Knowledge Mapping of Digital Twin and Physical Internet in Supply Chain Management: A Systematic Literature Review

Abstract

Physical Internet (PI) is an open global logistics system of which components are hyperconnected for increased efficiency and sustainability. Digital twin (DT), referring to the virtual representation of a physical object, is well-perceived as a key driver in the development of PI-based Supply Chain Management (SCM). Due to the capabilities of real-time monitoring and evaluation of large-scale complex systems, significant research efforts have been made to exploit values of PI/DT in SCM. Despite this, the current literature remained largely unstructured and scattered due to a lack of systematic literature reviews to synergise research findings, analyse the evolution of research fronts and extract emerging trends in the field. To address this issue, the paper deploys a bibliometric knowledge mapping approach to provide a bird's eye view of the current research status in the PI/DT-SCM area. Using CiteSpace's keyword co-occurrence network, 518 journal articles are clustered into 10 key research streams on PI/DT applications in: job shop scheduling, smart manufacturing design, PI-based SCM, manufacturing virtualisation, information management, sustainability development, data analytics, manufacturing operations management, simulation and optimisation, and assembly process planning. Based on citation burst rate, keywords representing research frontiers of the PI/DT are detected and their temporal evolutions are discussed. Likewise, some identified emerging research trends are production process and system, robotics, computer architecture, and cost. Finally, seven future research directions are suggested, which emphasise on several PI/DT-related issues, including business ecosystem, sustainability development, SC downstream management, cognitive thinking in Industry 5.0, citizen twin in digital society, and SC resilience.

Keywords: ***Digital Twin, Physical Internet, Supply Chain, Bibliometric Analysis***

1 Introduction

Fourth Industry Revolution (Industry 4.0) paradigm connotes the creation and convergence of cutting-edge technologies, e.g., Internet of Things (IoT), Cyber-Physical Systems (CPS), cloud computing, and digital twins, which are ubiquitous. These prevailing innovations are in dire need of productivity enhancement and automation that reduces human flaws and intervention (Gaikwad et al., 2020; Sheuly et al., 2021) .

Over the last decade, the terms of physical internet (PI), digital twin (DT) and their related innovations have gained many attentions among scholars. PI is defined as a seamless global logistics and distribution infrastructure incorporating physical objects (e.g., sensors) and interfaces to digitally interconnect (Montreuil, 2011). It is expected to help overcome the inefficiencies of the current logistics paradigm in the global volatile market context (Ballot et al., 2012). Indeed, significant efforts have been made to explore various applications and advanced techniques of PI in transportation and distribution aspects such as material handling system (Fahim et al., 2021; Hao Luo et al., 2021; Montreuil et al., 2010; Pan et al., 2017), interconnected modular containers (Lin et al., 2014; Sarraj et al., 2014), informational dimensions of PI-container (Sallez et al., 2016), auction logistics (Kong et al., 2016) and humanitarian SC (Grest et al., 2021). Its applications are also reaching to the operations of well-known firms such as Amazon, UPS and Fedex (Dans, 2019).

As the Covid-19 pandemic has been accelerating the transformation of digital economy and digital society, DT, which refers to the digital representation of non-living and living physical objects (e.g., people, process, system, and others), has soon become one of the key technological enablers in the new era. With the capabilities to generate virtual instances and control the changes of a physical object in real-time, DT is often integrated with advanced technologies such as IoT, big data analytics and blockchain, to develop smart, interconnected supply chain (SC) and logistics system, so called logistics/SC DT (Ivanov et al., 2019; Ivanov and Dolgui, 2021). Some perceived benefits of DT in SC management (SCM) are to remotely and instantly monitor the operations (e.g., production) and proactively mitigate risks and disruptions through timely decision makings (Ait-Alla et al., 2021; Tao et al., 2019b). Due to its functions, DT is thus well-known as a key driver of hyperconnected PI systems. Its applications and values have also been rapidly gaining relevancy in both academics and practices recently.

An initial observation during our data collection shows that scholars' works for PI/DT developments in SC and operations management have surged extraordinarily in recent years. However, despite the exponential growth, the extant literature remains largely unstructured and scattered across various disciplines, thus limiting the knowledge transfer and innovation of the subject area. For this reason, it is necessary to have systematic literature reviews which can synergise current research findings, detect research forefronts and draw on future directions.

Given the emerging nature of the PI/DT in SCM topic, not surprisingly, there is a limited number of literature reviews available, and most of them only focus on niche subject areas, for example, smart manufacturing system design (Leng et al., 2021; Semeraro et al., 2021), information sharing in remanufacturing (Chen and Huang, 2021a), product design and development (Lo et al., 2021), sustainable intelligent manufacturing (He and Bai, 2021), additive manufacturing (Zhang et al., 2020), auction logistics (Kong et al., 2018), and smart maintenance (Errandonea et al., 2020). Few review papers take more holistic view of PI/DT across various SCM disciplines. Sternberg and Norrman (2017) prominently focused on PI literature discussing about the concept and provided research agenda using content analysis. Treiblmaier et al. (2020) reviewed the evolution of PI in the context of logistics and SCM practices. These unveil a significant gap in exploring the evolution of PI and DT literature in the holistic SCM research domain. Furthermore, all the mentioned reviews adopted either conventional content analysis approach, bibliometric analysis such as co-citation, co-author analysis or text mining approach. They cannot fully capture the critical paths and evolution of research forefronts overtime. The work by Treiblmaier et al. (2020) did study the evolution of PI in SCM, but using only thematic analysis, which is subject to limitations such as time-consuming and susceptibility to human errors, hence, the inability to work with a large volume of literature.

To help fill in the research gap and overcome certain limitations in existing methodologies, this paper takes a holistic view of the literature in PI and DT in SCM, deploys a hybrid approach with bibliometric knowledge mapping using co-occurrence keywords, and timeline analysis to detect and analyse the research frontiers and their evolutions over time, thus triggering new research opportunities for future studies. The proposed approach is believed to be more robust and scalable than other comparable papers in the field. In particular, this literature review aims to address three key research questions as below:

RQ1: What are research frontiers related to PI and DT in the context of SCM?

RQ2: How have research frontiers of PI/DT in SCM evolved and interacted over time?

RQ3: What are the emerging research trends and future research directions in the PI/DT-SCM field?

The remain of the paper is organised as follows. Section 2 describes the research design of the study which explains our proposed methodological framework and descriptive analysis of the reviewed dataset. The content analysis of research fronts based on keyword clustering is discussed in Section 3. The timeline evolution of research fronts and emerging trends is presented in Section 4. Based on our findings, future research directions are suggested in Section 5. The final section is conclusion.

2 Research Design

2.1 Methodology Framework

This review is conducted based on the methodology framework depicted in

Figure **1**. Particularly, (1) the research background is first established for DT within SC domain to help (2) define the search terms for data collection. The obtained data is then (3) cleaned, removing any duplicated and invalid documents. Next, (4) the descriptive analysis is presented to provide some key overviews of the subject area, followed by (5) cluster analysis based on keyword co-occurrence network (KCN). (6) Timeline views are provided along with burst detection analysis to examine the evolution of research fronts and emerging trends. Finally, (7) future research directions are suggested and discussed.

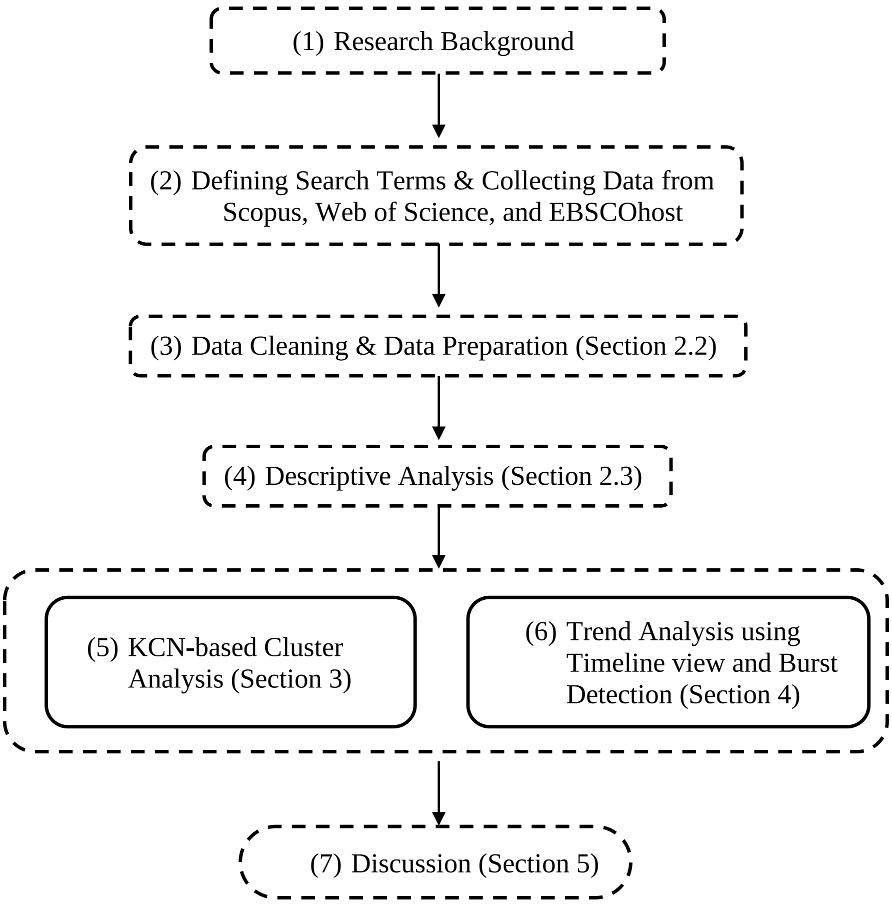


Figure 1. Methodology Framework

2.2 Data Collection and Preparation

The aim of this research is to explore the applications of DT in SCM. Therefore, two groups of keywords representing each topic were created to capture relevant research effectively as follows:

- DT-related keyword group: “*digital twin”, “physical internet”, “hyperconnected”.*
- SC-related keyword group as adopted from Nguyen et al. (2018): *“supply chain", "logistics", "manufacturing", "procurement", "inventory", "transport", "purchasing", "storage assignment", "order picking”.*

The search terms were formed as a combination of any keyword pair between these groups. The data used in this research were collected from three well-established academic databases, namely Scopus, Web of Science (WoS), and EBSCOhost to ensure no relevant works are missed out. Although there is no specific setting about year of publications, other important filters were applied to ensure that only English, peer-reviewed journal articles were obtained. The resultant dataset was then extracted and aggregated via Endnote software.

After excluding all duplicated results, the total number of documents obtained at this stage was 1858. We then reviewed the titles and abstracts of these articles based on the inclusion and exclusion criteria listed in Table 1.

Regarding inclusion criteria, studies that focusing on the application of DT or development of PI to solve SCM’s issues are included. Even though simulation is only one of the three important features of DT besides data and modelling, in the earlier years, most of the literature defined DT as multidisciplinary simulation without taking into consideration the real-time connection with the physical entity (M. Liu et al., 2021). Therefore, we included papers where the authors use simulation interchangeably with DT as well.

Papers were excluded when 1) they mainly focus on DT or PI but barely touched upon SCM (e.g., specific areas within healthcare, biochemical and engineering); or 2) they mainly focus on SCM but only slightly touched upon DT or PI; or 3) they use simulation concept that does not align with DT concept.

We are well-aware of the potential selection bias during the process, including bias in designing selection criteria and bias in selecting papers. In order to minimise these, three co-authors independently conducted the screening of papers using the same inclusion/exclusion criteria while all information of the articles were blanked out except for title and abstract. The results were then compared and whenever disagreement occurred, the full version of the article was restored and opinions from the fourth co-author were sought.

Table 1. Papers selection - inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
• Focus on DT/PI in the context of SCM • Simulation that the authors used interchangeably with DT	• DT/PI not related to SCM • SCM not related to DT/PI • Simulation that does not align with DT concept

This led to a reduced number of papers to 467. Among these papers, search was expanded to their reference lists. After filtering out only English, peer-reviewed academic articles, a new list of 1031 documents were gathered and assessed. Among these, only 51 are not duplications of any previously screened documents and satisfy the relevancy criteria based on their titles and abstracts. Thus, the final number of articles to be analysed in the next step is 518. The summary of this process can be found in Figure 2.

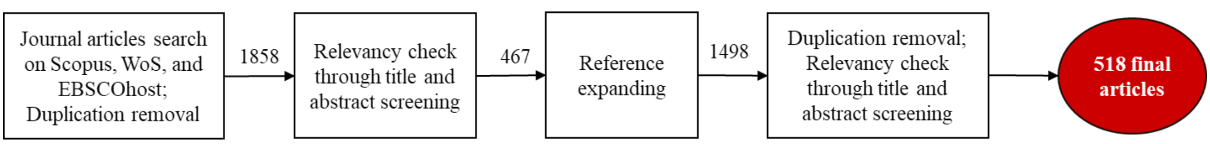


Figure 2. Paper's search and selection process

2.3 Descriptive Analysis

Descriptive analysis provides an overview of the collection of 518 documents collected, using each paper's basic information such as its publication year, journal publisher, and country of publication. The country of publication of each paper is decided by the affiliations of all the authors. For example, if an article has three authors from three different universities in – the UK, US, and China, the countries of publication of this article are the UK, the US and China. In other words, there are overlaps in publications between the publication countries, meaning one paper can belong to the UK, US, and China at the same time.

As can be seen in Figure 3, application of DT and PI in SCM started from 2013. However, the topic did not get much academic attention until 2018 when the number of publications increased exponentially by 162 articles within two years. Such extraordinary surge is expected to continue this year as the number of new publications in the first half year of 2021 has already been close to the figure in 2020.

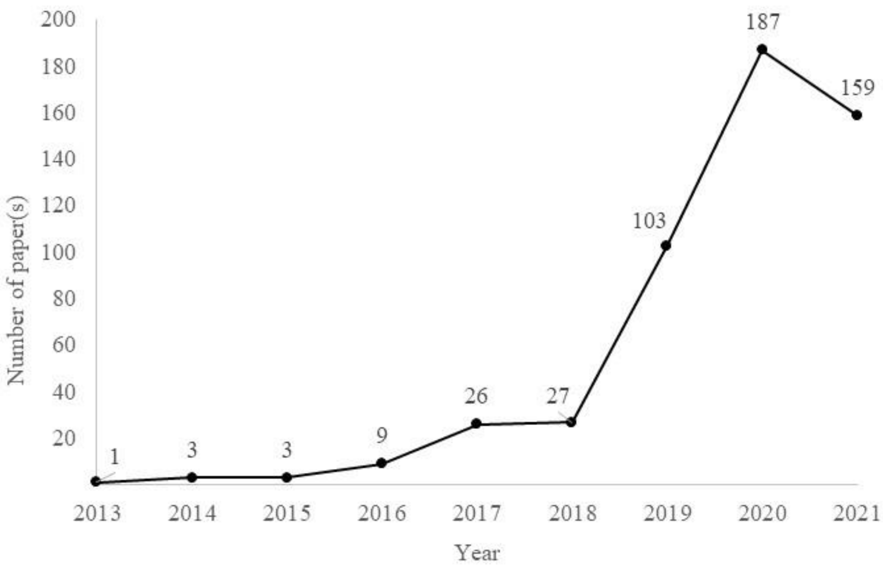


Figure 3. Publications by year

Figure 4 is the list of journals contributed more than 10 publications in this field. These 11 journals account for nearly half of all the publications. As can be seen, the majority of the journals in the list are manufacturing–related, which implies the active role of DT research in this domain. Other journals are interdisciplinary such as “Sustainability Switzerland”, “IEEE Access”, “Computers in Industry”, and “Applied Sciences Switzerland”.

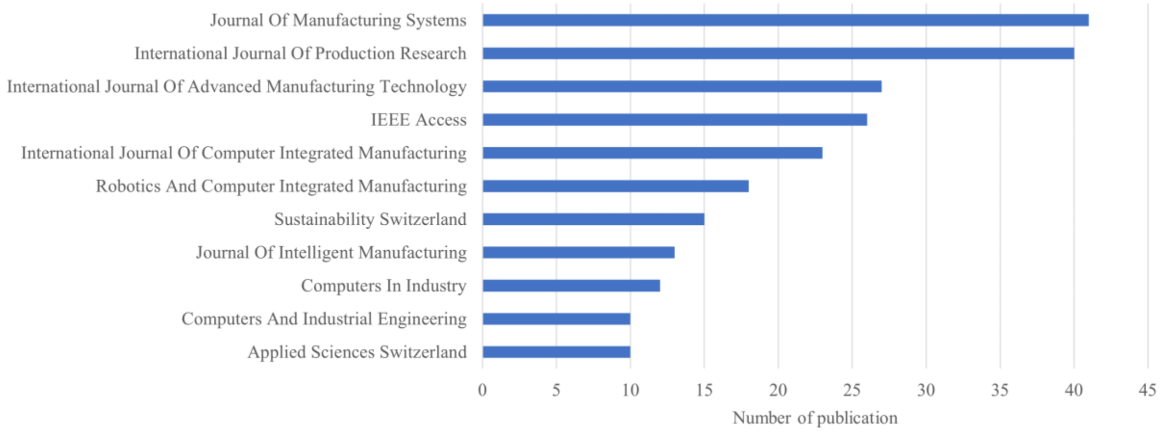


Figure 4. Publications by journal

Figure 5 suggests that publications from China account for about one third of the dataset (168 articles), and more than double the number of papers published from the United States which is currently at the second position.

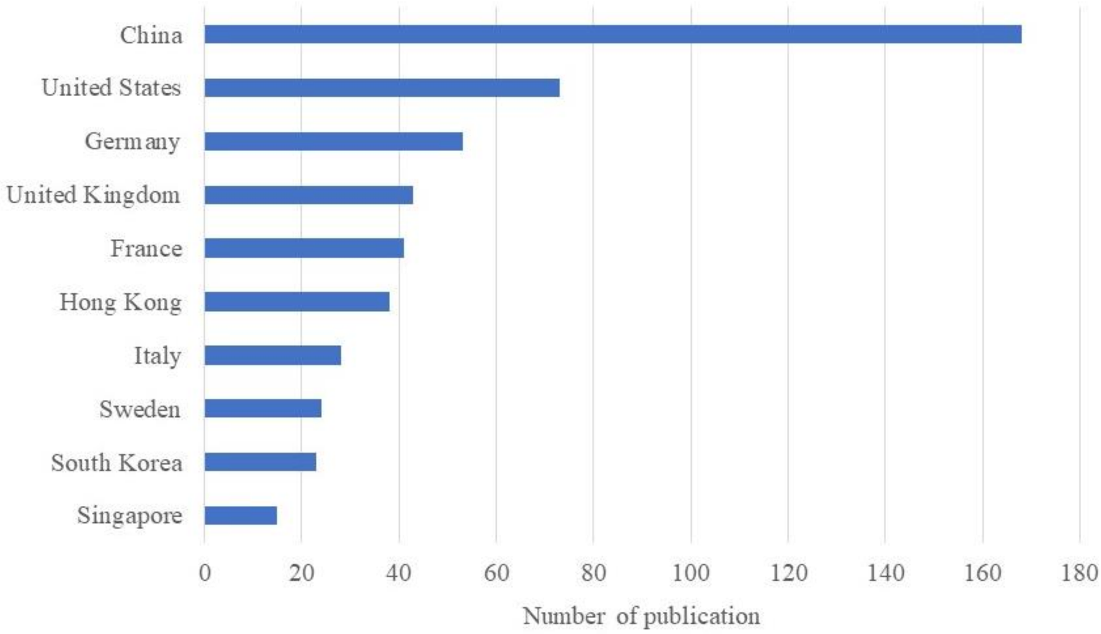


Figure 5. Publication by country/territory

2.4 KCN-based Cluster Analysis

To address RQ1, keyword co-occurrence network followed by content analysis were conducted on selective papers.

Bibliometric is one of the most common quantitative approaches for systematic literature review. The technique was first suggested by Alan Pritchard, a British intelligence scientist, in 1969. Since then, it has been widely adopted in a variety of fields such as medicine (Kokol et al., 2020), distribution (Z.-C. Li et al., 2020), SC finance (Xu et al., 2018), and marketing (Martínez-López et al., 2018). The frequency of keyword occurrence is a commonly used method in bibliometric analysis to identify research topics and research frontiers (Su and Lee, 2010). Keyword co-occurrence network (KCN) is the interconnected system between keywords that appear in at least two different articles. Typically, a KCN is formed by keyword nodes connected by links, of which the thickness indicates the number of times the keyword pair co-occurs (**Error! Reference source not found.**).

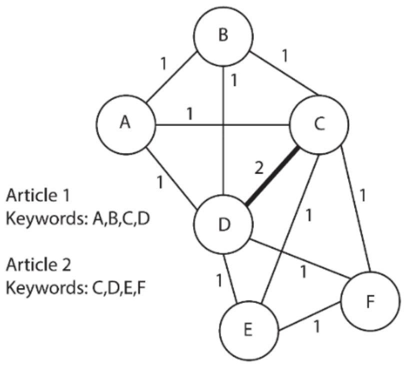


Figure 6. A simple keyword co-occurrence network (Radhakrishnan et al., 2017)

Since keywords reflect the main content of a research article, keyword analysis can reveal the key topics of the paper, as well as the relevancy of two or more documents. Therefore, the KCN can summarise a selected field more accurately by focusing more on the literature content rather than the results (Radhakrishnan et al., 2017). Furthermore, compared to other bibliometric techniques, the KCN analysis minimises the subjective bias in judgement (Peters and van Raan, 1993). Due to its advantages, KCN is performed in this paper to explore the emerging topic of DT in SCM.

2.5 Trend Analysis using Timeline view and Burst Detection

To address RQ2, we analysed CiteSpace's keyword citation burst and timeline view of the KCN, while emerging research trends as part of RQ3 were identified using CiteSpace's keyword citation burst.

Adapted from Kleinberg's (2002) burst detection algorithm, CiteSpace can extract the burst terms which are explosive keywords with sharp increases of interest over a certain period of time. The more abrupt change of the keyword, the more popularity and attention is being paid to it within the considered time interval, and to some degree, it represents the research front and hotspot of a subject area (Chen, 2006; Q. Li et al., 2020).

Timeline view is an effective visualisation approach which helps evaluating trends. This is based on human ability to capture spatial proximity between any two items and deduce their relation (Morris et al., 2003). Small and Greenlee (1989) used timeline view to show temporal relations between research topics along with their evolution and diversification in AIDS research from 1981 to 1987. Meanwhile, Braam et al. (1991) used timeline view to explore the growth of several characteristics, such as citation rates of key documents, or of a set of documents over time.

3 Keyword co-occurrence network analysis

3.1 KCN-based clustering on CiteSpace

CiteSpace is used in this paper to build the KCN and cluster analysis for 518 documents collected. The software is a Java-based application developed by Chen (2006), with scientific literature data mining and visualisation as the main feature. The CiteSpace parameter settings for KCN are as follow: (1) The time span is from 2013 to 2021, reflecting the publication period of all collected articles. Time slice is selected as one year. (2) Term sources include author keywords (i.e. author selected keywords in the published paper) and indexed keyword (i.e. publisher selected keywords), as suggested by Duvvuru et al. (2013). (3) Keyword is selected as the node type in the network as shown in **Error! Reference source not found.**. Finally, (4) G-index with k=7 is selected as criteria for cluster analysis.

A scaling value k of G-index (Egghe, 2006) is a metric using in CiteSpace to sample high cited papers to be visualised in the network (Diez-Martin et al., 2019; Zhu and Hua, 2017). It helps simplify the KCN while highlight the most impactful nodes in each cluster. The Silhouette metric is useful to evaluate the nature of a cluster by taking into account its keyword members (Diez-Martin et al., 2019). Several experiments with various k of g-index should be implemented to derive the optimal average Silhouette score (Chen Chaomei, 2020). Previous works have used the Silhouette score to evaluate the precision and degree of homogeneity between the keywords forming each cluster (Chen et al., 2010; Rawat and Sood, 2021). The default setting on CiteSpace is k = 25. After various k ranging from 5 to 35 were tested, k = 7 yields the best result for the clustering task (Silhouette values = 0.9481).

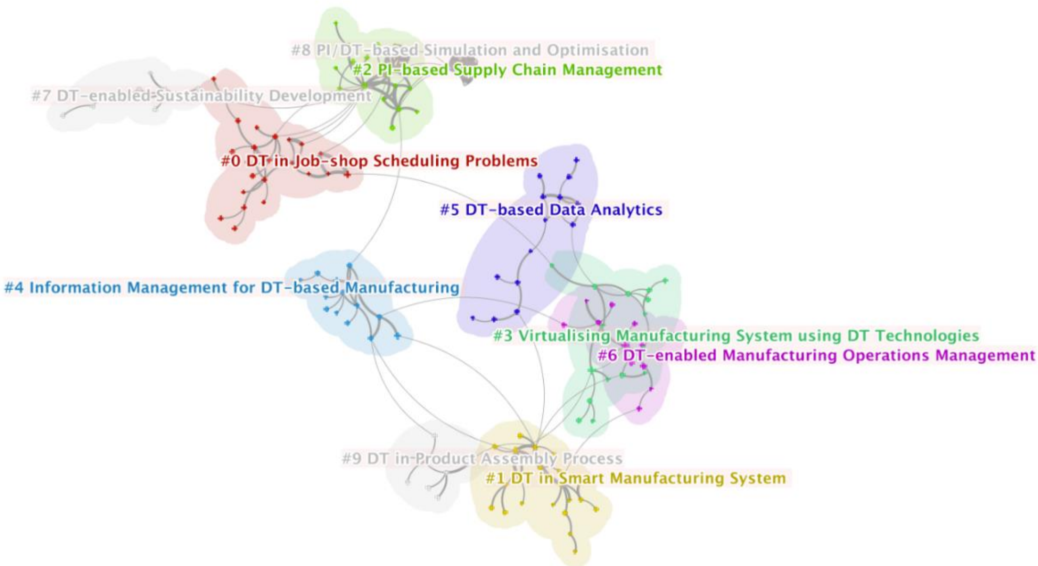


Figure 7. The keyword co-occurrence network

The clusters based on KCN are obtained and visualised in Figure 7. As a result, 10 labelled clusters are identified.

Table 2 shows the most important keywords for each cluster based on the Log-Likelihood Ratio (LLR) ranking system. LLR (Dunning, 1993) is a statistical metric to rank and test the significance of rare and common keywords. It is calculated by considering the frequencies of a keyword in all papers and number of keywords in each paper. A keyword with a high LLR represents the high strength of association within a set of papers.

The silhouette value of a cluster measures the quality of a clustering configuration. Its value ranges between -1 and 1. The closer the value to 1, the better the clustering quality (Chen, 2006). As the Silhouette score of each cluster is closed to 1, it indicates the reliability of the identified clusters.

The cluster labels were decided by the authors based on common themes among the top keywords ranked by LLR. Labelling cluster using common themes is a practical strategy as comprehensively identifying the nature of one group of research papers can be too complex (Chen et al., 2010). For instance, White and McCain (1998) along with Zhao and Strotmann (2008) relied on their decades of specialist knowledge to decide the common themes of the members of specialties.

From the original set of articles in every cluster that were obtained from CiteSpace (**518 papers**), the most representative papers for each cluster were selected (**211 papers** in total across all clusters) by matching each cluster's top ten keywords ranked by LLR as in Table 2. To determine the research focus for each cluster with in-depth content analysis, lead papers were identified using Scimago Journal Ranking (SJR) system. This is a common practice within bibliometric literature review (e.g., Fahimnia et al., 2015; Xu et al., 2018), where lead papers represent a general description of each cluster. Overall, out of 211 papers, **94 papers** published in journals of SJR Q1 (best quartile) were selected for further in-depth content analysis due to their generally higher academic rigour and quality. These papers are analysed in Section 3.2 around the corresponding cluster's keywords. The summary of paper members of each cluster can be seen in Appendix.

Table 2. Summary of ten clusters*

Cluster ID	Silhouette	Cluster label	Top keywords ranked by LLR
0	0.939	DT in Job-shop Scheduling Problems	scheduling, decision making, production control, production scheduling, intelligent scheduling, smart manufacturing, planning, traceability, physical internet (PI), decision support tool
1	0.971	DT in Smart Manufacturing System	cyber physical system, embedded system, cyber physical systems, smart manufacturing, reference modeling, internet of thing, production logistics, simulation, manufacturing proce, reference model
2	0.977	PI-based SCM	physical internet, digital twin, logistics, container, supply chain management, internet, city logistics, routing, optimisation, smart manufacturing
3	0.883	Virtualising Manufacturing System using DT Technologies	manufacturing proce, manufacture, simulation, manufacturing, digital twin, manufacturing equipment, computer control system, neural network model, object detection, quality assurance
4	0.924	Information Management for DT-based Manufacturing	big data, smart manufacturing, life cycle, digital storage, digital thread, industrial research, simulation, vertical integration, product life cycle, product life cycle management
5	0.973	DT-based Data Analytics	robotics, 3d printer, additive, additive manufacturing, defect, digital transformation, automation, industry 4.0, computer vision, laser powder bed fusion
6	0.888	DT-enabled Manufacturing Operations Management	industry 4.0, virtual reality, digital twin, intelligent manufacturing, product design, logistics, physical internet, augmented reality, robot, machine design
7	0.953	DT-enabled Sustainability Development	sustainable development, sustainable manufacturing, industrial internet of things, energy efficiency, blockchain, sustainability, perturbation, effectiveness, vehicle routing, rescheduling
8	0.971	PI/DT-based Simulation and Optimisation	two stroke cycle engine, financial metrics, production demand, real time forecasting, discrete event simulation, efficiency, service, heuristic algorithm, virtual product, financial information
9	1	DT in Product Assembly Process	machine learning, learning algorithm, automotive industry, sheet metal assembly, computer aided tolerancing, minimum redundancy maximum relevance, root cause analysis, quality management, supervised learning, selective assembly

*Note: the detailed discussion of each cluster is shown in Section 3.2

3.2 Cluster Analysis

The following clusters represent the research frontiers related to PI and DT in the context of SCM (RQ1).

3.2.1 Cluster 0: DT in Job-shop Scheduling Problems

The largest cluster refers to the application of DT in addressing a long-standing research problem of job shop scheduling within manufacturing domain. Despite extensive theoretical achievements in classical job shop scheduling study, there is still a big gap between the developed models and the actual production situation, making it difficult to guide the manufacturing practice. The emergence of DT technology during the past few years has presented new possibilities in tackling this gap.

Dynamic workshop scheduling is one of the most challenging problems that scholars have been trying to solve by exploiting the convergence of actual and simulated data from DT to optimise re-scheduling decisions whenever there are new events affecting the condition of the machine lines (Villalonga et al., 2021; Zhang et al., 2021). With the increasing trend of small-batch and multi-variety production modes, the flexible job shop scheduling model has quickly gained research attentions in the field of production scheduling. Yan et al. (2021) addressed the transportation constraint conflicts that limit the applicability of DT-based flexible workshop scheduling system in practise, while Nouiri et al. (2020) focused on optimising energy consumption by introducing green rescheduling algorithm.

At more integrative level, some papers focus on the architecture system design of the cloud computing enabled DT platform for production scheduling as a whole (eg. Pan et al., 2021; Yu et al., 2021). Shop scheduling is one of multiple stages within assembly execution for complex products, where a single source of product assembly data plays a critical role in helping decision makers to better control product quality. Against this context, (Zhuang et al., 2021) proposed a DT-based process traceability approach.

Apart from production scheduling, scholars have also explored DT-assisted real-time traffic scheduling in transportation (eg. Hu et al., 2021).

3.2.2 Cluster 1: DT in Smart Manufacturing System

With the widespread adoption of IoT, as an evolved form of embedded systems (Wu et al., 2011), leading to the availability of big data generated from different objects across the shop floor, there is a fast-growing interest of smart manufacturing research to make use of these data. One of the first attempts was Zhong et al. (2017) who extended the value of PI to manufacturing shop floor by using Big Data Analytics for data-driven decision making. This quickly evolved to the discussions to apply DT, which was only popular in machinery engineering domain previously, in manufacturing's process (Park et al., 2019b), and later in machine rotation via machinery fault diagnosis (Wang et al., 2019).

In the context of the emergence of smart manufacturing, CPS plays the centre role in integrating multiple systems together, including DT and its mirrored physical system, for collaboration. Unlike other systems, CPS does not just simply use DT as the simulation of real system, but also gives back the order of actions to the control system of the equipment following pre-defined rules. Works have been underway in establishing the CPS foundation to develop DT reference model for future product-level DT implementation, from the conceptual framework of CPS-based smart factory (Chen et al., 2020), CPS architecture design (Zheng and Sivabalan, 2020) to more specific design of smart manufacturing components operated within the system like Manufacturing Execution System (Negri et al., 2020) and knowledge-driven, AI-supported DT manufacturing system (Zhou et al., 2020).

3.2.3 Cluster 2: PI-based SCM

During the past few years, PI has been widely adopted to address a range of pressing issues within SCM. For vehicle routing and delivery scheduling problem, Yao (2017) introduced the PI as an important technical support into one-stop delivery mode for city logistics, while Fazili et al. (2017) compared the performance of PI-based, conventional and hybrid vehicle routing practice through Monte-Carlo simulation.

Inventory management is another topic within logistics that was mentioned alongside PI within this cluster, from PI-supported vendor-managed inventory strategy (Yang et al., 2017a) to PI-supported inventory control in response to potential SC disruptions (Yang et al., 2017b).

Resource planning also attracted interests from the academia. To support the transition towards more cooperative shipping in a PI-SC, Vanvuchelen et al. (2020) proposed a machine learning (ML) algorithm to optimise the joint policies for replenishments between a group of collaborating companies. From a more strategic point of view, Luo et al. (2021) suggested a PI decision support platform to deal with the overall resource planning.

At more integrative viewpoints, PI has been used to support the decisions within smart manufacturing for integrated production-inventory-distribution problems (Darvish et al., 2016; Ji et al., 2019; Peng et al., 2020; Zhang et al., 2016). One critical component to the successful implementation of the PI in logistics is a standardised container design, which was discussed in Sternberg and Denizel (2021).

3.2.4 Cluster 3: Virtualising Manufacturing System using DT Technologies

Before smart manufacturing development, the pioneering application of DT was to use virtual reality technologies in digitalising products and manufacturing system. However, there is a lack of conceptual basis to increase the applicability of DT on various production activities. Thus, general frameworks and reference models were developed for physical product simulation (Schleich et al., 2017), shop-floor virtualisation (Tao and Zhang, 2017), and resource simulation (Lu and Xu, 2018).

Past literatures on human-machine interaction for hybrid computer control system in manufacturing were abundant. Still, the increasing need for flexibility, adaptability, and safety motivates further studies on complex and error-prone human-robot collaborative system (Malik et al., 2020; Oyekan et al., 2019). A more robust approach is the use of advanced AI tools such as neural network model to improve object detection (Q. Wang et al., 2020) and quality assurance (Scheffel et al., 2021).

Another research topic is about Virtual Prototype (VP) which was referred as Pre-DT by Madni et al. (2019). Pre-DT as the virtual model of the system is built before the physical prototype is created, with the primary purpose for quality assurance – minimise technical issues before launching. VP, or pre-DT, was brought up by Barbieri et al. (2021) to generate simulated environment aiming to verify the design and integration of DT architecture before implement physically. Meanwhile, to evaluate the practicality of the DT-based virtual factory concept (in which VP is one of the most popular applications), Yildiz et al. (2021) provided a demonstration using two wind turbine manufacturing cases.

3.2.5 Cluster 4: Information Management for DT-based Manufacturing

To realise the full potential of DT in facilitating seamless horizontal and vertical integration in smart manufacturing, where big data enables real-time monitoring, simulations and decisions, the management of information plays a critical role. This research branch within industrial research has thus received extensive attentions. One of the research streams is to optimise database architecture of which key issues relating to data construction, data exchange (interoperability), digital storage (scalability) and processing architecture (effectiveness) were are addressed (Havard et al., 2020; Kong et al., 2021; Luo et al., 2021).

Data management framework for DT system is another widely discussed topic within this cluster, for instance in metal additive manufacturing (Liu et al., 2020) or assembly process (Zhuang et al., 2021). Digital thread is the record of a system/product life cycle – from its conception to its removal. To better capture the evolution of the state information across the product life cycle, data management framework for digital thread also attracts some attentions (Gopalakrishnan et al., 2020).

With an increasing complexity of the multi-stage SC, more concerns are raised regarding data quality and information security. Blockchain is one of the most discussed emerging technologies with huge potentials for information management within DT-based SC system. Some of the obvious advantages of blockchain-based system are the ability to improve data monitoring while ensuring a single version of truth across the product life cycle (Ho et al., 2021). Experiments to combine DT and blockchain technology in industrial research have already been underway as a more trustful method for the cyber-physical integration process (Huang et al., 2020; Tao et al., 2020).

3.2.6 Cluster 5: DT-based Data Analytics

This cluster focuses on data analytics of DT-generated data using AI and ML approach. The invention of AI-related techniques were triggered in the 90s while DT was in the early of the 21st century (Tao et al., 2019b; Toorajipour et al., 2021). They are often considered separately in operations and SC sectors. The recent years have seen a growing trend towards the confluence of both concepts in the same stage, which is often referred to as the Fourth Industrial Revolution (Industry 4.0). The frequent co-occurrences of such 'machine learning', 'computer vision', 'robotics' and 'digital transformation' keywords manifest the tendency of DT-AI collaboration in SC and operations research.

There are two main research streams in DT-AI-based approaches: (1) monitoring and forecasting, and (2) defect detection. For monitoring, with growing digital transformation and the integration of sensors and cameras in manufacturing sector, DT-based technologies such as computer vision can generate both synthesis and real-time data (e.g., image, 3D and historical data). It empowers AI techniques, e.g., deep learning (DL) and ML to monitor and predict the WIP and machine quality in material processing (e.g., welding, metal), machine maintenance and assembly (Aivaliotis et al., 2021; Alexopoulos et al., 2020; Klingaa et al., 2021; Q. Wang et al., 2020; Yi et al., 2021). In terms of defect detection, product or process-generated data from IoTs can be used to visualise as a digital replica of a physical object. By building ML/DL predictive models, a simulation of scenarios and errors can be visible in a complex manufacturing process, hence helps minimise defect rate (Sheuly et al., 2021; Xia et al., 2021). This approach has also been widely studied specifically in laser powder bed fusion, one of the most popular additive manufacturing (3d printing) processes (Gaikwad et al., 2020; Mukherjee and DebRoy, 2019).

Also in this cluster, DT is recognised as a supportive tool to develop robotic automation and machine systems via design, simulation and validation in smart manufacturing and food/medical store SC (Morgan et al., 2021; Sharma et al., 2020).

3.2.7 Cluster 6: DT-enabled Manufacturing Operations Management

Operations management issues related to the implementation of DT-based manufacturing system, are at the main research stream in this cluster. Various elements of the (re)manufacturing system including logistics, diagnosis and assessment, disassembling and quality management activities are simulated and optimised (Barari et al., 2021; Yangguang Lu et al., 2019).

As of the progression of DT-related studies, an emerging research stream in this cluster refers to the notion of disruptive maintenance from industry 4.0 where DT is combined with virtual reality, augmented reality and Big Data analytics to proactively generate data-driven predictive maintenance and enhance the monitor and control for unpredictable and remote tasks (Navas et al., 2020).

Researchers also recognise the difficulties in transforming from conventional to intelligent manufacturing due to the complexity of product design/process and expensive capital investments. Hence, some studies focus on evaluating economic values of DT system when addressing task allocation, order scheduling or monitoring without investing too much into advanced machine design (Guo et al., 2021; K. J. Wang et al., 2020).

Scholars also used DT-based technologies to deploy PI through building systematic information and communication interfaces such as human machine interfaces (Ardanza et al., 2019; Redelinghuys et al., 2020), or asset administration shell (Arm et al., 2021) for customising 3D printer production line, real-time monitoring or robotic manipulations. DT also provides means to develop customised product designs with various value-added services (Zheng et al., 2018).

3.2.8 Cluster 7: DT-enabled Sustainability Development

This cluster presses researcher concerns in sustainability development in three main sectors: manufacturing, retails and logistics. In that account, DT plays an important key as a means to attain a sustainable manufacturing in terms of energy efficiency, resources, pollution etc. For example, in the course of developing a sustainable manufacturing process, Kannan and Arunachalam (2019) studied the resilience of grinding wheel machine to build a product integrated and DT-based knowledge sharing platform that can predict the causes for the perturbation of the machine’s condition. Li et al. (2020) proposed a DT-driven information assessment to evaluate the sustainability of manufacturing. Broo and Schooling (2021) initiated the use of DT-enabled data-driven approach as a core to maintain the operations of sustainable smart manufacturing infrastructure.

Energy efficiency in manufacturing is also another significant stream in this cluster. Several studies developed energy-efficient models to achieve the effective real-time interoperability by integrating DT, data and industrial IoTs, thereby reducing unnecessary energy use (Lu et al., 2019; Park et al., 2019a). Energy-efficient scheduling and rescheduling method was also proposed by Nouiri et al. (2020).

As blockchain is a vital element for sustainable information sharing and transparency, scholars also worked on blockchain-driven models using DT-based techniques in a wider spectrum of logistics finance for e-commerce (Li et al., 2020), social manufacturing (Leng et al., 2019a), and vehicle routing in urban logistics (Tian et al., 2021).

3.2.9 Cluster 8: PI/DT-based Simulation and Optimisation

This cluster focuses on the novelty of simulation and optimisation methods in the context of PI/DT-embedded system. Simulation has long been used to develop virtual products (Schleich et al., 2017) or to improve performance of industrial machines such as two stroke cycle engines (Perumal Venkatesan et al., 2020). In manufacturing process setting, several studies have developed large-scale simulation and optimisation approaches that can deal with production data with high volume and high velocity in effective manners. In this account, a commonly used approach is discrete event simulation (DES) model. The DT-based DES approach is used to simulate the non-automated manufacturing process (Santos et al., 2020), evaluate the configuration design of the DT-based complex manufacturing system (Ait-Alla et al., 2021; Jiang et al., 2021; Murphy et al., 2020), detect production bottlenecks and faulty (Jung et al., 2021), as well as in service scheduling and failure probability prediction (Negri et al., 2021). Another application of this simulation approach is assessing the efficiency of an open and interconnected PI under various transportation protocols and scenarios (Sarraj et al., 2014). Beyond production metrics, financial information is also used as an important metric to carry out DES-based real time forecasting for business cash flow with stochastic production demand (Murphy et al., 2020).

Apart from DES, other innovative methods to address the large-scale problems are also proposed. A prime example is Zhang et al. (2020)'s multi-fidelity simulation-based optimisation for a DT workshop which can co-use different fidelity simulation models in parallel to yield higher accurate estimations while heuristics algorithms is applied to reduce computational costs. Hierarchical aggregation/disaggregation is another improved optimisation approach that can speed up the repeated computations in simulation and decision making in the DT-embedded manufacturing system (Seok et al., 2021).

3.2.10 Cluster 9: DT in Product Assembly Process

Assembly is the last production process and plays a vital role in ensuring quality, performance, and reliability of a product. Recently, DT has been integrated to improve assembly efficiency through exploiting real-time data to feed advanced big data analytics tools such as machine learning, especially assembly shopfloor for complex products such as missile, satellite, rocket, and aircraft (Zhuang et al., 2018). In particular, Ezhilarasu et al. (2021) proposed a quality management framework using mRMR algorithm (minimum redundancy maximum relevance) to select the optimal set of data variables collected from aircraft sensors, then supervised learning algorithms to detect faults. When product failures occur, then root-cause analysis is required. A dedicated research by Detzner and Eigner (2021) evaluated different methods and suggested an optimal one for feature selection in root-cause analysis. Other works with similar direction include improving assembly process quality management supported by learning algorithm (Franciosa et al., 2020), and process dynamic optimisation (Wang et al., 2021). At the same time, general framework for DT-based assembly process planning and dynamic evaluation method was also proposed (Zhang et al., 2020).

In complex products, compliant, or non-rigid (lightweight) parts are used widely in many industries. Existing geometrical deviations management methods are not able to be used for this important type of part as opposed to rigid parts. However, with the availability of DT tools enabling a continuous single flow of information along the product lifecycle, obtaining accurate geometrical deviations of compliant parts could become feasible. In particular, DT of product design could be built to send real-time specifications information and variation information to support the general assembly planning (Franciosa et al., 2020; Polini and Corrado, 2020; Sierla et al., 2018), including in automotive industry (Balakrishnan et al., 2019). Meanwhile, others attempted to use selective assembly technique – product simulation (Computer-Aided Tolerancing tool) to find the optimal combination of individual parts to assemble the best quality final product, in sheet metal assembly (Rezaei Aderiani et al., 2019).

Against this backdrop, some research focus on more niche areas such as DT-enabled fixed-position assembly islands where DT-enabled intelligent manufacturing system is adopted to minimise the uncertainties and complexities come with the sophisticated product and assembly operations (Guo et al., 2020).

In response to RQ1, ten clusters representing the research frontiers are summarised in Table 3.

Table 3. Summary of the research frontiers

Cluster ID	Cluster label	Area of research focus
0	DT in Job-shop Scheduling Problems	The application of DT in addressing research problem of job shop scheduling within manufacturing domain
1	DT in Smart Manufacturing System	Smart manufacturing using big data of different objects across the shop floor generated from IoT
2	PI-based SCM	Application of Physical Internet in addressing different problems within production, inventory and distribution system

3	Virtualising Manufacturing System using DT Technologies	Frameworks and reference models for the application of virtual reality in digitalising products and manufacturing system
4	Information Management for DT-based Manufacturing	Develop information architecture and data management framework to enable DT-based smart manufacturing
5	DT-based Data Analytics	Application of AI and ML in monitoring, forecasting and fault detection across the DT-based manufacturing system
6	DT-enabled Manufacturing Operations Management	Implementation of DT-based technologies to address different operations management issues within manufacturing
7	DT-enabled Sustainability Development	The role of DT in designing sustainable manufacturing, retails and logistics system
8	PI/DT-based Simulation and Optimisation	The novelty of simulation and optimisation methods in the context of PI/DT-embedded system
9	DT in Product Assembly Process	DT application in improving efficiency of the assembly process using real-time data

4 Trend Analysis

This section discusses the keyword evolution and emerging trends of DT in SCM research by analysing CiteSpace's keyword citation bursts and the timeline view of the KCN. RQ2 is addressed in section 4.1 and 4.2, while the emerging research trends within RQ3 are identified in section 4.3.

Top 20 keywords with the strongest citation bursts are presented in Figure 13, in which "Year" represents the starting time of the analysis, "Strength" shows the burst rate, "Begin" and "End" indicate the starting and ending year of the burst duration. As can be seen, prior to 2019, a larger extent of research efforts was into the technological development of PI-based system as keywords with high citation bursts are *"physical internet"*, *"internet"*, *"internet of thing"*, *"virtual reality"*, *"big data"*, *"digital storage"*, and *"computer simulation"*. From 2019 onwards, as the technological capabilities become more matured, the research focus has shifted towards the implementation of PI and DT in SC applications, in which several operational management issues are addressed as implied in burst terms like *"production system", "production process", "robotics",* and *"cost"*.

Table 4. Top 30 keywords ranked by Sigma

Frequency	Burst	Centrality	Sigma (Σ)	Keyword
57	10.16	0.65	166.51	physical internet
9	5.08	0.74	16.69	container
33	7.58	0.23	4.75	logistics
13	8.09	0.2	4.36	internet
27	3.37	0.47	3.65	flow control
16	3.18	0.46	3.33	digital storge
5	2.99	0.49	3.31	floor
43	3.31	0.23	1.99	internet of thing
24	2.56	0.26	1.82	big data
3	2.03	0.3	1.71	computer simulation
27	3.37	0.1	1.37	product design
2	1.36	0.09	1.12	chain
17	2.13	0.05	1.11	production system
6	3.72	0.03	1.1	transportation
28	2.98	0.03	1.08	virtual reality
14	2.12	0.03	1.05	internet of things (iot)
9	1.12	0.03	1.03	robotics
8		0.69	1	design
51		0.57	1	embedded system
27		0.36	1	optimization
139		0.34	1	manufacture
2		0.31	1	product life cycle management
2		0.29	1	inventory
49		0.28	1	supply chain
2		0.28	1	inventory control
366		0.21	1	digital twin
16		0.19	1	sustainability
2		0.19	1	sensitivity analysis

Apart from citation burst, research fronts can also be identified based on the keyword's betweenness centrality and Sigma (∑). The centrality estimates the number of times a node belongs to the shortest paths of any pair of nodes in the KCN (Radhakrishnan et al., 2017). The keyword with higher centrality reflects the greater influence in the KCN. Sigma (∑) combines both the burst rate and betweenness centrality to indicate the transformative strength of a keyword over a time interval (F.-F. Cheng et al., 2018). Hence, to capture a more integrative view of research frontiers, we identify top 30 most important keywords based on their Sigma values, as presented in Table 4.

To investigate the origin of the evolution of the research front over years, the timeline view on CiteSpace was deployed (Figure 8). This timeline view shows all nodes having direct and indirect connections with "physical internet" and "digital twin". As the largest cluster by keywords number, cluster 0 spans for 5 years from 2016 until 2021, so does cluster 1 and 3. Meanwhile, cluster 4 and 6 started only a year later from 2017. Cluster 2 has been active for the longest duration, 8 years since 2013. Cluster 8 only existed for a short period during 2013. As can be clearly seen, the most active period was 2019-2020 when nodes across all clusters (except cluster 8) were recorded. This also corresponds to the exponential growth of documents published within our database during the same period (see Figure 3 above). This is evident that studies during 2019-2020 spread across diverse areas of DT-SC.

The first keyword within DT/PI application in SCM research domain was "computer simulation" from 2013. This was followed by the concept of "physical internet" from 2014, and later "digital twin" from 2017. It is safe to say that "computer simulation" within cluster 8 established the foundation for the development of "physical internet" and "digital twin", which was also agreed by some researchers (Grieves and Vickers, 2017; Ivanov et al., 2019).

In the following sub-section, we move from the bird-eye view of the KCN to a more focused analysis of how the PI/DT research fronts and emerging trends evolve over time. It is worth noting that as our initial search during data collection stage looked for PI and DT keywords in both title and abstract, there are papers that contain PI and DT in either title or abstract but do not have PI or DT as (system predefined) index keywords or author decided keywords. Therefore, the sum of papers examined in both section 4.1 and 4.2 may not necessarily be the same with the original number of input papers at 518.

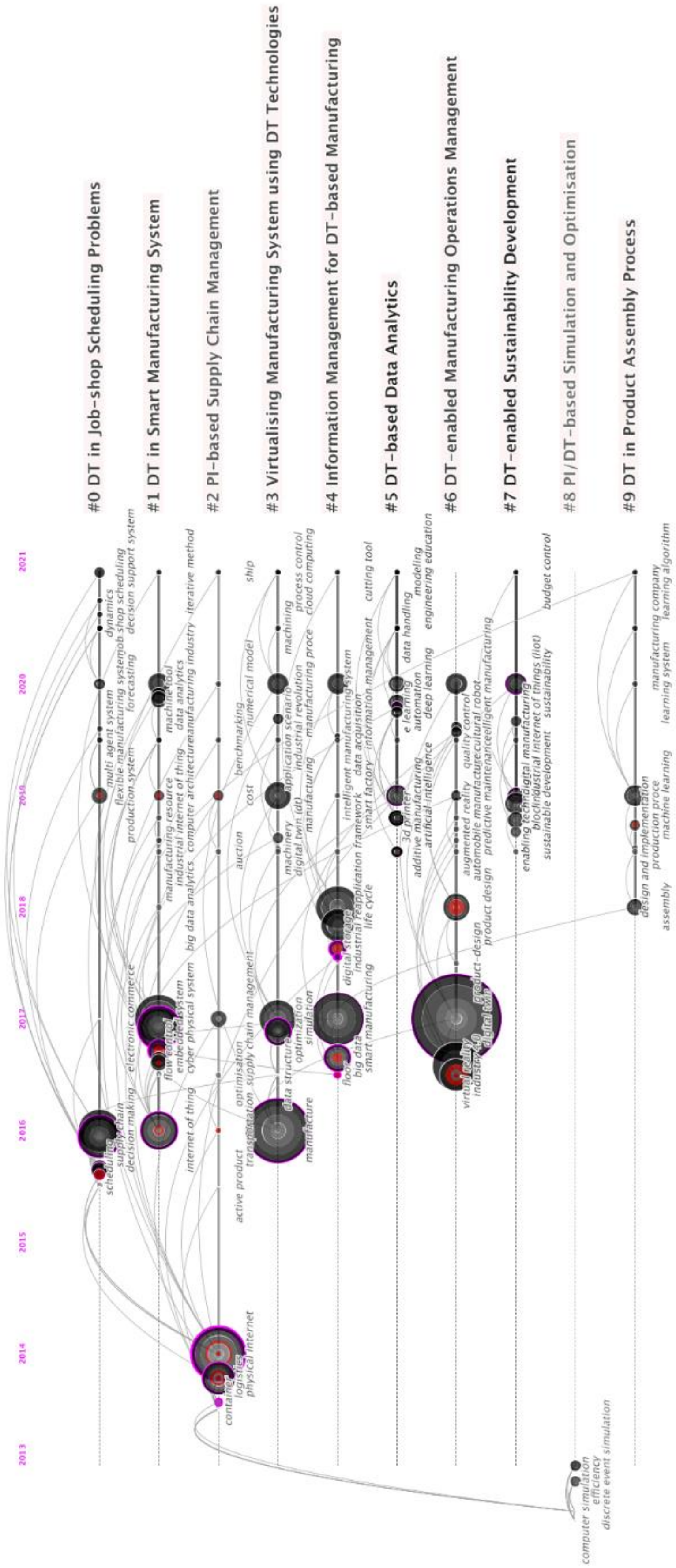


Figure 8. Timeline view of KCN

4.1 Research Evolution of Physical Internet-based Supply Chain

The evolution of "*physical internet*" keyword in the KCN can be seen in Figure 9 (only shows nodes having direct connection with "physical internet") and Figure 10 below. Starting from 2014, PI was first brought up as an approach to improve the logistics efficiency by creating synchronised interconnections between logistics networks (Sarraj et al., 2014). In the same year, to establish the foundation for PI, Lin et al. (2014) initiated the idea of standardising packaging and containers for more efficient product handling across the network. During 2015 – 2016, while there were still works on PI-container design (Sallez et al., 2016), a fast-growing number of research worked on PI-based logistics operations issues such as transportation and inventory problem (Pan et al., 2015) or resource allocation (Walha et al., 2016). From 2017 to 2018, while logistics problems remained of interest (Onal et al., 2018; Yang et al., 2017a), researchers started to extend the PI concept to manufacturing shop floor (Onal et al., 2018; Zhong et al., 2017) and urban logistic (Ben Mohamed et al., 2017; Fazili et al., 2017; Sun et al., 2018). In 2019, blockchain was first discussed alongside PI as one of the key technological enablers (Meyer et al., 2019), even though the general theme was still logistic network and manufacturing related. Some new research streams were also emerged to bring PI implementation closer to the practice, for example cost minimisation (e.g. Ji et al., 2019) and sustainability assessment (e.g. L. Li et al., 2020). With the maturity of IoT and ML techniques, 2020 witnessed a rise of works in utilising big data-driven and ML-supported solutions to different DT-based SC problems (Kantasa-ard et al., 2020; Vanvuchelen et al., 2020). During the first half of 2021, most research was to tackle transportation, and vehicle routing problem (Ancele et al., 2021; H Luo et al., 2021; Yee et al., 2021).

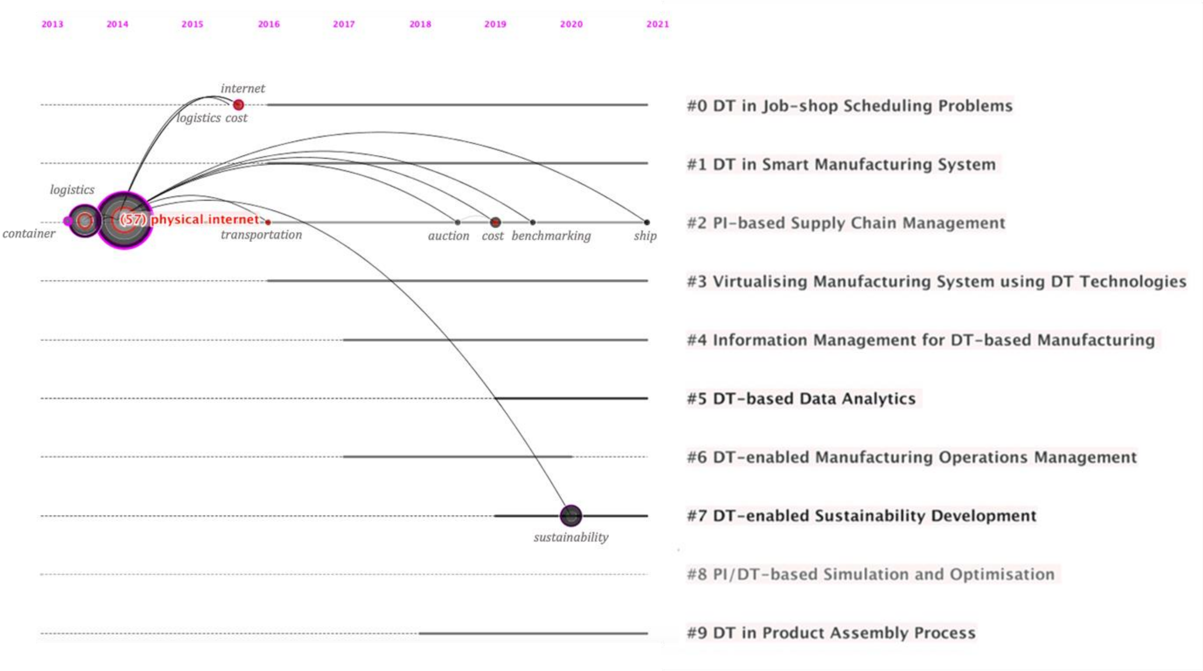


Figure 9. Timeline view of "*physical internet*" keyword

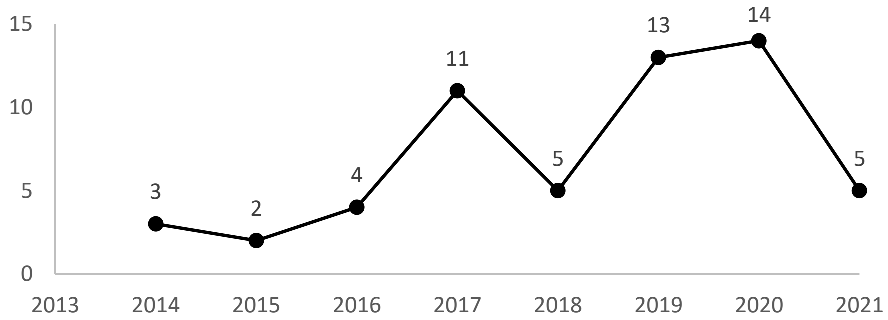


Figure 10. Number of papers with "*physical internet*" keyword

4.2 Research Evolution of Digital Twin-based Supply Chain

While PI-related research is spreading over longer span of years, DT-related works in SCM have just begun since 2017. Despite that, the current number of publications with DT keyword is more than 6 times to that of PI keyword (366 compares to 57), indicating the popularity of the subject area.

The evolution of "*digital twin*" keyword in the KCN can be seen in Figure 11 (only shows nodes having direct connection with "digital twin") and Figure 12. At the early stage in 2017, works were mainly focused on the introduction of DT concept into manufacturing (Brenner and Hummel, 2017; Tao and Zhang, 2017; Uhlemann et al., 2017; Zhang et al., 2017), and exploring DT's potential in virtualising machines (Angrish et al., 2017) or manufacturing process (Moreno et al., 2017). Moving on to 2018, while works were still underway in virtualisation of manufacturing process (Lu and Xu, 2018), researches focused more on exploiting the convergence of physical and virtual data in DT-enabled smart manufacturing (Y. Cheng et al., 2018; Qi and Tao, 2018; Zheng et al., 2018; Zhuang et al., 2018). In the meantime, new paradigms were added and even carried into 2019 such as cloud technology (Lu and Xu, 2019; Urbina Coronado et al., 2018), and DT-driven product design (Tao et al., 2019a, 2018). Despite those, the main theme for 2019 was DT-based manufacturing CPS design (Ding et al., 2019; Leng et al., 2019b; Liu et al., 2019). With the Covid-19 pandemic hit the global SC hard since early 2020, it is not surprising that epidemic impact prediction and mitigation strategies has been at research forefront (Ivanov, 2020; Ivanov and Das, 2020). Still, scholar works for DT-driven system towards smart manufacturing was gathering pace (Cheng et al., 2020; Leng et al., 2020a; Zhou et al., 2020), while blockchain was introduced in DT along the way (Leng et al., 2020b). The research focus during the first half of 2021 has been more or less similar to that of 2020.

In the wake of the on-going pandemic, researchers started to realise the potential of DT in developing SC resiliency in response to disruption risks (Ivanov and Dolgui, 2021). Apart from this, as in 2020, DT-driven smart manufacturing design continues to attract a lot of academic attentions (Q. Liu et al., 2021; Wei et al., 2021; Yi et al., 2021).

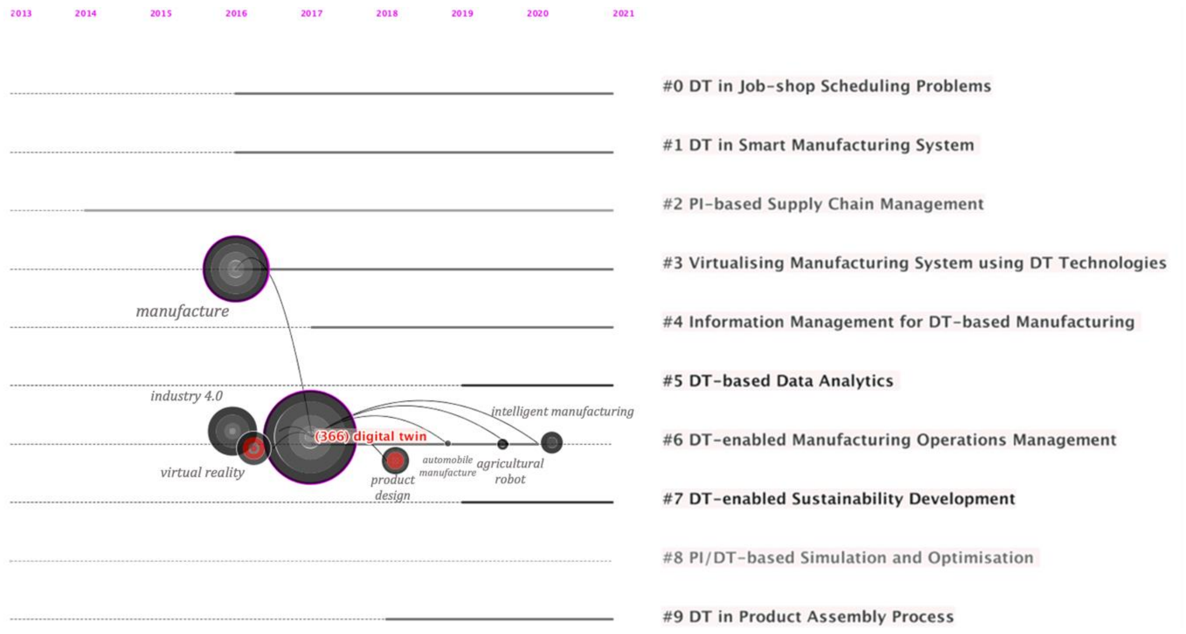


Figure 11. Timeline view of "digital twin" keyword

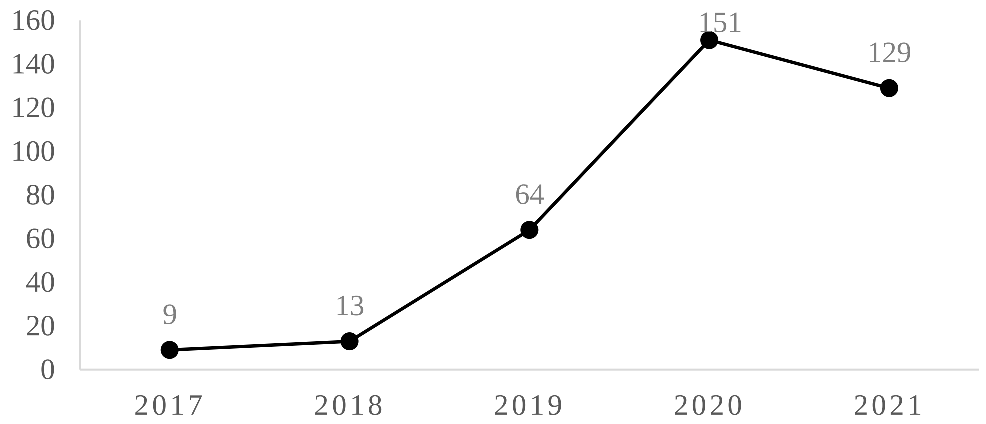
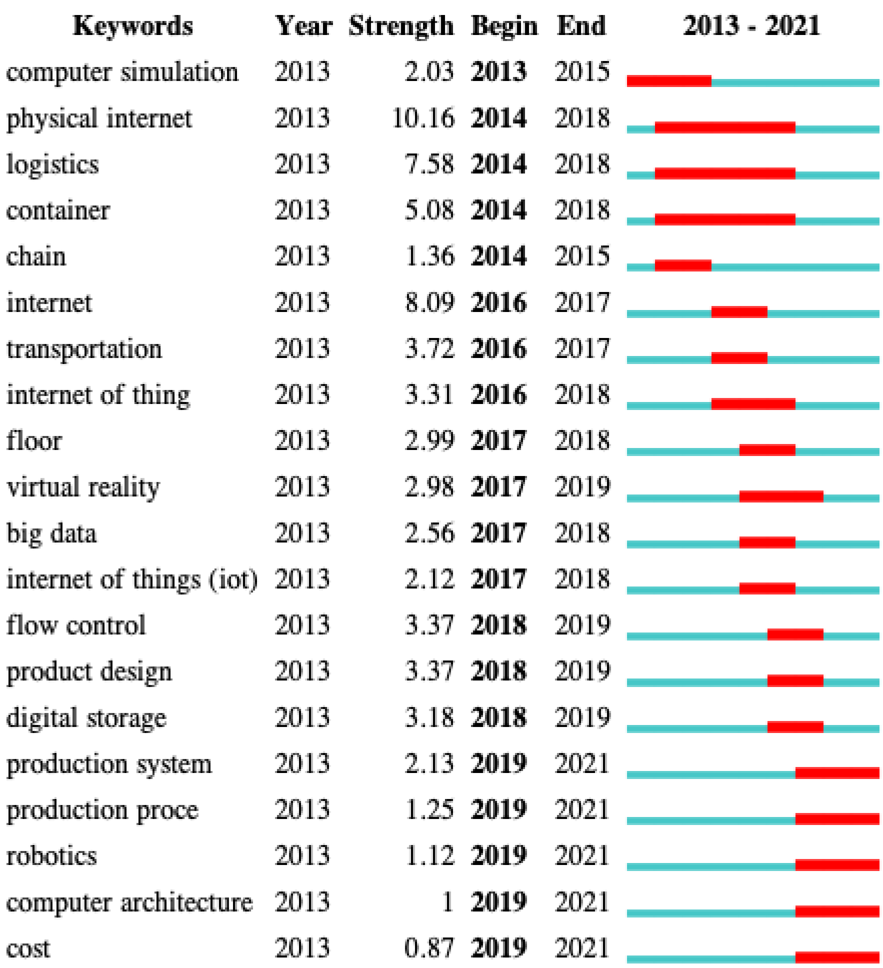


Figure 12. Number of papers with "digital twin" keyword

4.3 Emerging Research Trends

Keywords with highest burst rates over the recent time interval (2019-2021) represent current hotspots in the research area (Chen, 2006). As can be seen in Figure 13, five keywords have burst until 2021, namely "production system", "production process", "robotics", "computer architecture", and "cost". The first two suggests the upcoming research trends in DT-driven production system design, along with DT-enabled production process improvement. In fact, these two topics have been of research interest since 2019 but are still underexploited. On the other hand, “robotics” and “computer architecture” indicate that the high-level autonomous manufacturing system supported by state-of-the-art information architectures could be the key drivers to achieve the former two topics. Finally, “cost” is now at the research front, signalling the need of evaluating viability and feasibility of the PI/DT adoption in practice.



Keywords	Year	Strength	Begin	End	2013 - 2021
computer simulation	2013	2.03	**2013**	2015	
physical internet	2013	10.16	**2014**	2018	
logistics	2013	7.58	**2014**	2018	
container	2013	5.08	**2014**	2018	
chain	2013	1.36	**2014**	2015	
internet	2013	8.09	**2016**	2017	
transportation	2013	3.72	**2016**	2017	
internet of thing	2013	3.31	**2016**	2018	
floor	2013	2.99	**2017**	2018	
virtual reality	2013	2.98	**2017**	2019	
big data	2013	2.56	**2017**	2018	
internet of things (iot)	2013	2.12	**2017**	2018	
flow control	2013	3.37	**2018**	2019	
product design	2013	3.37	**2018**	2019	
digital storage	2013	3.18	**2018**	2019	
production system	2013	2.13	**2019**	2021	
production proce	2013	1.25	**2019**	2021	
robotics	2013	1.12	**2019**	2021	
computer architecture	2013	1	**2019**	2021	
cost	2013	0.87	**2019**	2021	

Figure 13. Top 20 keywords with strongest citation bursts

5. Future Directions

The findings discussed above highlight some research opportunities for future studies of PI/DT applications in the context of SCM. This section gives future research directions in response to RQ3.

Direction 1: Developing PI/DT-centred Business Ecosystems

From the cluster analysis, it is clear that research in PI/DT application in SCM is still in its infancy and highly fragmented. In order to accelerate the PI/DT adoption and maximise its full potentials, it is critical to develop an integrated business ecosystem with supporting policies. A business ecosystem includes: business context (missions, drivers, barriers and lifecycle stages), cooperation and governance mechanism with partners, infrastructure, SC configuration, capacity building and managing changes (Rong et al., 2015). In addition, supporting policies are the development of national and organisation level of strategies and initiatives to promote the digitalisation transformation.

Studies on ecosystems have addressed a wide range of topics such as innovation, mobility, knowledge and IoT, all of which could be parts or the extension of PI/DT-centred business ecosystems.

Direction 2: Leveraging PI/DT to Enhance Sustainability

The content analysis of cluster 7 exposes the potential gaps of using PI/DT as a means to achieve sustainability. Some attempts have been made into the sustainability development of the DT-based manuanufacturing and logistics system by minimizing its environmental impact through optimising energy efficiency or green job shop scheduling (Nouiri et al., 2020). However, a number of sustainable issues such as emission evaluation or social welfare associated with DT-enabled SC operations are still overlooked in literature and should be further investigated.

As suggested by cluster 4, in line with the transition towards circular economy, the traceability of PI/DT can play a key role in improving the performance of reverse logistics and closed loop-SC operations. For example, to enhance product recycling rate, PI/DT can help firms track and trace the whole product life cycle including its reverse flows, thereby accurately predicting the quality, quantity and timing of the core returns. Prior studies have explored the value of PI/DT in remanufacturing (Chen and Huang, 2021b); however, by elaborating its benefits to address the issues of return uncertainty across closed-loop SC, this can be a valuable and fruitful research area for future scholars.

Direction 3: DT/PT-enabled supply chain resilience

The Covid-19 pandemic is a lesson for many firms in tackling unprecedented and sudden SC disruptions. Not only pandemic, threats may also stem from various forms such as economic and political crisis, natural disasters or terrorist attacks. As mentioned in section 4.2, recent works have started to explore the potential of DT in developing SC resiliency in response to disruption risks. DT/PI-based technologies can help firms develop SC resilience by providing real-time and remote monitoring and foreseen visability in a large-scale and dynamic business context, thereby proactively generating timely contingency and recovery plan. Although there were some recent articles which studied the generic role of DT/PI SC in managing the disruption risks using big data-driven simulation and optimisation (Ivanov et al., 2019; Ivanov and Das, 2020; Ivanov and Dolgui, 2021), research should further investigate specific problems of SC disruption in logistics routing, warehousing/manufacturing locating, supplier selection, etc.

Direction 4: SC Downstream Focused PI/DT Applications

As dominated in the cluster analysis and evidenced from emerging trends of "production system" and "production process", DT/PI applications in the SC upstream including production, distribution and inventory management have been at research forefront since beginning. However, its applications in the SC downstream such as sales & marketing and last-mile delivery are still largely understudied. The applications, for example, DT-enabled 3D model to layout a floor plan, and DT/PI enabled interface in a last-mile delivery system in which customers can directly see and interact with the operations and delivery process, could consolidate the transparent ability and add more values to retailer's products and services.

Direction 5: Cognitive Thinking in Industry 5.0

In-depth content analysis across all cluster has exposed research gap in product and process customisation. It is witnessed that Industry 4.0-related terms have been dominating the PI/DT recent research and application across SC aspects. Robotic automation has been prevalent and is still one of the emerging trends in both manufacturing and distribution literature, but it neglects the individualism in product and process. An article from Forbes indicates that personalisation is trendy which can significantly reward firms in terms of relationship strengthening and profit margin (Morgan, 2020). However, it has always been challenging to design personalised products and services in a large scale. With the concept of embedding cognitive thinking from human into automation robotic intelligence in Industry 5.0, PI/DT could support visualise, simulate and monitor human collaboration with automation machine in a large manufacturing scale. This orientation could be explored further into other SC aspects such as logistics, warehousing or retail to attain more personalised and efficient process.

Direction 6: Citizen Twin for the Development of Digital Society

Covid-19 is pushing people to work from home which accelerates digital transformation. A report from Gartner indicates a new term, 'citizen twin', as an emerging technology in the next 5-10 years (Panetta, 2020). Citizen twins are defined as digital models of humans which replicate a real human in many aspects such as voice, vision, gesture or even brain. This concept could be considered as a health passport for an individual. Citizen twins can also supplement research in SC downstream focused DT/PI application (Direction 4) while foster product customisation (Direction 5), by providing naturally digital footprints of customers with emerging behaviours in the way of living and shopping. Hence, future research should redesign and adapt the SC strategy and practices to capture the new social norms in the new digital society.

Direction 7: Cost and Revenue Management of PI/DT Implementations

Our results show that cost management is one of the emerging trends for future research. It could be due to the fact that the adoption of advanced technologies such as IoT, robotic machines and PI/DT requires extensive capital investment and resources. In addition, the complex processes and products puzzle the traditional costing strategies. Hence, to increase the feasibility and viability of PI/DI-enabled system in practice, future research should study more about cost management and revenue sharing between stakeholders in the PI/DI-SC system.

5 Conclusion

This study offers a systematic literature review of 518 journal articles to investigate the temporal evolution of research fronts and emerging research trends in the field of PI/DT in SCM by adopting a bibliometric knowledge mapping approach.

- The research frontiers (RQ1) can be clustered into ten themes, including PI/DT applications in job shop scheduling, smart manufacturing design, PI-based SCM, manufacturing virtualisation, information management, sustainability development, data analytics, manufacturing operations management, simulation and optimisation, and assembly process planning.
- The research evolution of "physical internet" and "digital twin" (RQ2) started when "computer simulation" laid the foundation for the development of "physical internet" concept in 2014, and "digital twin" not long after in 2017. Throughout the years, "physical internet" was investigated from the logistics and manufacturing perspective. Meanwhile, "digital twin" was mostly adopted as an enabler for smart manufacturing, and most recently, for SC resilience development in response to the on-going pandemic.

- Emerging trends (RQ3) are also unveiled including “production system”, “production process”, “robotics”, “computer architecture”, and “cost”. Furthermore, seven research agenda for future works are suggested, highlighting PI/DT-related issues in business ecosystem development, sustainability, SC downstream management, SC resilience, cost and revenue management, citizen twin in digital society, and cognitive thinking in Industry 5.0.

This paper also emerges some limitations. Firstly, the associated author and indexed keywords are generic, then may not exhaustively reflect the details of a specific paper. To address this problem, further research can analyse the articles’ abstract or title, though it may require higher computational expenses. There is also technical challenge when dealing with titles and abstracts since noun phrases can be noisy, meaningless, overlap, and irrelevant which requires advanced text pre-processing techniques such as Natural Language Processing (NLP). Secondly, this work only targets peer-reviewed articles which might be insufficient for practitioners to align. A future work is encouraged to extend the focus to non-academic literature such as government and company reports, white papers which consolidates for academic contributions.

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Appendix

Cluster Label	Paper	Research Problem and Key Research Activities	Focused Area	Methodology
Cluster 0: DT in Job-Shop Scheduling Problems	Nouiri et al. (2020)	Addressing scheduling and rescheduling problems using a Green Scheduling method in the context of PI-based manufacturing and inventory distribution	Job shop scheduling	Modelling and experiments
	Hu et al. (2021)	Addressing a traffic data sparsity problem using a DT-assisted real-time traffic data prediction for the scientific traffic scheduling	Traffic flow control	Predictive Modelling
	Pan et al. (2021)	Monitor and evaluate operational dynamics using a multi-level cloud computing enabled DT system	Production Logistics	Modelling and Case Study
	Villalonga et al. (2021)	Addressing unfeasible and inefficiency in production scheduling using DT-based optimisation (i.e., fuzzy inference system)	Production	Modelling and Optimisation
	Yan et al. (2021)	Addressing a flexible job shop scheduling problem in the context of workshop DT system	Job shop scheduling	Modelling
	Yu et al. (2021)	Addressing the job shop scheduling problem using DT-based cloud platform	Job shop scheduling	Survey
	Zhang et al. (2021)	Addressing dynamic job shop scheduling such as machine availability prediction and disturbance	Job shop scheduling	Modelling and Simulation

		detection using DT system to merge the real and synthesis data		
	Zhuang et al. (2021)	Data management based on DT and process traceability approach are proposed for complex products	Assembly line	Modelling and Case Study
Cluster 1: DT in Smart Manufacturing System	Zhong et al. (2017)	Extends the PI concept into manufacturing shop floors including a Big Data Analytics for RFID logistics data	Intelligent manufacturing shop floor	Conceptual Framework and Experiments
	Park et al. (2019)	Addressing the cost and production inefficiencies in a connected micro factory (as a factory-as-a-service system) using a DT application and IoTs	Smart manufacturing	Conceptual Framework and Case study
	Wang et al. (2019)	DT reference model for rotating machinery fault diagnosis	Smart manufacturing	Modelling and Experiments
	Chen et al. (2020)	DT-based smart factory in the context of CPS	Smart manufacturing	Conceptual Framework and Case study
	Negri et al. (2020)	The lack of two-way interaction between physical and digital objects, called a digital shadow problem. To address this problem, an integration of digital shadow simulation model and the manufacturing	Smart manufacturing	Conceptual Framework and Case study

		execution system was proposed		
	Zheng and Sivabalan (2020)	The gap in the technical aspects of DT. To address this gap, a generic DT with a novel tri-model-based approach	Smart manufacturing	Conceptual Framework
	Zhou et al. (2020)	Addressing learning and cognitive capacities for manufacturing cell using a general framework of knowledge-driven DT manufacturing cell.	Intelligent manufacturing	Modelling, Simulation and Experiments
Cluster 2: PI-based Supply Chain Management	Darvish et al. (2016)	Solving a production planning and distribution problem using an interconnected open global logistics system	Production planning and distribution	Optimisation
	Zhang et al. (2016)	The inefficiencies in terms of information sharing, cost, environmental orientation and optimisation in logistics systems. It can be solved by introducing a smart box-enabled product-service system with PI and cloud computing	Logistics	Mathematical modelling and optimisation
	Fazili et al. (2017)	Make a comparison between conventional logistics system and PI-based logistics system in terms of truck and driver routing	Logistics	Monte-Carlo simulation and optimisation

	Yang et al. (2017)	Addressing supply chain disruptions in inventory using PI-based interconnected logistics services	Supply Chain	Modelling, Simulation and Optimisation
	Yang et al. (2017b)	A PI-logistics-enabled innovative vendor-managed inventory strategy to enhance resources planning and allocation in the inventory and transportation	Inventory management	Modelling, simulation and optimisation
	Yao (2017)	Using a PI-based one-stop delivery mode to address logistics cost inefficiencies, varying information sharing	Delivery scheduling	Mathematical modelling and a multi-objective optimisation
	Ji et al. (2019)	Enhancing cost performance in the PI-based logistics network via open PI hubs and standard PI-containers	Supply Chain Network	Mixed-integer linear programming and solution
	Peng et al. (2020)	Investigating the performance of sustainability of three dimensions of production, inventory and distribution using a multi-objective mixed integer programming model	Production-inventory-distribution and sustainability	Modelling and Solution
	Vanvuchelen et al. (2020)	Finding the optimal policy for a replenishment problem in the context of PI	Distribution	Deep reinforcement learning data-driven for optimisation

	Luo et al. (2021)	Establishing a PI-enabled customised furniture delivery system (smart logistics facilities) to address the conventional problems of resource planning	Transportation and distribution	Mathematical Modelling and Solution
	Sternberg and Denizel (2021)	Addressing the PI-containers' repositioning issue in terms of design and characteristics using a linear programming model	Logistics	Modelling and optimisation
Cluster 3: Virtualising Manufacturing System using DT Technologies	Schleich et al. (2017)	A DT-based and virtual reality-based Skin Model Shapes is proposed to converge the gap between design and manufacturing	Manufacturing	Conceptual Framework
	Tao and Zhang (2017)	A DT-based shopfloor is to converge the manufacturing physical world and the virtual world	Smart manufacturing	Conceptual framework
	Lu and Xu (2018)	A DT-based test-driven resource virtualisation framework is adopted to enhance the production speed of personalised products at a large scale	Smart manufacturing	Conceptual framework
	Q. Wang et al. (2020)	Neural network model empowers virtualisation of welding process monitor and control	Manufacturing	Deep learning and simulation
	Oyekan et al. (2019)	Using DT-based virtual reality to understand human reactions to both predictable and	Robotic	Conceptual framework and experiments

		unpredictable robot motions.		
	Scheffel et al. (2021)	Automated fault detection enabled by sensors, IoT, then input into deep learning model to process	Smart manufacturing	Deep learning and simulation
	Malik et al. (2020)	Using virtual reality to conceptualise and develop a human-machine interaction system to overcome the problem of future production systems	Manufacturing	Event-driven simulation and optimisation
	Barbieri et al. (2021)	Dealing with uncertain events by using DT-enabled architecture and a virtual commissioning method	Manufacturing	Conceptual framework and case study
	Yildiz et al. (2021)	Addressing the complexity and short lifecycles of product and process in manufacturing by using a DT based virtual factory concept as a simulation model	Smart manufacturing	Conceptual framework and demonstrations
Cluster 4: Information Management for DT-based Manufacturing	Ho et al. (2021)	A DT blockchain-based for tracing and tracking in aircraft industry to deal with the complexity of aircraft parts	Inventory management	Conceptual framework
	D. Luo et al. (2021)	A DT-based data-driven cloud simulation architecture for automated flexible production line	Production	Data-driven simulation
	Zhuang et al. (2021)	A DT-based assembly data management and	Assembly	Conceptual framework

		process traceability approach for complex products		
	T. Kong et al. (2021)	Data construction method to deal with inefficiencies and inaccuracy operations and support a DT system	Manufacturing	Conceptual framework
	Havard et al. (2020)	Managing a huge data using a database architecture and a data model in the context of DT	Production	Conceptual framework and case study
	Tao et al. (2020)	Addressing the inefficiencies and trust problem between stakeholders and the platform using a DT and blockchain technology	Smart manufacturing	Conceptual framework
	Liu et al. (2020)	Using a DT-enabled data management for metal additive manufacturing systems to address the lack of process robustness, stability and repeatability	Manufacturing	Conceptual framework
	Huang et al. (2020)	A DT blockchain-based product lifecycle management deals with the complication of product data.	Product management	Conceptual framework
	Gopalakrishnan et al. (2020)	Suggest a data management framework for digital thread	Manufacturing	Conceptual framework and case study
Cluster 5: DT-based Data Analytics	Alexopoulos et al. (2020)	Using DT-driven machine learning workflows to generate synthesis data	Manufacturing cyber physical system	Data-driven simulation and conceptual framework

	Gaikwad et al. (2020)	Addressing production process faults using DT machine learning/forecasting approach	Production	Data-driven simulation
	Q. Wang et al. (2020)	Joint growth monitoring and penetration control for welding quality using deep learning-empowered DT	Welding manufacturing	Data-driven
	Aivaliotis et al. (2021)	Addressing the lack of historical data and the intricate design of industrial machine using DT-based robot	Manufacturing system	Modelling
	Klingaa et al. (2021)	Typical quality metrics of metal additively manufactured components is underperformed. Using DT and sensor data to create a fast computation in the monitoring system	Metal additive manufacturing	two response surface methodology-based design of experiments
	Mukherjee and DebRoy (2019)	Using DT consists of statistical models, machine learning and big data to reduce trial and error testing in additive manufacturing	Additive manufacturing	Statistical model and machine learning
	Sheuly et al. (2021)	Faulty products and production process - anomaly detection using statistical and machine learning analysis from DT-based sensors	Manufacturing power transfer units	Data analytics approach and case study

	Xia et al. (2021)	Processing large manufacturing dataflows using DT simulation and communication technologies	Smart manufacturing plant	Data-driven methodology
	Yi et al. (2021)	Mechanical product assembly using a DT reference model for process design	Assembly	Conceptual framework and case study
	Sharma et al. (2020)	Germ transmission at store, hoarding and price gouging due to the scarcity and disruption of the supply during the covid-19 pandemic using a simple, affordable and contact-less robotic system	Supply Chain	Simulation
	Morgan et al. (2021)	The requirement for scale and customise product variety and product volume in distributed and decentralised machine control and machine intelligence	Reconfigurable manufacturing systems	A research review
Cluster 6: DT-enabled Manufacturing Operations Management	Ardanza et al. (2019)	The fast evolution of the technology prompts the creation of a DT-based human machine interfaces	Manufacturing	Conceptual framework and experiments
	Lu et al. (2019)	Dealing with the complication of remanufacturing process using IoT, historical data from DT-based sensors and RFIDs	Engine remanufacturing factory	Efficiency validate analysis - simulation

	Zheng et al. (2018)	Providing personalised products with value-added services using a DT-enabled platform-based, data-driven approach	Production and service	Conceptual framework and case study
	Navas et al. (2020)	The need of reducing the cost of supervision remote control and diagnostic system using DT-based disruptive maintenance system	Manufacturing	Conceptual framework
	Redelinghuys et al. (2020)	As the development of industry 4.0, the urgence to transform from physical to digital is considered. Creating a DT-based data and information exchange system	Manufacturing	Conceptual framework and case study
	K. J. Wang et al. (2020)	Dealing with the challenge in designing a dt-based framework for a manufacturer who has a limited resource (conventional machines) using an economic DT framework	Manufacturing	Conceptual framework and case study
	Arm et al. (2021)	Addressing the slow process of industry 4.0 implication using two communication protocols Message Queuing Telemetry Transport (MQTT) and Open Platform Communication-Unified Architecture (OPC UA)	Manufacturing	Conceptual framework and case study

	Barari et al. (2021)	Finding the applications for intelligent manufacturing	Manufacturing	A review
	Guo et al. (2021)	The complexity and uncertainty in product and operations management using a DT-enabled Graduation Intelligent Manufacturing System	Manufacturing	Conceptual framework
Cluster 7: DT-enabled Sustainability Development	Kannan and Arunachalam (2019)	Improving resource productivity using a DT-based web-based knowledge platform	Sustainable manufacturing process	Conceptual framework and case study
	Leng et al. (2019)	The growth of personalised demands forces the creation of a DT-based blockchain model	Social manufacturing	Conceptual framework and case study
	Park et al. (2019a)	Dyeing and finishing in manufacturing is consuming energy significantly as well as SMEs cannot afford investing into energy-efficient equipment. Creating a service-oriented platform to achieve this remit	Energy-efficient manufacturing	Conceptual framework and case study
	Nouiri et al. (2020)	Presenting an energy-efficient scheduling and rescheduling method for production and logistics system	Energy-efficient production and logistics	Mixed integer programming
	Y Lu et al. (2019)	The need of expanding energy-efficient manufacturing strategy	Energy-efficient manufacturing	Conceptual framework and case study

		towards a global production network using a DT-based energy model		
	M. Li et al. (2020)	Capital shortages due to the broaden scope and accelerated goods. Addressing this challenge with a DT-based blockchain-enabled logistics finance execution platform	E-commerce retail	Conceptual framework and case study
	Li et al. (2020)	The need for sustainable development for severe environmental challenges using a DT-driven information architecture	Manufacturing	Mathematical framework and case study
	Broo and Schooling (2021)	More attention should be brought to developing new ways of designing, constructing, operating sustainably using a physical-cyber system	Sustainability in smart manufacturing	Conceptual framework and case study
	Tian et al. (2021)	The rapid development of urbanisation and changes of consumer's demand prompts the development of a DT-based blockchain-based evaluation approach	Sustainable urban logistics	Conceptual framework and experimental simulation
Cluster 8: PI/DT-based Simulation and Optimisation	Sarraj et al. (2014)	The logistics networks are fragmented and lacking consolidation as a harmony, then using a PI-based modular container to address this problem	Transportation and storage facility	Simulation

	Perumal Venkatesan et al. (2020)	Using simulation to improve design and efficiency of two stroke cycle engine	Production	Simulation
	Ait-Alla et al. (2021)	Addressing the exceed of data in production using a DT-based interface and simulation	Cyber-physical production	Conceptual framework and case study
	Murphy et al. (2020)	The challenge in generating financial metric from simulation output production metrics is addressed by using a digital simulation	Production	Modelling and simulation
	Santos et al. (2020)	The simulation approach cannot adapt with the high velocity and volume of changes. The new Discrete Event Simulation-based Digital Twin for a non-automated process	Production	Simulation
	Zhang et al. (2020)	The outdate of discrete event simulation in DT due to the time consuming for large scale problem optimisation. A multi-fidelity simulation-based optimisation method is proposed	Production	Modelling and simulation
	Jiang et al. (2021)	How to effectively create a DT model during the design stage	Production	Modelling and simulation
	Jung et al. (2021)	The bottlenecks in the garment production line and delays, hence reducing productivity can	Production	Simulation

		be addressed by using a DT simulation-based hybrid optimisation method		
	Negri et al. (2021)	Uncertainty such as failure probability can be addressed by using a field-synchronised DT framework	Production	Simulation
	Seok et al. (2021)	Dealing with time consuming using digitally cloned discrete-event models for wafer fabrication using a hierarchical aggregation/disaggregation method	Manufacturing	Modelling and simulation
Cluster 9: DT in Product Assembly Process	Sierla et al. (2018)	a DT-based digital product description for assembly planning and orchestrate the production resources in a manufacturing cell	Assembly	Conceptual framework and case study
	Zhuang et al. (2018)	A DT-based smart production management and control approach for complex product assembly shopfloors.	Assembly	Framework validated by a case study
	Ezhilarasu et al. (2021)	Proposing a streamlined DT-based methodology for faulty detection in aircraft systems	Assembly	Machine learning and simulation
	Detzner and Eigner (2021)	Feature selection methods are suggested for root-cause analysis among top-level product attributes	Manufacturing	Machine learning and simulation

	Rezaei Aderiani et al (2019)	Selective assembly technique is not applicable in sheet metal assemblies. Using DT in the production process for this problem	Assembly	Simulation and optimisation
	Franciosa et al. (2020)	A DT framework for assembly systems with compliant parts	Assembly	Conceptual framework, deep learning and simulation
	Guo et al. (2020)	Reducing the complexity and uncertainty using a DT-enabled graduation intelligent manufacturing system	Fixed-position assembly islands	Conceptual framework and case study
	Balakrishnan et al. (2019)	IoT and DT-based machine learning model are used to predict failures in automobiles	Automotive manufacturing	Conceptual framework, machine learning, and simulation
	Polini and Corrado (2020)	A DT tool to support the lightweight design of assemblies in composite material.	Composite assembly manufacturing process	Modelling and numerical and experimental analysis
	X. Zhang et al. (2020)	Developing an assembly process evaluation driving by a DT system	Assembly process	Framework validated by a case study
	Wang et al. (2021)	An DT-based assembly precision analysis method for the assembly quality of products	Assembly process	Simulation