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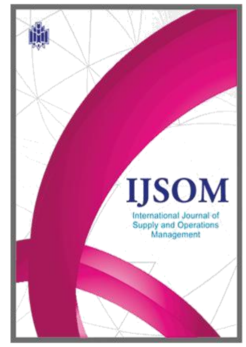

A Systematic Literature Review on the Application of Industry 4.0 Technologies in Manufacturing Supply Chain Planning Phase

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Abstract

Supply chain systems have become crucial in today's highly competitive and ever-changing industrial environment; hence, effective management of supply chains is required to achieve operational excellence. Planning is the first stage of supply chain systems and is crucial to ensure overall optimization of the supply chain and business sustainability. With various business processes adopting industry 4.0 technologies for optimization, the supply chain system is not an exception. Also noting that, organizations based in the least developed and developing countries need more support in adopting 4IR technologies. Thus, the objective of the study is to investigate, through literature, the key 4IR technologies that have been applied within the supply chain planning phase of manufacturing organizations. A five-step systematic literature review was adopted to carry out the research. The steps included the identification and selection of a database, keywords development, and selection of inclusion and exclusion criteria through database filters and search categories. The findings of this systematic review revealed Industry 4.0 technologies that have been deployed in the supply chain planning phase of manufacturing organizations. These include Simulation, Machine Learning, Digital Twin, and Internet-of-things. While manufacturing supply chain planning departments are faced with myriads of operational challenges and constraints, the deployment of Industry 4.0 technologies serves as a potential solution towards promoting effective supply chain operations, thereby stimulating sustainable supply chain management. The results of this study serve as a revelation to Supply Chain Managers to identify the latest trends and gain insights into appropriate Industry 4.0 technologies that could be deployed to ensure effective supply chain planning.

Keywords: Supply Chain; Production Planning and Scheduling; Industry 4.0 Technologies; Manufacturing.

1. Introduction

In today's rapidly evolving industrial landscape, supply chain planning has become increasingly pivotal to achieving operational excellence and competitive advantage (Bueno, Godinho Filho & Frank, 2020). According to El-Garaihy (2021), supply chain planning is the first of the six (6) processes based on the Supply Chain Operations Reference (SCOR) model (i.e., Planning, Sourcing, Production, Delivering, Returning, and Enabling). It comprises of various production planning and control (PPC) activities such as material requirement planning, demand planning, enterprise resource planning, inventory planning and production scheduling, capacity planning, facility layout planning and maintenance planning, production scheduling (Pereira, Oliveira & Carravilla, 2020).

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As manufacturers strive to meet rising demands for efficiency, flexibility, and innovation, the integration of Industry 4.0 technologies into supply chain planning process has emerged as a game-changer (Bueno *et al.*, 2020). The paper not only explores the profound impact that advanced technologies have on the way manufacturers strategize and execute their production processes, but the study also seek to become a knowledge blueprint for developing countries with limited resources on ascertaining appropriate 4IR technologies to deploy for supply chain planning activities. According to Anaba, Kess-Momoh & Ayodeji (2024), by leveraging digital tools and data-driven insights, companies can enhance accuracy, reduce lead times, and optimize resource allocation, thereby transforming traditional manufacturing paradigms.

2. Background

In 2015, the United Nations established 17 global objectives as part of the 2030 agenda for Sustainable Development (United Nations, 2024). Goal 12 of the Sustainable Development Goal (SDGs) focuses on responsible consumption and production (Ramirez Lozano, Peñaflor Guerra & Sanagustin-Fons, 2024). To achieve the goal, eleven (11) targets were formed and the study focusses on target 12a, which speaks to supporting developing countries with an intention of strengthening their scientific and technological capacity to move towards more sustainable patterns of consumption and production. Chen *et al.* (2016) highlighted that, majority of the African countries form part of the least developed and developing countries and South Africa is one of the developing countries in Africa. A study by Makazhe and Maramura (2023) explored the effect of 4IR technologies on sustainability and in conclusion, their study recommended the adoption of 4IR technologies for sustainable development. Industry 4.0 technologies, such as the Internet of Things (IoT), Artificial Intelligence (AI), Advanced Analytics, Machine Learning, Cloud Computing, Simulation, Additive Manufacturing (3D printing), Advanced Robotics, Big Data Analytics, Radio Frequency Identification (RFID) technologies, Deep Learning, Augmented Reality, Digital Twinning, and Cyber Security offer a range of benefits that are reshaping the product manufacturing planning landscape (Saturno *et al*., 2018; Jamwal *et al*., 2021; Rad *et al.*, 2022). The application of these technologies enables real-time monitoring, predictive maintenance, and smarter decision-making, thereby improving overall production efficiency, productivity improvement and agility (Bai *et al.,* 2020). Hence, the objective of the study is to investigate through literature analytics, 4IR technologies that have been applied within the supply chain planning phase of manufacturing organizations.

3. Methodology

A Systematic Literature Review (SLR) methodology was adopted in this study. An SLR is a research methodology that uses a logical process to gather, categorize, and evaluate various existing research papers (Mohamed Shaffril, Samsuddin & Abu Samah, 2021). SLR encourages researchers to source for studies outside their own subject areas and networks through the introduction of extensive searching methods, predefined search strings, and standard inclusion and exclusion criteria (Paul *et al.*, 2021). A method used by Carrera-Rivera *et al*., (2022) was adapted to carry out the systematic review and achieve the study's main objective. The adapted step-by-step process is presented in Figure 1.

Step one (1) was the selection of digital libraries also known as databases. This is a crucial step since the validity of literature review studies is dependent on how well a researcher chooses the database (Carrera-Rivera *et al*., 2022). This is because a database needs to sufficiently cover the topic being studied (Mohamed Shaffril *et al*., 2021). The Scopus database was selected and used for this study. According to Abalkina (2024), Scopus is one of the international bibliographic databases that focus on indexing high-quality journals. This was supported by Baas *et al.* (2020), who further indicated that Scopus is a curated database and can support large-scale analyzes.

Step two (2) involved searching documents of related topic, this was done using keywords. When generating the keywords, their synonyms were also considered. Boolean operators such as AND, OR, parentheses (), asterisks * and quotation marks “” were used, the purpose of each operator is presented in Table 1.

The Boolean search string of keywords used in this study is presented in Table 2. The string shows that the intention is to search for documents that discuss any 4IR technology in any planning phase activity within the manufacturing sector.

Step three (3) of the SLR “filters” refers to the inclusion and exclusion criteria as presented in Figure 1. The first inclusion criterion is period i.e., only documents published from 2019 to date i.e., June 2024 were considered for the review, this was to ensure that, only recent and relevant literature were considered for the study. The second and third inclusion criteria focused on the document and source type, in which only documents from Journals and Conferences were reviewed in the study. Also, only documents presented in English were reviewed.

Step four (4) of the review process entails guiding the database where to search, in this study the selected keywords were searched on the article title only. This exercise was carried out with a view to get results that are much more relevant in achieving the primary objective of the study. The results obtained after step four were exported to a CSV file and analyzed on VOSVIEWER software. Furthermore, using the "analyze results" feature on the Scopus database, a summary of the number of documents per year, source and country of origin was generated.

Step five (5) focused on the abstract analysis of the obtained documents. The documents were skimmed through to detect studies that focused on the application of 4IR technologies within the supply chain planning phase of manufacturing organizations. Theoretical-inclined research articles did not meet the criteria and were therefore excluded in the final review and analysis. The results obtained from the described five-step methodology are presented in the next section.

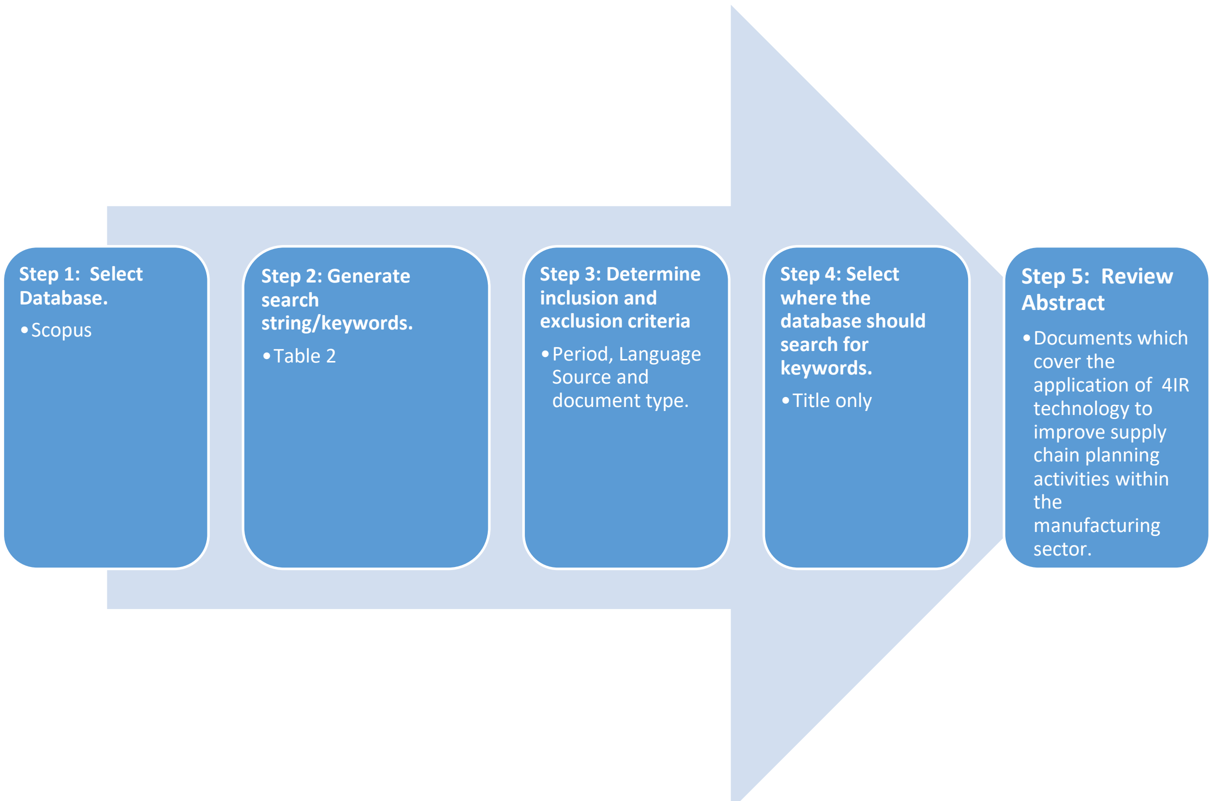

Figure 1. Systematic Literature Review Methodology

Table 1. Definition of Boolean Operators (*Adapted: Mohamed Shaffril et al., 2021*)

Boolean Operator	Purpose
AND	Search for sources that contain **all keywords.**
OR	Search for sources that contain **either keyword.**
()	Group keywords and search for them in a **specific order.**
*	Include results that contain a **variation of the keyword.**
""	Search for the **exact phrase.**

Table 2. Boolean search string summary

Boolean search string	Description
("manufacturing planning" OR "supply chain planning" OR "production planning" OR "production scheduling" OR "facility planning" or "demand forecasting" OR "material requirement planning")	The first part of the string is keywords representing the supply chain planning phase, which includes activities that occur within manufacturing organizations.
("4.0 technology" OR "4IR technology" or "industry 4.0" OR "fourth industrial revolution technology" OR "4.0 technologies" OR "industry 4.0 technology" OR "artificial intelligence" OR "machine learning" OR "big data" OR "data mining" OR "augmented reality" OR "simulation" OR "system integration" OR "additive manufacturing" OR "3D printing" OR "cloud computing" OR "cyber security" OR "RFID technology" OR "internet of things" OR "IOT" OR "digital tw*")	The second part of the string is keywords that represent the 4IR technologies.
("manufacturing" OR "production")	The third and last string is keywords that represent the industry.
("manufacturing planning" OR "supply chain planning" OR "production planning" OR "production scheduling" OR "facility planning" OR "demand forecasting" OR "material requirement planning") AND ("4.0 technology" or "4IR technology" OR "industry 4.0" OR "fourth industrial revolution technology" OR "4.0 technologies" OR "industry 4.0 technology" OR "artificial intelligence" OR "machine learning" OR "big data" OR "data mining" OR "augmented reality" OR "simulation" OR "system integration" OR "additive manufacturing" OR "3D printing" OR "cloud computing" OR "cyber security" OR "RFID technology" or "internet of things" or "IOT" or "digital tw*") AND ("manufacturing" OR "production").	

4. Results and Discussion

This section presents results of the five-step methodology discussed in the previous section. Step 1 to 4 of the methodology resulted in reviewing of 174 documents. These documents comprise of 86 Journal articles and 88 Conference papers. From the 174 documents, 27, 28, 31, 36, 37 and 15 were published in 2019 ,2020, 2021, 2022, 2023 and 2024 (up to June) respectively as depicted in Figure 2. The database cannot filter per month, but June 2024 was the latest publication period for the extracted data; thus, the 2024 output will deviate if more documents in the scope of work are published post June 2024.

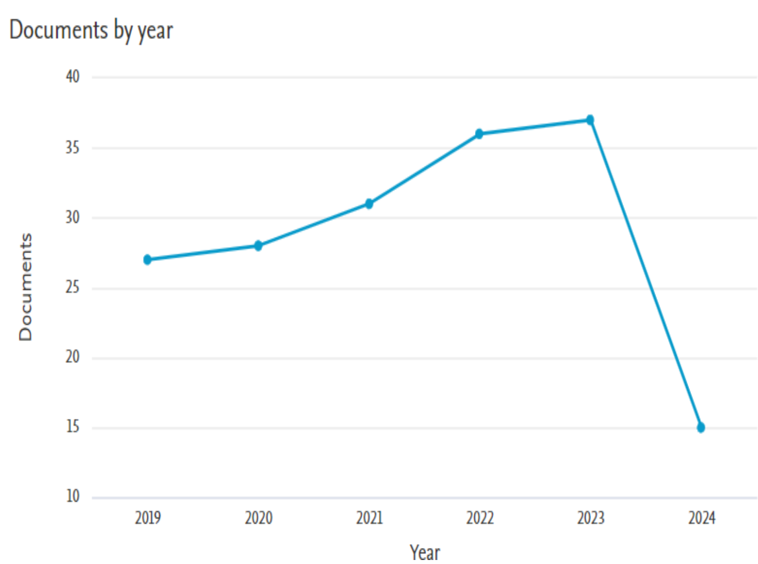

Figure 2. Annual output of journal articles and conference papers on 4IR technologies in manufacturing planning from 2019- (June) 2024

A summary of the number of documents per source, i.e., Journal name or Conference proceeding was also analyzed as depicted in Figure 3. Based on the adopted methodology, the top ten sources are IFAC Papers Online, International Journal of Production Research, Computers and Industrial Engineering, Procedia Computer Science, Proceedings Winter Simulation Conference, Procedia CIRP, Journal of Intelligent Manufacturing, Proceedings of the Summer School Francesco Turco, ACM International Conference Proceeding series and Academic Journal of Manufacturing with 16, 7, 5, 5, 5, 5, 3, 3, 2 and 2 resulting in 30.4% of the 174 documents and 69 other sources contributing 69.6% of the papers accumulated in the period from 2019 to June 2024. However, ACM International Conference Proceeding Series and Academic Journal of Manufacturing are a part of the top 10 arbitrarily, since sources such as Academic Journal AIP Conference Proceedings, Computational Intelligence and Neuroscience, Computers and Operations Research, Computers in Industry, Energies, Energy, International Journal of Production Economics, Journal of Industrial Information Integration, Machines and Processes also had two (2) documents each.

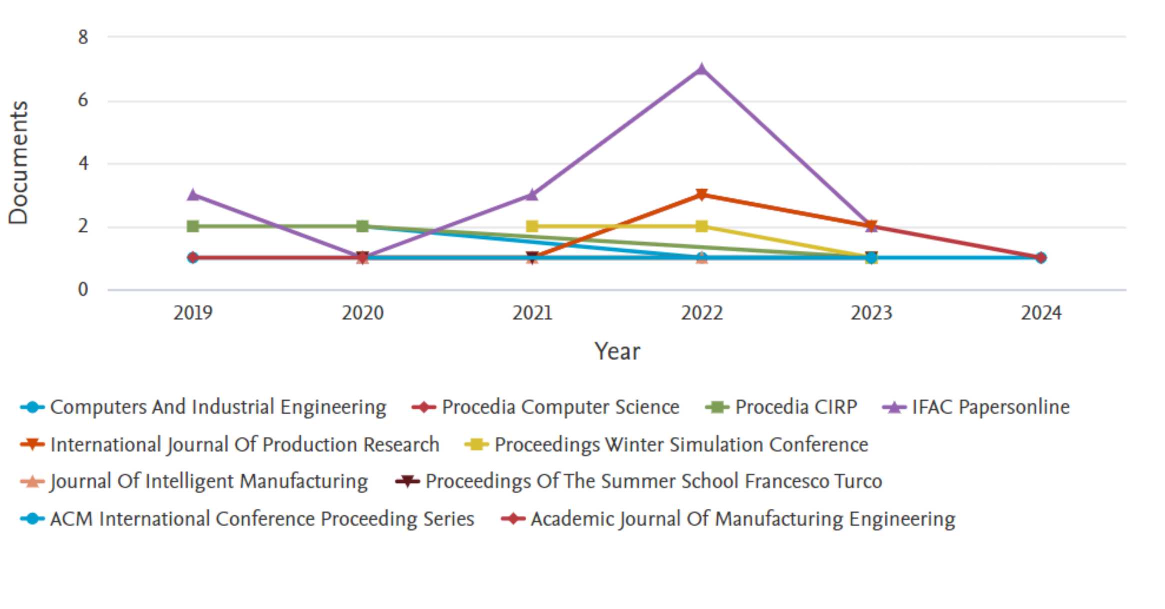

Figure 3. Top Ten sources of papers on 4IR technologies in supply chain planning within the manufacturing sector from 2019 - 2024

The analysis further revealed that, the top ten countries that have published work in the topic are China, Germany, Italy, United States, France, Brazil, Canada, India, United Kingdom and Japan, who published 39, 31, 19, 12, 8, 8, 7, 7, 7 and 6 documents respectively as depicted in Figure 4. This accounts for 83% of the documents obtained from the database search. Additionally, out of the 174 documents, none of the published documents are from African Continent.

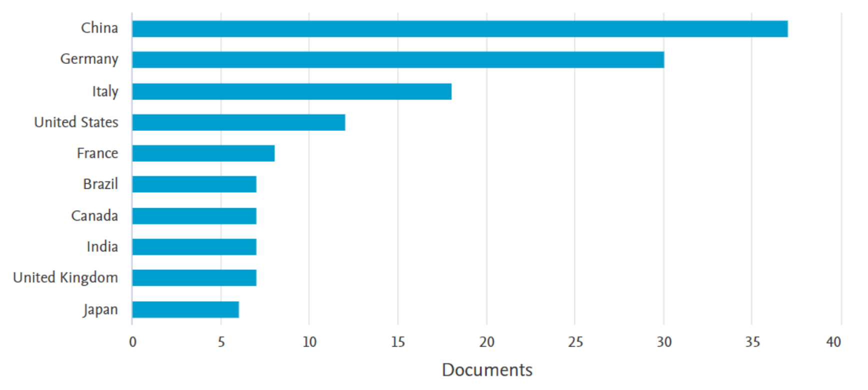

Figure 4. Output of Top 10 Countries that contributed journal articles and conference papers on 4IR technologies in manufacturing supply chain planning

The data obtained from Scopus database was exported to VOSVIEWER for additional analysis which includes keywords co-occurrence i.e. the total number of articles in which two keywords appear together (Ikeziri, Souza, Gupta & de Camargo Fiorini 2019), and bibliographic coupling which is focused on identifying similarities such as countries, authorship and publications between articles (Phoong, Phoong & Khek 2022).

This resulted in network visualization maps in which the size of the node depicts how frequent the keywords occur. The bigger the node, the higher the frequency of occurrence (Irawan, Rosjanuardi & Prabawanto 2024; Ikeziri *et al.* 2019). Congruently, the distance between two nodes, represent the frequency of their co-occurrence, i.e. the shorter the distance, the higher the frequency of co-occurrences (Yu *et al.* 2020). An overlay visualization map highlighting the correlation between the keywords and publication year i.e. keywords used in 2019 publications are shown in dark blue and gradually transition to yellow, towards recent years' worth of keywords (until Mid-2024).

A network visualization map of co-authorship relation amongst countries is depicted in Figure 5.

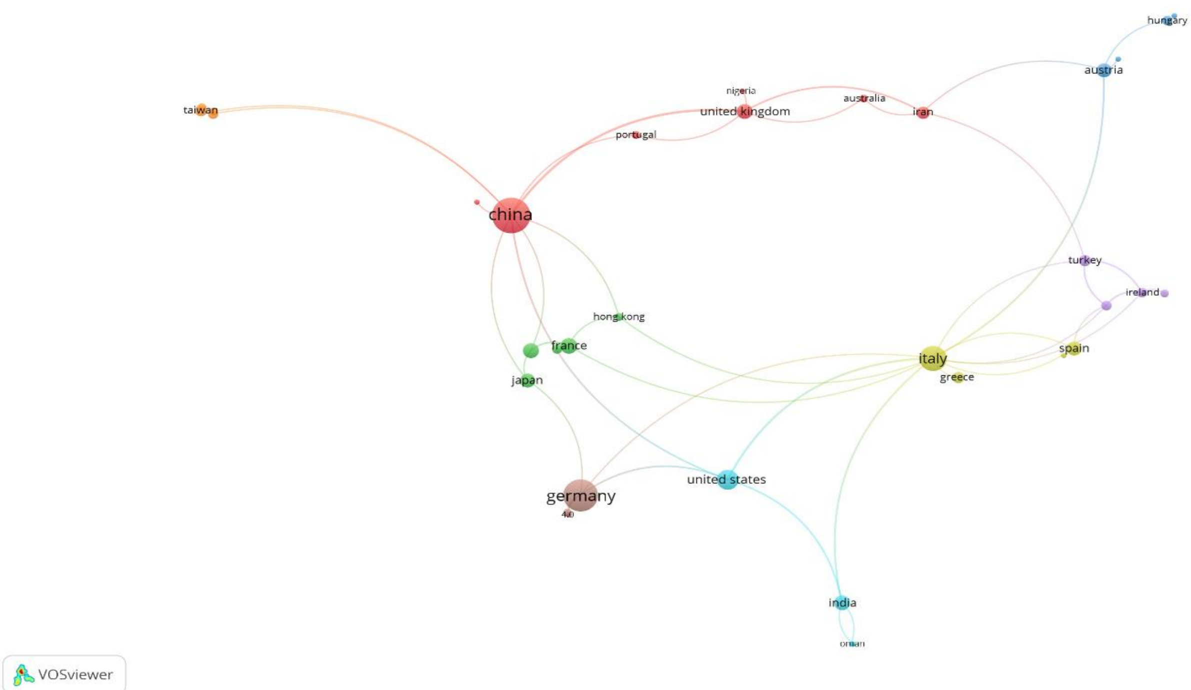

Figure 5. Network visualization Map of co-authorship relation amongst countries based on document output

The size of each circle represents the number of articles written by authors from that country. Each link connecting two circles indicates the co-authorship between the organizations in two different countries. Based on Figure 5, it is evident that Italy has more links, i.e. 11 links, followed by China with 9 links, and both Germany and the United Kingdom with 5 links. The four countries are part of the top 10 countries that contributed to the topic, this indicates that, authors from these four countries collaborated with authors from other countries. Focusing on China, which is the number one contributing country, it is noted that authors from the country collaborated with authors from Macao, Taiwan, United Kingdom, Portugal, Hong Kong, United States, Japan, Singapore, and Canada. This indicates a cross-continental collaboration i.e. Europe (United Kingdom and Portugal) and North America (United States and Canada) accounting for 44% of their collaborations, with 56% of their collaborations within the same continent of Asia i.e. Macao, Taiwan, Hong Kong, Japan, and Singapore. Figure 5 also highlights that South Africa did not contribute any document and the African continent contributed four (4) documents holistically i.e. one (1) from Nigeria and three (3) from Morocco, that is, a contribution of only 2.29 % of the documents. This indicates the poor contribution to literature on the topic from the African continent. Furthermore, the map in Figure 5 reveals that, there is no collaboration or link between these two African countries Nigeria and Morocco.

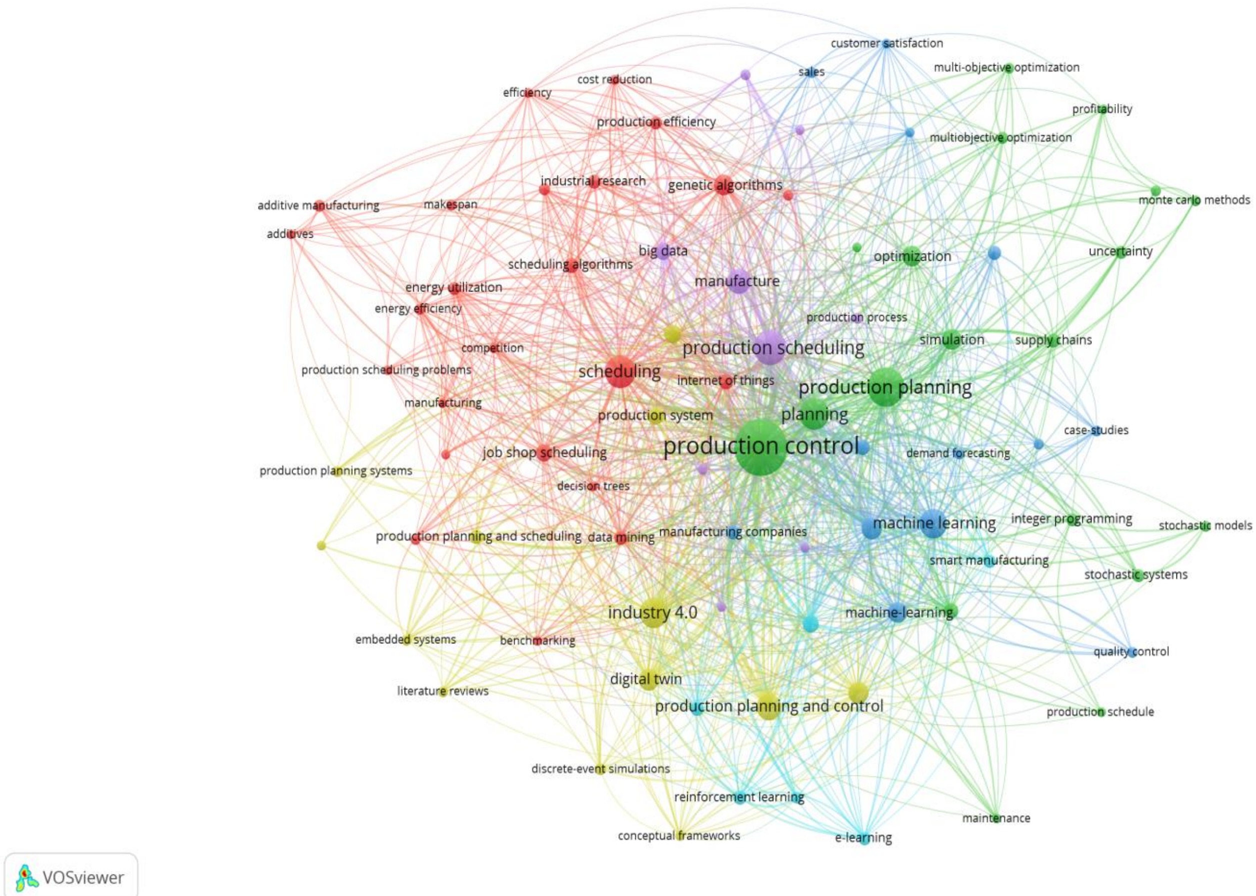

Figure 6. Network visualization of keywords

Figure 6 presents the results of co-occurrence analysis in which all keywords were taken into consideration. However, the map was restricted to keywords referenced at least four (4) times in each document resulting in 84 keywords, the popular keywords with bigger nodes are production control, production planning and production scheduling and scheduling. This indicates that most documents refer to the supply chain planning activities such as production control, production planning and scheduling within the manufacturing sector. Seven distinct clusters are distinguished, each of which displays keywords that frequently co-occur and, thus, suggest a likely theme relationship. A summary of clusters generated is presented in Table 3.

As depicted in Figure 7, the overlay visualization revealed that the correlation between the keywords and publication year i.e., keywords used in 2019 publications are shown in dark blue and gradually transition to yellow, highlighting recent years' worth of keywords (until Mid-2024).

The overlay visualization i.e., Figure 7 highlights that, although there were multiple papers published regarding the planning phase of supply chain and 4.0 technologies since the year 2019, majority of the papers used specific names of these technologies i.e., digital twin, machine learning, simulation, and others from the year 2022. This is deduced since there are little to no specific technology names on nodes with darker shades of blue. Furthermore, the overlay map correlates with Figure 2, indicating that most of the documents were published in 2021, 2022 and 2023.

Table 3. Major clusters of co-occurring keywords

Cluster	Colour	Keywords
1	Red	Additive Manufacturing, Additives, Benchmarking, Competition, Cost Reduction, Data Mining, Decision Trees, Efficiency, Energy Efficiency, Energy Utilization, Genetic Algorithms, Genetic Algorithm, Heuristic Algorithms, Industrial Research, Internet of Things, Job Shop Scheduling, Job-Shop Scheduling, Makespan, Manufacturing, Manufacturing Process, Production Efficiency, Production Scheduling Problems, Scheduling, Scheduling Algorithm.
2	Green	Decision support system, inter programming, maintenance, Monte Carlo methods, Monte Carlo simulation, Multi objective optimization, multi objective optimization, optimization, planning, production control, production planning, production schedule, profitability, simulation, stochastic models, stochastic systems, supply chains and uncertainty.
3	Blue	Case-Studies, computer aided manufacturing, customer satisfaction, Decision Making, Big Data, Cost Reduction, Demand Forecasting, Forecasting, Machine Learning, Machine-Learning, Manufacturing company, quality control, sales, semiconductor device manufacturer and supply chain management.
4	Yellow	Artificial intelligence, Conceptual frameworks, Digital Twin, Discrete Event Simulation, Discrete Event-Simulation, embedded systems, Industry 4.0, literature reviews, Production Planning and Control, Production Planning and scheduling, Production Planning systems, Production scheduling system, and Production system.
5	Purple	Big Data, intelligent manufacturing, manufacture, Manufacturing Industries, Optimizations, Product Design, Production Process, production scheduling, scheduling optimization.
6	Light/sky blue	Deep Learning, E-Learning, Learning Systems, Reinforcement Learning, Reinforcement Learnings, and Smart Manufacturing.

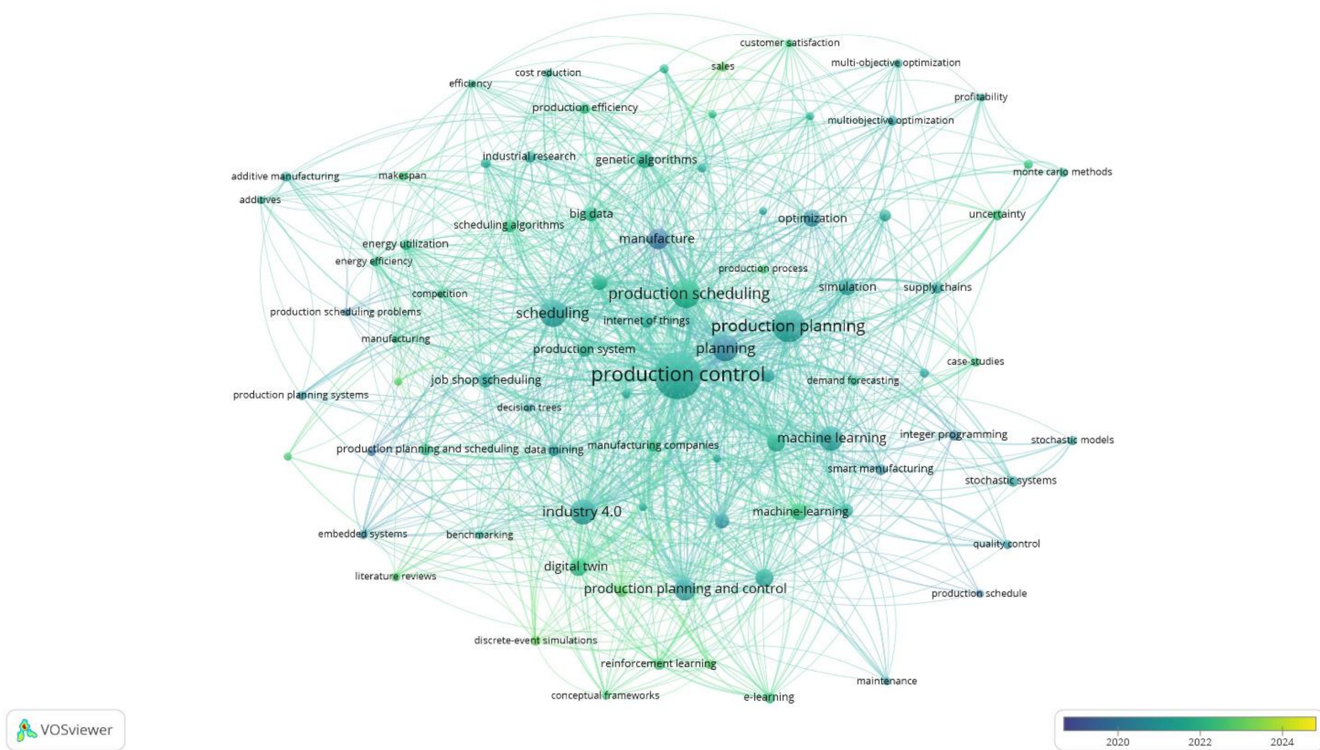

Figure 7. Overlay visualization map

Figure 8 unveiled the density visualization map of the key words that revolves around the research subject matter.

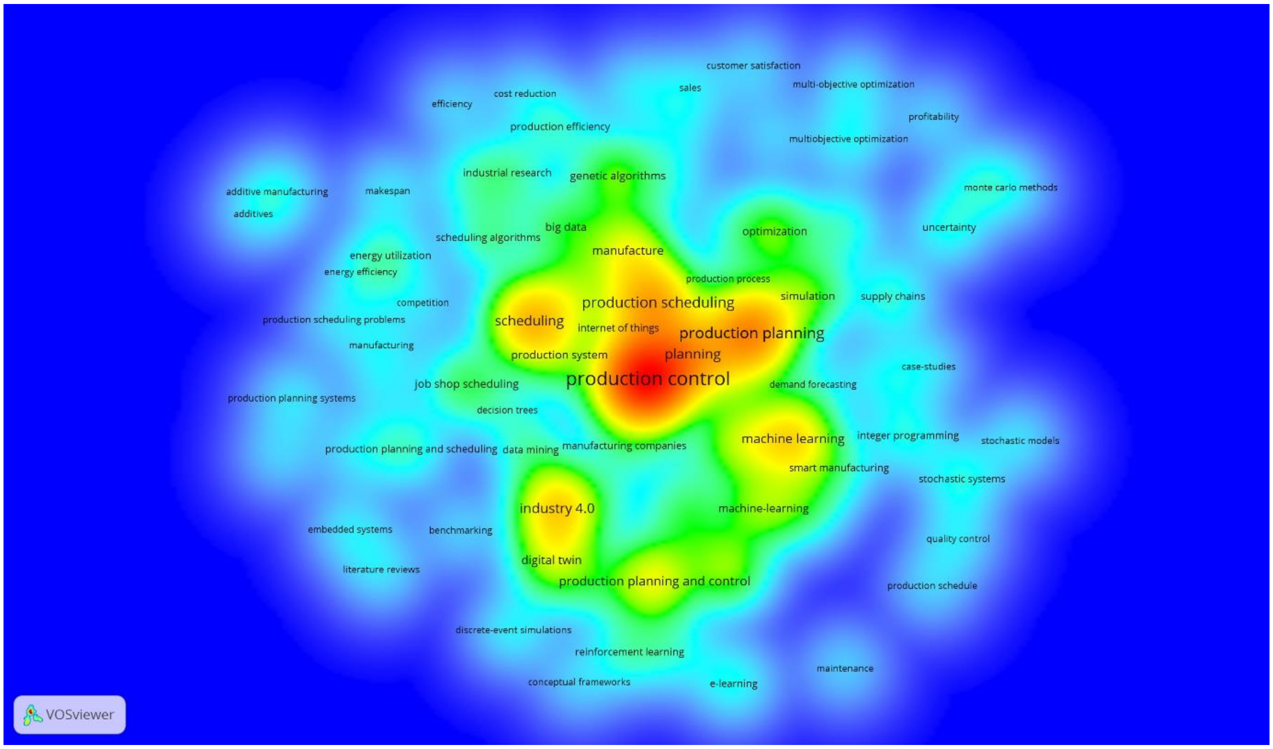

Figure 8. Density visualization map

Based on Figure 8, the density indicates that industry 4.0 technologies such as Internet-of-Things, Simulation, Machine Learning, Artificial Intelligence, Digital Twin, and Big Data co-occur with these planning activities. The frequency of co-occurrence i.e. the distance between the node of the planning activity and the 4.0 technology analysis revealed that Internet-of-Things (IOT) and Simulation frequently co-occur with Production Scheduling and Production Planning and Control. Similarly, with Big Data that co-occur with Production Scheduling, Digital Twin is intricately linked to Production Planning and Control. Machine Learning also often co-occurs with Production Control and Demand Forecasting.

Considering that the first batch of documents retrieved from the database search includes both empirical and theoretical studies, an additional exclusion criterion was introduced as discussed in the methodology section. Documents that do not focus on the application of 4IR technologies within the planning phase in manufacturing organizations were excluded. This resulted in 89 documents to be analyzed and reviewed in the next section.

4.1. Application of 4IR technologies in manufacturing planning

The fifth step, i.e., abstract review resulted in output of 89 documents. These documents revealed that Simulation is a frequently adopted 4.0 technology in manufacturing planning, followed by Machine Learning, Digital Twin, and Internet-of-Things with 36, 21, 17 and 9 documents. A summary of the abstract review exercise is presented in Table 4.

It is important to note that some of the reviewed documents discussed the application of one industry 4.0 technology for more than one supply chain planning activity, while others used multiple industry 4.0 technologies for one supply chain planning activity.

Table 4. A summary of 4.0 Technologies applied in supply chain planning phase.

	Production planning and control	Production Scheduling	Forecasting	Maintenance planning	Total	Frequency (%)	Cumulative Frequency (%)
Simulation	21	13	1	1	36	36%	36%
Machine Learning	14	4	3	0	21	21%	57%
Digital Twin	9	7	0	1	17	17%	74%
Internet of Things	2	5	1	1	9	9%	83%
Artificial Intelligence	1	2	2	0	5	5%	88%
Big Data	1	2	1	0	4	4%	92%
3D printing/Additive manufacturing	3	1	0	0	4	4%	96%
Deep Learning	1	1	0	0	2	2%	98%
Data Mining	1	0	0	0	1	1%	99%
Augmented Reality	0	1	0	0	1	1%	100%

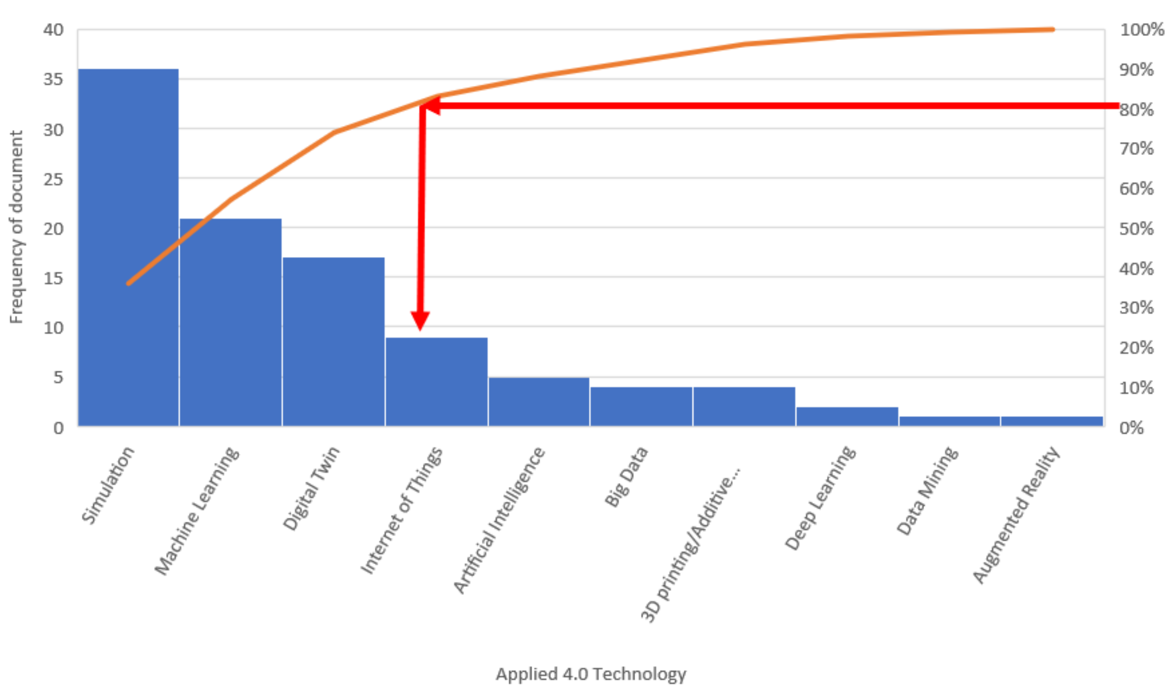

Figure 9. Pareto Analysis of frequency of documents in which 4.0 technologies were applied in supply chain planning phase used in manufacturing organizations

Using data from Table 4, a Pareto Chart was created as depicted in Figure 9. Based on the 80/20 rule, the reviewed literature indicated that technologies such as Simulation, Machine Learning, Digital Twin, and Internet-of-Things account for 83% of the industry 4.0 technologies applied within the supply chain planning phase.

5. Discussion

Simulation is an industry 4.0 technology that makes it possible to replicate real-world systems or processes in a repeatable and regulated setting (Mourtzis, 2020). In the study of Woschank et al. (2024) in which simulation was applied in production planning of an electronic manufacturing organization, the study highlighted that simulation offers the benefits of high internal validity and reliability in decision-making. This was supported by Cruz, Salles-Neto and Schenekemberg (2024), whom in their study developed the Monte Carlo simulation routine for the analysis of production planning in a dairy product manufacturing organization in Brazil. The authors further recommended simulation as a tool for developing management plans for safety stock level. Also, applying the Monte Carlo simulation method, a study by Olanrele et al. (2023) revealed that this industry 4.0 technology provides an efficient way to manage demand uncertainties, meet customer demand and minimize costs. Benefits of adopting simulation were also highlighted in studies by Andrés, Alvaro, and Julian (2019); Belil, Tchernev and Kemmoé-Tchomté (2019); Müller *et al*. (2019), Sabah, Nikolay and Sylverin (2019); Sobottka *et al.* (2019); Song, Xie and Rou (2019); Chai, Zhao and Li (2020); Fabianova, Kacmary and Janekova (2020); Hatami-Marbini, Sajadi and Malekpour (2020); Rodrigues de Pinho and Sena (2020); Russkikh and Kapulin (2020); Zhang *et al.* (2020); Ziarnetzky, Mönch and Uzsoy (2020); Chiadamrong and Tangchaisuk (2021); Barreto, Sagawa and Silva (2021); Laroque *et al.* (2021), Pirola, Zambetti and Cimini (2021); Nekrasov and Pravdivets (2022), Okubo and Mitsuyuki (2022); Panasri, Samattapapong and Sangthong (2022); Rashidifar, Chen and Tran (2022); Wang *et al.* (2022); Behrendt *et al.* (2023); Bojic *et al*. (2023); Dcoutho, Eisenbart and Kulkarni (2023); Ding *et al*. (2023); Fani *et al.* (2023); Hong *et al*. (2023); Lan and Chen (2023); Muehlbauer, Rissmann and Meissner (2023); Chu and Karomati Baroroh (2024).

According to Rai et al. (2021), Machine Learning is the capability of machines to learn and effectively decide, carry-out tasks and forecast based on acquired data with no human intervention. Machine learning was applied in the supply chain planning phase of an electronic manufacturing organization, in which the results obtained indicated that, the application of machine learning provided critical insights to guide the decision-making process and predicted sales quantities, enabling an accurate view of future demands (Vaz et al. 2020). A study by Chen, Zhou, and Zhang (2021) also supported that Machine Learning based decisions increase profit by over 10% compared to profits of individual based decisions. A study by Nakao and Nishi (2022) proved how generating customer purchasing behavior model using Machine Learning can improve customer satisfaction and increase profits. Benefit such as production plan accuracy using Machine Learning was realized in a study by Togo, Asanuma, Nishi, and Liu (2022), while a study by Pereira *et al.* (2024) reported on reduced makespan (i.e. the amount of time to process all of the tasks) and accurate energy consumption plan for upcoming production schedule using Machine Learning. Optimized production and scheduling plan are achieved through the application of Machine Learning (Alexopoulos *et al*. 2023; Chen, Zhou & Zhang 2020; Elbasheer *et al*. 2022; Fülöp *et al.* 2022; Garcia-Arismendiz *et al.* 2023; González Rodríguez, Gonzalez-Cava & Méndez Pérez 2020; Guo, Yang & Zhu 2020; Heesch, Ehrhardt, & Niggemann 2024; Jayant, Agarwal, & Gupta 2021; Kim & Maravelias 2022; Muehlbauer *et al.* 2023; Ryback *et al.* 2019; Santander *et al*. 2023; Vithitsoontorn & Chongstitvatana 2022; Yu *et al*. 2023).

Digital Twin is a digital representation of a physical system and its continuous operations that is set up via a data connection and enables the transformation of the physical system into a virtual system while preserving a high degree of synchronization between them (Mashaly, 2021). Digital twining offers a novel and practical way to promptly address the disruption brought on by dynamic occurrences in the workshop said Li *et al.* (2023) based on the results of their study. A study by Pandhare *et al.* (2024) incorporated digital twin in production scheduling process, which resulted in improved and better makespan estimations as opposed to the former production schedule without digital twin incorporation. Biesinger *et al.* (2019); Chiurco, Elbasheer *et al.* (2022); Ghasemi *et al.* (2023); Kuo *et al.* (2023); Liu *et al*. (2021); Macchi, Ragazzini and Negri (2023); Magnanini *et al*. (2021); Negri *et al.* (2022); Negri *et al.* (2021); Novák, Vyskocil and Wally (2020); Wang and Wu (2022); Xu and Xie (2021), reported on benefits of adopting digital twin in the planning phase of manufacturing supply chains. However, Atibodhi *et al.* (2023) reported on the challenges experienced during implementation and adoption stage, highlighting the importance of incremental continuous improvement as opposed to radical enhancement.

Internet-of-Things (IoT) is an industry 4.0 technology that connects and exchanges data and systems via the internet by embedding a network of physical objects with sensors and/or software (Garg *et al.* 2022). According to Liu, Ma and Huang (2024), application of an Internet of Things-Based Production Scheduling reduced order delays and increased profits. Chen (2020) in addition, highlighted that real-time monitoring of the workshop's state and equipment status, as well as real-time tracking of the manufacturing workshop products, which can be achieved through the application of IoT. Ghaleb, Zolfagharinia and Taghipour (2020) in their study reported the impact of using real-time data through Internet of Things technologies to generate and update production schedules, this allowed the manufacturing organization to model machine availability, pinpoint, and address issues such as uncertain job arrivals and random breakdowns. Studies by Berlak *et al.* (2020); Dimoudis *et al*. (2023); Eljaouhari *et al*. (2022); Kocsi *et al*. (2020), also realized the benefits obtained from the application of IoT in supply chain planning phase such as optimized processes and efficient decision making.

Essentially, the literature indicates low output and poor collaboration from authors in countries within the African continent. The African continent, with majority of countries considered least developed or developing, contributed 2.29% of the documents covering the topic. It was noted that the top 10 countries with regard to paper contribution collaborated with authors globally, with majority of collaborations being with countries in the same continent. The literature further indicated that IFAC-PaperOnLine is the number one source for the topic, contributing approximately 10% of the reviewed papers.

In addition, the results of the literature review indicated that production planning, production scheduling, production control and scheduling were the common terms used for the supply chain planning phase. Forecasting was also observed in the co-occurrence map and the cluster table. However, other planning activities predefined keywords in the search string such as facility planning and material requirements planning, did not show up in the results. On the other hand, deep learning which was not part of the predefined keywords in the search string showed up on the results. The keywords in the cluster summary depicted in Table 3 also revealed how one keyword can be documented differently, thus impacting the size of the node on the VOSviewer maps, for example, a simulation 4IR tool is documented as (i) Simulation, (ii) Discrete Event Simulation, (iii) Discrete Event-Simulation and (iv) Monte Carlo Simulation. Other ways of documenting keywords included the use of hyphens (-) and keywords noted as singular and plural words, resulting in multiple keywords which point out to one concept.

6. Conclusion and recommendation

The primary objective of the study was to determine 4IR technologies used to improve the supply chain planning phase of manufacturing organizations. The first finding was that more literature recognizes production planning and control, production scheduling, demand forecasting and maintenance planning as activities in the planning phase of manufacturing supply chains. The second finding was that most of the literature, based on the outlined methodology, covers the application of Simulation, Machine Learning, Digital Twin, and Internet-of-Things for the supply chain planning phase used in manufacturing organizations. Furthermore, the last finding reveals positive outcomes for the application of Simulation, Machine Learning, Digital Twin, and Internet of Things. That is, the application allows for better decision making within the planning phase, resulting in meeting customer requirements and minimizing costs.

Based on the above findings, the study recommends the following:

- Conducting studies on the application of 4IR technologies in the supply chain planning department of manufacturing organizations located in Africa, in which the implementation processes, the challenges faced, and adoption feedback are disclosed.
- Literature review studies to determine 4IR technologies that should be used to improve or remedy challenges within the sourcing, production, delivering, returning, and delivering phases of the supply chain.
- Collaboration should be fostered amongst authors in the African continent on studies pertaining the application of 4IR technologies in the planning phase of supply chains within manufacturing organizations.
- Conducting a study that will develop a database of keywords pertaining to various topics, to feed into software like VOSviewer so as to ensure that variants of one keyword do not impact the analysis maps.

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