial Informatics
Digital twin in manufacturing: A categorical literature review and classification [85]	2018	711	IFAC Papersonline
Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case [86]	2020	660	Transportation Research Part E-Logistics and Transportation Review
Digital twin and big data towards smart manufacturing and Industry 4.0: 360 degree comparison [83]	2018	569	IEEE Access
A review of the roles of digital twin in CPS-based production systems [57]	2017	534	27th International Conference on Flexible Automation and Intelligent Manufacturing, FAIM2017
About the importance of autonomy and digital twins for the future of manufacturing [82]	2015	531	IFAC Papersonline
The future of manufacturing industry: a strategic roadmap toward Industry 4.0 [87]	2018	498	Journal of Manufacturing Technology Management
Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing [88]	2017	479	IEEE Access
Shaping the digital twin for design and production engineering [89]	2017	470	CIRP Annals-Manufacturing Technology

The sixth most cited paper by Negri et al. [57] explored digital twin in the scientific literature and identified the role of digital twin for manufacturing in the Industry 4.0 era. This paper reviewed the concept of digital twin in industrial engineering and the supply chain. The seventh most cited paper by Rosen et al. [82] focused on the importance of modularity, connectivity, autonomy, and digital twin in the design of products and production. This paper addressed the opportunities to apply simulation for improving the production planning in the supply chain. The next most cited paper by Ghobakhloo [87] reviewed the Industry 4.0 phenomenon, determined its key design principles and technology trends, and offered a strategic roadmap as a guide for the process of Industry 4.0 transition. Industry 4.0 enabled an automated creation of products, services, supply, and product delivery. Tao and Zhang [88] discussed the digital twin shop-floor based on digital twin and its key components, namely, physical shop-floor, virtual shop-floor, shop-floor service system, and shop-floor digital twin data. This paper addressed the needs of application of digital twin in smart manufacturing to improve the supply chain management. The 10th most cited paper by Schleich et al. [89] presented a comprehensive reference model that serves as a digital twin of the physical product in design and manufacturing. Model conceptualization, implementation, and application along the product life-cycle in the supply chain were addressed.

Based on the most cited publications described above, the supply chain management system tends to be intelligent with the development of information technology. The use of technology in the supply chain is enhanced by emerging technologies such as artificial intelligence, digital twin, and big data. According to Xue et al. [90], the future development of the supply chain should study the impact of emerging technologies for continuous improvement. Xue et al. [90] conducted a review of supply chain management and suggested that emerging technologies can be integrated into the supply chain model. Moreover, the application of block chain and Industry 4.0 in the supply chain has received great attention. According to Fang et al. [91], the research of intelligent supply chain driven by new technologies includes block-chain-technology-driven as well as big-data-analysis-technology-driven research. In line with our study on technology-driven research, our paper presents a bibliometric analysis of digital twin in the supply chain to help researchers, industry practitioners, and academics to understand the trend, development, and focus of the areas of digital twin in the supply chain.

Co-citation analysis studies at least two publications cited by another article. The co-cited references show the classical research area in the field [79]. The top 10 co-cited references are listed in Table 8. Among them, eight articles are among the top 10 cited papers. Figure 4 depicts the reference co-citation analysis diagram.

Table 8. Top 10 co-cited references.

Co-Cited References	**Total Link Strength**
Digital twin-driven product design, manufacturing and service with big data [13]	5911
Digital twin in industry: state-of-the-art [84]	4467
Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing [88]	4276
Digital twin in manufacturing: a categorical literature review and classification [85]	4222
Digital twin and big data towards smart manufacturing and Industry 4.0: 360 degree comparison [83]	3811
A review of the roles of digital twin in CPS-based production systems [57]	3718
Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems [92]	3699
Shaping the digital twin for design and production engineering [89]	3548
About the importance of autonomy and digital twins for the future of manufacturing [82]	3493
Digital twin-driven smart manufacturing: connotation, reference model, applications, and research issues [93]	3293

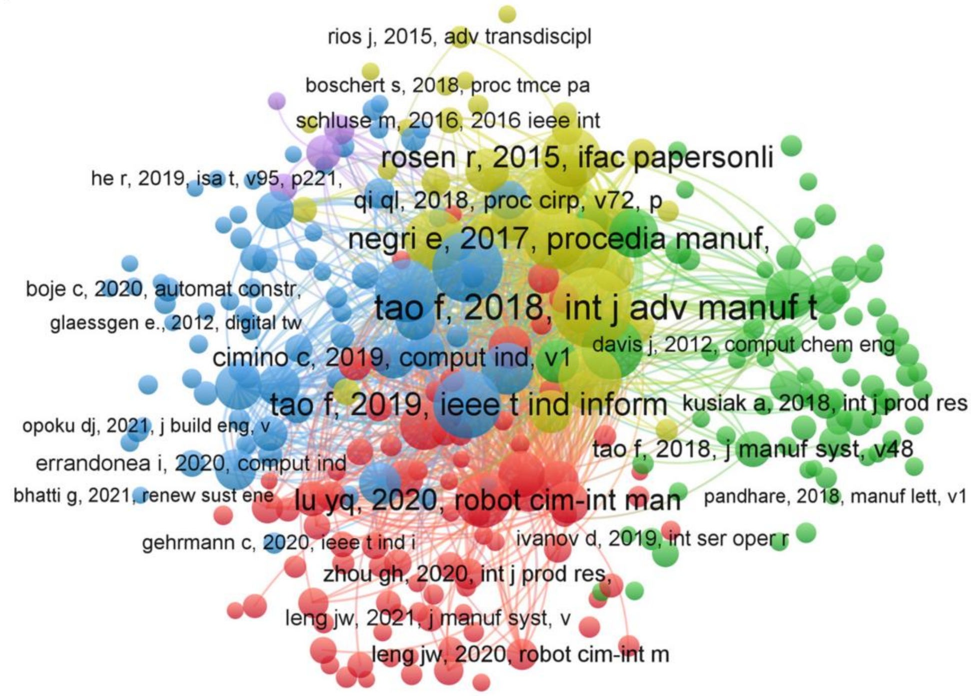

Figure 4. Co-citation analysis of references.

The top 10 co-cited authors are shown in Table 9, while Figure 5 describes the author co-citation network. It is worth to note that Tao, F., is an expert in intelligent manufacturing and authored the papers “Digital twin-driven product design, manufacturing and service with big data” [13], “Digital twin in industry: state-of-the-art” [84], “Digital twin and big data towards smart manufacturing and Industry 4.0: 360 degree comparison” [83], and “Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing” [88], which received 1002, 814, 569, and 479 citations, respectively. Grieves, M., whose expertise is in product life cycle management, authored the book chapter “Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems” [92], with 1033 citations on Scopus and 2010 citations on Google Scholar. J. W. Leng’s work focuses on blockchain, mass individualization, smart manufacturing, and Industry 5.0. He wrote the paper “A digital twin-based approach for designing and multi-objective optimization of hollow glass production line” [94], with 208 citations on the Web of Science database.

Table 9. Top 10 co-cited authors.

Co-Cited Authors	Affiliations
Tao, F.	Beihang University, Beijing, China
Grieves, M.	University of Central Florida, Florida, United States
Leng, J. W.	Guangdong University of Technology, Guangzhou, China
Qi, Q. L.	Beihang University, Beijing, China
Lu, Y. Q.	The University of Auckland, Auckland, New Zealand
Negri, E.	Politecnico di Milano, Milan, Italy
Schleich, B.	University of Erlangen-Nuremberg, Erlangen, Germany
Uhlemann, T. H. J.	Bayreuth University, Bayreuth, Germany
Kritzinger, W.	Fraunhofer Austria Research GmbH, Vienna, Austria
Glaessgen, E.	NASA Langley Research Center Hampton, Virginia, United States

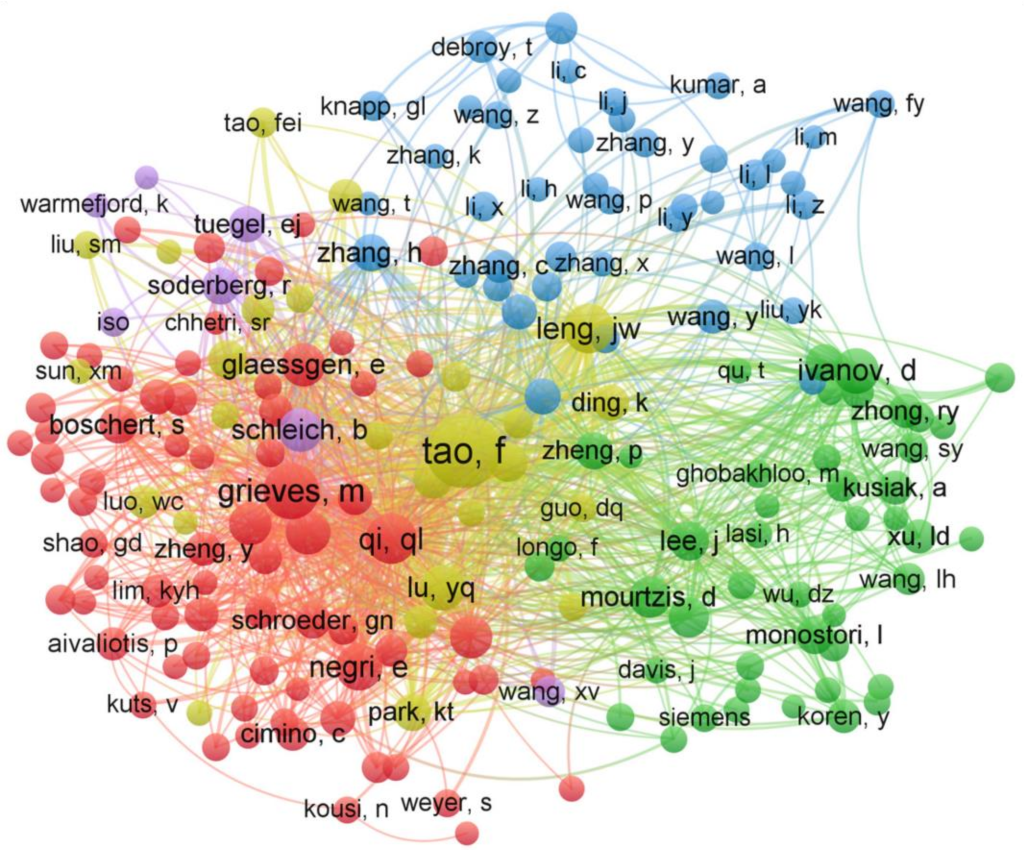

Figure 5. Co-citation analysis of authors.

The co-citation of publication title is presented in Figure 6. The *International Journal of Advanced Manufacturing Technology* (IF = 3.563, Q2); *International Journal of Production Research* (IF = 9.018, Q1); *Journal of Manufacturing Systems* (IF = 9.498, Q1); *IEEE Access* (IF = 3.476, Q2); *Procedia CIRP, CIRP Annals—Manufacturing Technology* (IF = 4.482, Q2); *Procedia Manufacturing, Robotics and Computer-Integrated Manufacturing* (IF = 10.103, Q1); *Journal of Cleaner Production* (IF = 11.072, Q1); and *IFAC Papers-Online* are the top 10 co-cited sources.

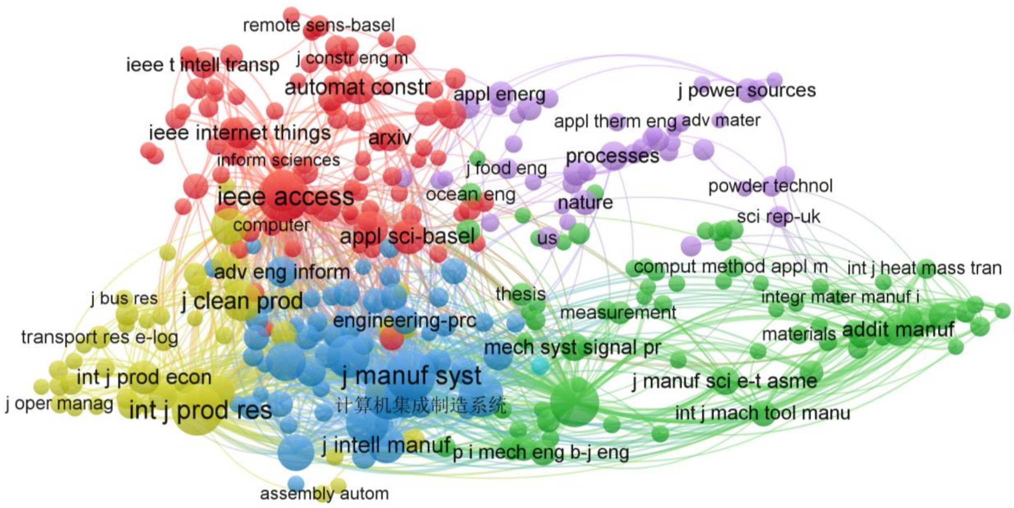

Figure 6. Co-citation analysis of publication titles.

3.6. Keyword Analysis

Table 10 shows the top 10 keywords regarding digital twin in the supply chain. Figure 7 describes the keyword co-occurrence map. As shown in Figure 7, the first cluster in red focuses on the process of designing and building a digital twin model, where the keywords are made up of architecture, artificial intelligence, big data, blockchain, cloud computing, cyber–physical system, data models, edge computing, Internet of Things, security, and sensors. The second cluster, which is green, involves the implementation and integration of digital twin to increase the efficiency in industrial uses, with keywords such as augmented reality, building information modeling (BIM), decision-making, discrete event simulation, industry, integration, logistics, manufacturing system, performance, resilience, supply chain, sustainability, and virtual reality. The third cluster is in blue and focuses on digital twin in quality controls and improvements. The keywords in this cluster are data analytics, deep learning, fault diagnosis, genetic algorithm, intelligent manufacturing, machine learning, optimization, prediction, predictive maintenance, and quality. The fourth cluster is in yellow and highlights the contribution of digital twin in digitalization and industrialization. The keywords are automation, digital manufacturing, digital transformation, Industry 4.0, modeling, and smart factory.

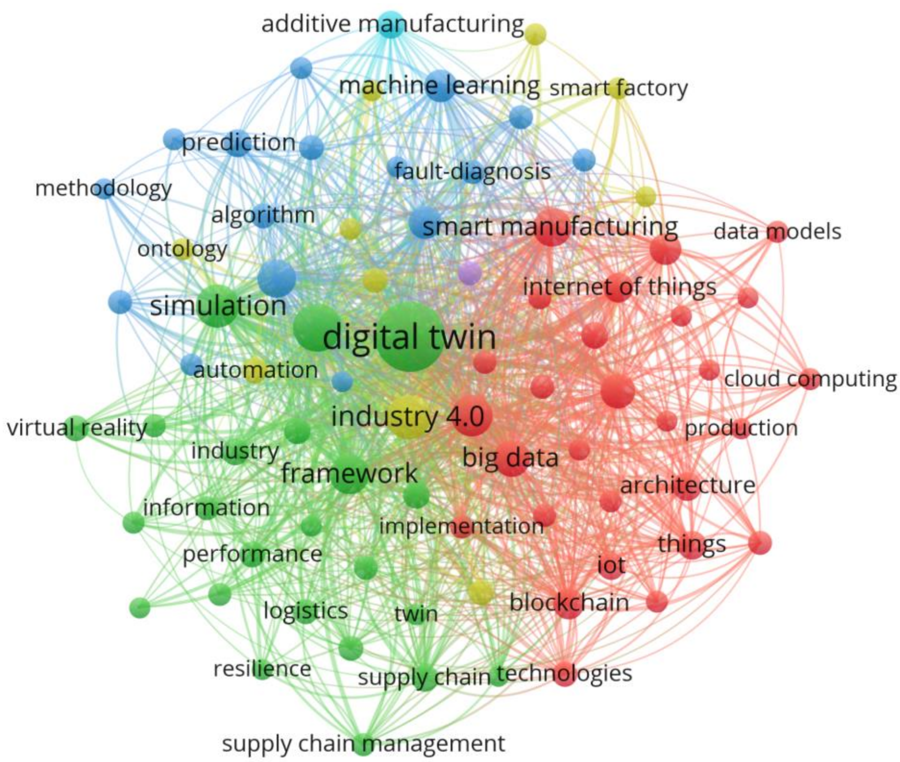

Figure 7. Keyword co-occurrence analysis.

Figure 8 displays the trends and developments of the keywords in recent years. The lighter colors show the recent study areas of researchers in digital twin in the supply chain. They include deep learning, machine learning, data models, edge computing, artificial intelligence, and supply chain management. Nowadays, researchers are engaging in integrating digital twin with machine and deep learning. Fischer et al. [95] used the artificial neural network, which was a part of deep learning, for activity recognition, which was then used to perform discrete-event simulation. The digital twin technology and functional block has an application domain for data visualization and analytics, which is a part of machine learning [96]. The digital twin of an entity is also able to train deep learning algorithms [97]. There is also a potential research gap for the application of digital twin in a deep learning architecture for mobile edge computing. Moreover, Yang et al. [98] proposed a model with model reduction and deep neural network as a basic to develop digital twin for nuclear power system but noted that there was still a research gap to increase the efficiency of the model. Moreover, digital twin is also seen as a driver to speed up the realization of Industry 5.0 in the future [99].

Table 10. Top 10 keywords.

Keywords	Occurrences	Total Link Strength
Digital twin	1546	4340
Design	413	1769
Industry 4.0	319	1360
Framework	218	1165
Big data	166	1011
Simulation	289	996
Smart manufacturing	193	848
Optimization	193	806
Cyber–physical systems	140	779
Blockchain	91	523

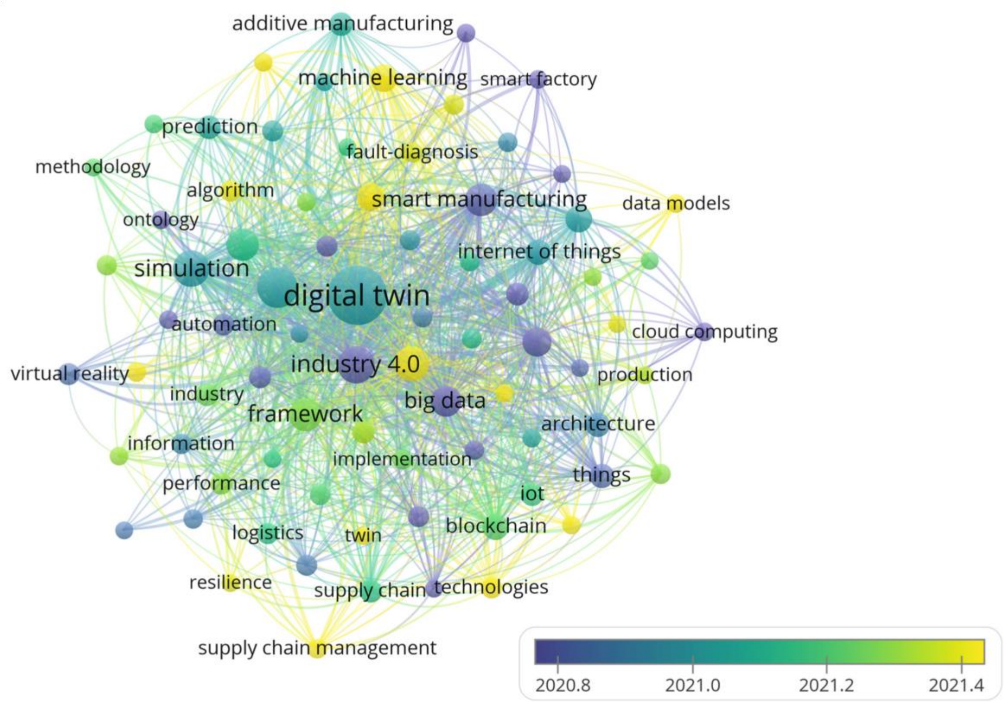

Figure 8. Keyword overlay analysis.

As the world is moving towards human-centric industrialization, there are also huge research gaps with the application of digital twin and deep learning, machine learning, and artificial intelligence to achieve mass personalization through intelligent transformation [100,101]. In the supply chain where all the logistics processes are interconnected and would largely impact the next step of operation, there exists a gap between digital twin applications, deep learning, machine learning, and artificial intelligence for occupational safety and health to prevent accidents and hazards for the wellbeing of the workers [102]. Digital twin could analyze the potential areas and degree of severity of accidents and help the companies to visualize a proper floor plan to minimize the adverse effects and losses due to the potential hazards [103]. Digital twin can also study the movement and interaction of humans in the workplace to reduce their risk of accident [104,105]. For better personalized working experience, digital twin can help workers visualize the outcomes of their actions and design mitigation strategies to enhance their own productivity. All these are still in the development phase, and there are boundless prospects.

The sustainable development goals (SDGs) focus on smart yet sustainable industrialization and manufacturing. Therefore, digital twin can be applied for sustainable intelligent transformation [106–108]. This involves transformation in the equipment, systems, and services that interconnect with each other. When broken down, the equipment consists of units and lines; systems start from designing, producing, logistics, and selling, while services range from innovating, manufacturing, and post-purchase assistances [109]. Meanwhile, digital twin could also help with the maintenance, overhauls, and repairs of complex systems, products, and equipment [110–112]. Moreover, for optimization in resource allocation, digital twin can complement edge computing, improve efficiency, and reduce wastage [113,114]. Various digital twin infrastructures could be explored to support different phases in sustainable intelligent transformation with the integration of deep learning, machine learning, and artificial intelligence.

3.7. Research Evolution

Based on the bibliometric analysis above, the evolution of research trends can be divided into three stages, namely, the embryonic, developmental, and prosperity stages [90]. In the Web of Science, the research on digital twin in the supply chain began in 2014. Therefore, the embryonic stage of the research of digital twin in the supply chain is from 2014 to 2017, since the number of publications listed on the Web of Science was still low. Then, the developmental stage of the research was from 2018 to 2020. The prosperity stage of the research is from 2021 onwards.

3.7.1. Embryonic Stage (2014–2017)

The embryonic stage of the research of digital twin in the supply chain on the Web of Science database began years after NASA introduced digital twin in their roadmap. During this period, about 66% (29 documents) were proceeding papers. In this first stage, several papers tested out the digital twin concept in the production line. Vachálek et al. [115] proposed the digital twin concept for the production of pneumatic cylinders by creating a virtual model of the hydraulic pistons. The changes in the virtual model were almost instantaneous with a difference of one second. This proposed digital twin model was still basic with limited optimization, proactive maintenance, and sensors for big data analysis. Zhang et al. [94] developed a digital twin for the hollow glass production line. Digital twin started to be involved in the cyber–physical system in the supply chain during this period. Realizing that small and medium enterprises were not aware of digital twin, Uhlemann et al. [116] presented a CPS learning concept for real-time data acquisition, automated optimization, and data capturing. Cai et al. [117] developed a CPS system for a three-axis vertical milling machine. The digital twin produced was limited to a single milling machine and only two sensors and low sensory data. For shopfloor planning, Brenner and Hummel [118] started to build a learning factory and noted that artificial intelligence such as self-calibrating localizations were part of the future of digital twin. Blum and Schuh [119] developed a digital twin that was limited to real-time order processing with potential improvements for big data analytics and integration with other production logistics activities. In this stage, ideas have also slowly been proposed and explored to apply digital twin in wider areas of the supply chain such as additive manufacturing and 3D printing [120,121].

3.7.2. Developmental Stage (2018–2020)

This stage highlights the connection of digital twin with components of Industry 4.0. Tao et al. [13] and Qi and Tao [83] started to emphasize the combination of digital twin and big data to create cyber–physical data for designs, production, and service in the supply chain. These papers noted that big data analysis could help users detect the causes of problems and find solutions in the virtual model that were significant in smart manufacturing. Integration of digital twin with machine learning also started in this stage, as Xu et al. [122] developed a digital twin for fault diagnosis with deep transfer learning. Several machine learning techniques had also been incorporated into digital twin [123–125]. Industrial Internet of Things, edge computing, and cloud-based systems were also introduced in digital twin [126–131]. The security awareness while using digital twin was enhanced with the application of blockchain for cryptographic hashing algorithms, decentralization, and immutability [132–135]. In this stage, the need for more sensitive and efficient sensors for digital twin modeling arose. Jin et al. [136] developed triboelectric nanogenerator sensors for a soft-robotic gripper system for digital twin models for assembly lines and automated warehouses. Research in this stage also started to move towards sustainable digital twin applications [137]. Sustainable designs, productions, logistics, sales, and services made up the sustainable closed loop for sustainable intelligent manufacturing in a study by He and Bai [106]. Kaewunruen and Lian [138] constructed a 6D building information system with digital twin for sustainable railway turnout for economy and sustainability. Digital twin was also used to develop a sustainable business model for a comprehensive network that focused on several product life cycles [139]. Digital twin was also used for sustainable performance assessment of the production system [140]. Wang et al. [141] developed a big-data-driven digital twin to configure sustainable products and remanufacture processes. Optimal selection of green materials using digital twin was also established [50].

3.7.3. Prosperity Stage (2021–Present)

The spike in the number of papers in this stage was mainly driven by the COVID-19 pandemic, where industries realized that resiliency was important to manage operating cost and profit for sustainability during an emergency [142–144]. Digital twin was also used to perform impact analysis for the food retail supply chain to help the companies cope with the adverse impacts of COVID-19 [145]. Digital twin as a service started to become a highlight in this stage as mass individualization became important in manufacturing [101,146,147]. The research of digital twin in the supply chain became more specific as digital twin was implemented in actual environments such as ports and other maritime operations [148–151]. Big data, deep Q-learning, and generative adversarial networks were also used in digital twin for traffic prediction [152]. The research on production logistics was also enhanced with deep neural network and Internet of Things [153]. Sustainability is also a part of the digital twin research in the supply chain to reduce raw material consumption [154]. In this stage, research highlighting digital twin as an enabler of Industry 5.0 has started to emerge, as digital twin is a supporting technology for Industry 5.0 [155–157]. Digital twin as an enabler in Industry 5.0 consists of seven elements, namely, technologies, humans, management, organizations, scopes, tasks, and modelling, while the types of digital twin in the supply chain involve product, process, organization, supply chain, and network-of-networks [158]. In using digital twin for Industry 5.0, the cyber–physical manufacturing system has now been shifted to cyber–physical human-centered systems for smart and sustainable manufacturing [159,160].

3.8. Citation Metrics

Table 11 presents the citation metrics of the publications of digital twin in the supply chain. A total of 2652 documents have been published from 2014 to 2023 as of 10 May 2023. In total, 40,768 citations have been obtained from these publications, with a *h*-index of 87 and a *g*-index of 153.

Table 11. Citation metrics of digital twin publications in the supply chain.

Items	Metrics
Extraction date	10 May 2023
Total publication	2652
Total citation	40,768
Number of years	10

Table 11. *Cont.*

Items	Metrics
Citation per year	4076.80
Citation per paper	15.37
Citation per author	12,295.62
Papers per author	781.8
Authors per paper	4.33
h-index	87
g-index	153

4. Conclusions

In this bibliometric analysis, 2652 documents published from 2014 to 2023 were extracted to study the research trend, development, and focus of digital twin in the supply chain. Digital twin in the supply chain is an emerging field in the midst of Industry 4.0. As Industry 5.0 is still in its infancy, the development and implementation of digital twin will accelerate the connection of the physical and digital environments. As such, this bibliometric analysis serves as an important reference for researchers, academics, and industry practitioners to understand the development of digital twin in the supply chain.

The total annual publication has been low from 2014 to 2017. From 2018 onwards, the number of publications rose quickly and reached its peak at 880 publications in 2022. The citation per publication (273.50) and citation per cited publication (273.50) were the highest in 2015 as they were contributed to by the paper by Rosen et al. [82] titled "About the importance of autonomy and digital twins for the future of manufacturing", which has received 531 citations. The highest *h*-index (51) was in 2020, which means that 51 publications in 2020 received at least 51 citations until 10 May 2023.

The publications were mostly articles, proceeding papers, and review articles in the subjects of engineering, computer science, and automation control systems. China (650) had the most publications on digital twin in the supply chain. China also had the highest number of citations, which amounted to about 36% of the total citations of the 2652 publications. China also had the highest *h*-index (59) and *g*-index (110). The strongest country collaborations existed between China and the United States (49), followed by China and Sweden (33), and China and England (31).

The top publication titles were Applied Science (IF = 2.838, Q2), IFAC PapersOnLine, and Journal of Manufacturing Systems (IF = 9.498, Q1). IEEE Access (IF = 3.476, Q2) had the highest total citations for publications on digital twin in the supply chain. The paper "Digital twin-driven product design, manufacturing and service with big data" published by Tao et al. [13] was the top cited publication, with 1002 total citations. This paper was also the highest co-cited reference, while the main author, Tao, F., was also the top co-cited author, followed by Grieves, M., and Leng, J. W. The International Journal of Advanced Manufacturing Technology (IF = 3.563, Q2), International Journal of Production Research (IF = 9.018, Q1), and Journal of Manufacturing Systems (IF = 9.498, Q1) journals were the top three co-cited publication titles.

In the initial stage of research, the documents revolve around conceptualizing digital twin in the production line. However, the advantages of digital twin in application were low as the models could only handle limited data and optimization. Digital twin was introduced into the cyber–physical system in this initial stage, with prospectives in smart manufacturing. Then, during the development of digital twin research, the capabilities of digital twin expanded as some limitations were removed with the integration of the components of Industry 4.0 such as big data, Industrial Internet of Things, cloud computing, edge computing, blockchain, and machine learning technologies. Digital twin also helped to visualize sustainable intelligent manufacturing. After the outbreak of the COVID-19 pandemic, companies realized that resiliency in the supply chain was important for survival and sustainability during emergency and digital twin was a potential solution. This drove the spike in the number of research on digital twin in the supply chain. Recently, several researchers have begun to explore the application of digital twin in the supply chain for the future in Industry 5.0.

This bibliometric analysis has several limitations. Firstly, the Web of Science database is updated regularly. Hence, this bibliometric analysis may be revisited in the future for the understanding of evolving trends. Secondly, this study focused on the Web of Science database. Therefore, future studies may consider other databases for the bibliometric analysis of digital twin in the supply chain.

Author Contributions: Conceptualization, W.S.L. and W.H.L.; methodology, W.S.L., W.H.L. and P.F.L.; software, W.S.L. and P.F.L.; validation, W.S.L. and W.H.L.; formal analysis, W.S.L., W.H.L. and P.F.L.; investigation, W.S.L., W.H.L. and P.F.L.; resources, W.S.L., W.H.L. and P.F.L.; data curation, W.S.L., W.H.L. and P.F.L.; writing—original draft preparation, W.S.L., W.H.L. and P.F.L.; writing—review and editing, W.S.L., W.H.L. and P.F.L.; visualization, W.S.L., W.H.L. and P.F.L.; supervision, W.S.L. and W.H.L.; project administration, W.S.L. and W.H.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: This research is supported by the Universiti Tunku Abdul Rahman, Malaysia.

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

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