Annals of Operations Research (2024) 338:1359–1401
https://doi.org/10.1007/s10479-024-05879-9

ORIGINAL - SURVEY OR EXPOSITION

Frontiers and trends of supply chain optimization in the age of industry 4.0: an operations research perspective

Zhitao Xu[1] · Adel Elomri[2] · Roberto Baldacci[2] · Laoucine Kerbache[2,3] · Zhenyong Wu[4]

Received: 1 June 2023 / Accepted: 30 January 2024 / Published online: 29 February 2024

Abstract

Industrial 4.0 (I4.0) is believed to revolutionize supply chain (SC) management and the articles in this domain have experienced remarkable increments in recent years. However, the existing insights are scattered over different sub-topics and most of the existing review papers have ignored the underground decision-making process using OR methods. This paper aims to depict the current state of the art of the articles on SC optimization in I4.0 and identify the frontiers and limitations as well as the promising research avenue in this arena. In this study, the systematic literature review methodology combined with the content analysis is adopted to survey the literature between 2013 and 2022. It contributes to the literature by identifying the four OR innovations to typify the recent advances in SC optimization: new modeling conditions, new inputs, new decisions, and new algorithms. Furthermore, we recommend four promising research avenues in this interplay: (1) incorporating new decisions relevant to data-enabled SC decisions, (2) developing data-enabled modeling approaches, (3) preprocessing parameters, and (4) developing data-enabled algorithms. Scholars can take this investigation as a means to ignite collaborative research that tackles the emerging problems in business, whereas practitioners can glean a better understanding of how to employ their OR experts to support digital SC decision-making.

Keywords Supply chain optimization · Operation research methods · Industrial 4.0 · Literature review · Data analytics

✉ Adel Elomri
aelomri@hbku.edu.qa

1 College of Economics and Management, Nanjing University of Aeronautics and Astronautics, 29 Jiangjun Avenue, Nanjing, China

2 College of Science and Engineering, Hamad Bin Khalifa University, Doha, Qatar

3 HEC, Paris, France

4 School Management of Science and Engineering, Nanjing University of Information Science and Technology, Nanjing, China

1 Introduction

Over the last decades, supply chain (SC) management has been driven by the boom of industrial 4.0 (I4.0) toward a more efficient and greener system. The notion of I4.0 was initially coined by the German economic development agency to represent the emerging information and communication technologies that connect the physical and digital domains in industry (Olsen & Tomlin, 2020). Individually and collectively, this concept encompasses a set of future industrial developments regarding the Internet of Things (IoT), cyber physical systems (CPS), artificial intelligence (AI), machine learning (ML), data mining (DM), cloud computing (CC), blockchain, and big data (BD) analytics. The SC in I4.0 is also labeled as a smart system (Zhang et al., 2022a, 2022b) or a digital system (Agrawal et al., 2023; Seyedghorban et al., 2020). Although different notions have been used to label the SC in I4.0, two streams of underlying data technologies are worth noting. The first group is relevant to data generation, such as sensors and Radio Frequency Identification (RFID), while the second group is data analytical techniques, such as AI and ML. For SC management, I4.0 builds a data-enriched environment and offers the possibility of cost reduction, flexibility enhancement, and delivery improvement as well as the opportunity to alleviate the inherent tensions between these pivotal operational priorities (Nayernia et al., 2022; Taddei et al., 2022).

The increasing significance of the data to organizational success has stimulated the SC community to explore data-intensive SC optimization (Liu et al., 2021; Nguyen et al., 2022a, 2022b). I4.0 also creates unprecedented modeling challenges for traditional Operation Research (OR) methodologies (Gupta et al., 2022; Hazen et al., 2018; Jabbour et al., 2020). Although the articles in this domain have experienced remarkable increments in recent years, the existing insights are scattered over different literature sources and there is a lack of a structured and unbiased review methodology to systematize the OR methods for SC optimization in I4.0. A comprehensive analysis of noteworthy contributions made in the SC optimization domain can build better OR methods and refine the underlying theories in I4.0.

This paper aims to depict the state-of-art articles on SC optimization in I4.0 and identify the frontiers and limitations as well as the promising research avenue in this interplay. In this study, the systematic literature review (SLR) methodology integrated with the content analysis is adopted to survey the literature on the topic of SC optimization and explore the OR innovations in the context of I4.0 to realize the following: (1) The I4.0 technologies that can be implemented for SC optimization; (2) The SC decisions that can be optimized in I4.0; (3) Establishing the OR methods to address the SC optimization in I4.0; (4) The current challenges for SC optimization while implementing I4.0, and the future directions to be taken in terms of innovations in OR methodology.

To the best of our knowledge, it is among the first efforts to review the present status of the articles on SC optimization in I4.0 from an OR perspective. The linkage between the OR methods and the I4.0 technologies established in this review provides valuable insights to the academic community and industry in exploiting SC optimization at different decision levels.

The rest of the paper proceeds as follows. Section 2 analyzed the previous reviews in this area and identified the research gaps. The research methodology is presented in Sect. 3. The statistical observations are presented in Sect. 4. The review findings are presented in Sect. 5. Section 6 summarizes the gaps and future research needs. Finally, in Sect. 7, we present our conclusions as well as the main contributions. The abbreviations used in this study are presented in Appendix 1.

2 Previous reviews and research gaps

A set of literature reviews on I4.0 technologies and SC has been conducted by scholars. In order to clarify the need for this study, the OR methodologies, Industrial 4.0 technologies, topic, and the year of the review articles of the recent review studies are compared with our paper in Table 1.

Table 1 reports that no comprehensive review analysis in SC optimization, which connects I4.0 technologies with the OR methods, is observed in the current literature. Most of the review papers concentrate on the potential of the I4.0 in SC management, for instance, BDA (Kumar et al., 2023; Talwar et al., 2021) and Blockchain (Antônio Rufino Júnior et al., 2022; Risso et al., 2023). Although the studies by Nguyen et al., (2022a, 2022b) and Agrawal et al., (2023) have used I4.0 and digitalization to represent the data enablers in SC, both of them fall into the description of the potential applications as well as the associated benefits of the data technologies. Gupta et al., (2022a) studied the role of AI in decision support systems with OR approaches. Among all the review papers, only two studies, by Kumar et al., (2023) and Jahani et al., (2023), have mentioned the OR methods in SC management. However, both of them have not addressed the fundamental components in problem-solving, like the decision variables and modeling procedure.

The current studies have paid attention to the impacts of I4.0 on SC but failed to explore how emerging data technologies can contribute to the decision-making process in SC. Moreover, after 2020, a literature review that considers a broad perspective of OR methods crossing maps with the application of I4.0 is still absent. It is worth noting that academic research and industrial engagement in this transformation have been booming in the past years. By completing an up-to-date analysis of current research published from 2013 to 2022, the present study attempts to close this gap.

3 Research methodology

The SLR method and the content analysis were employed to provide an exhaustive overview of the literature on SC optimization in I4.0. The SLR requires a comprehensive research design and has the advantage of minimizing potential bias in collecting and extracting published papers by bringing together the material in an explicitly structured fashion (Kim & Fortado, 2021). The three phases of the SLR are assembling, arranging and assessing of literature, which refers to the acquisition, purification, and evaluation of the candidates (Kumar et al., 2023). We conducted a content analysis of the selected articles during the assessing phase in order to determine the specific categories that could encompass each of these studies. Content analysis is known as a replicable technique that allows researchers to evaluate texts systematically by creating fewer content categories with a manual coding approach (Kim & Fortado, 2021). Thus, the combination of the SLR method and the content analysis enabled us to recognize and highlight the theories and techniques used and reveal similarities, differences, original research gaps, and promising avenues for future research.

3.1 Literature collection and extraction

Literature inclusion and exclusion followed a structured screening process while confining our search to papers published in the period 2013–2022. Figure 1 summarizes the systematic article search and extraction processes.

Table 1 Comparison of this study with previous reviews

Paper	OR methodologies	SC decisions	Industrial 4.0 technologies	Methodology	Topic	Year of the reviewed articles
Gupta et al., (2022)	N	N	Artificial Intelligence	Systematic literature review	Decision support systems	2008–2018
Talwar et al., (2021)	N	Y	Big data	Systematic literature review	Application areas and benefits	2012–2020
Lim et al., (2021)	N	N	Blockchain	Non-specific	Application areas and benefits	2017–2020
Deiva Ganesh and Kalpana (2022)	N	Y	Artificial Intelligence	Systematic literature review	Supply chain risk	2010–2021
Nguyen et al., (2022a, 2022b)	N	Y	Hybrid	Bibliometric analysis	Application areas and benefits	2013–2021
Sahoo et al., (2022)	N	N	Blockchain	Bibliometric analysis	Supply Chain Visibility	2016–2021
Xie et al., (2022)	N	N	Blockchain	Content analysis	Application areas and benefits	2018–2022
Antônio Rufino Júnior et al., (2022)	N	N	Blockchain	Systematic literature review	Battery supply chain monitoring and battery trading	2016–2020
Kumar et al., (2023)	Y	Y	Big data	Systematic literature review	Supply chain decarbonisation	2016–2021
Van Nguyen et al., (2023)	N	Y	Blockchain	Text mining and Latent Dirichlet Allocation -based topic modeling	Application areas and benefits	2017–2022
Trevisan and Formentini (2023)	N	N	Hybrid	Systematic review	Food Loss and Waste Prevention	2016–2022

Table 1 (continued)

Paper	OR methodologies	SC decisions	Industrial 4.0 technologies	Methodology	Topic	Year of the reviewed articles
Agrawal et al., (2023)	N	N	Hybrid	Systematic review integrating bibliometric analysis	Drivers, barriers, and challenges in applications	2012–2022
Risso et al., (2023)	N	N	Blockchain	Systematic literature review	Application areas and benefits	2017–2022
Han and Fang (2023)	N	Y	Blockchain	Systematic review integrating bibliometric analysis	Application areas and benefits	2017–2022
Jahani et al., (2023)	Y	Y	Big data and Data science	Systematic review integrating bibliometric analysis	SC decisions equipped with data science	2005–2022
Kumari et al., (2023)	N	N	Machine learning and artificial intelligence	Bibliometric analysis	Agriculture SC	2006–2022
Out study	Y	Y	Hybrid	systematic literature review	SC optimization equipped with industrial 4.0	2013–2022

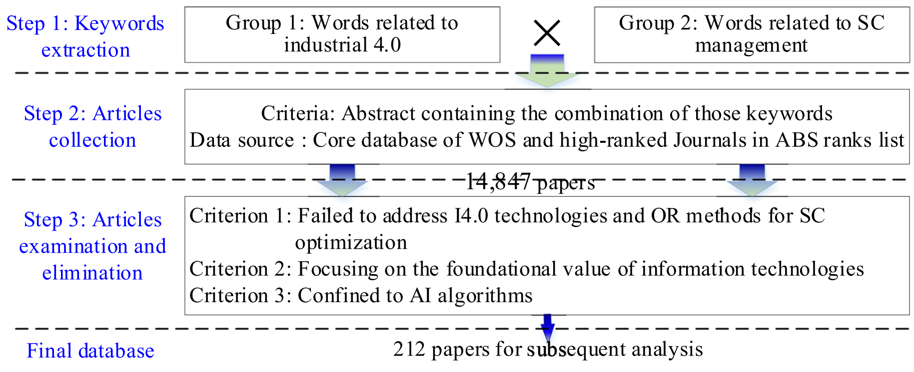

Fig. 1 Overview of search strategies and collective results

In Step 1, the scope of the target articles was delimited by focusing on SC optimization in I4.0. Thus, two groups of keywords created 44 combinations of keyword pairs for collecting articles between 2013 and 2022:

Group 1: Words related to industrial 4.0: “RFID”; “cyber”; “big data”; “Industrial 4.0″; “AI/artificial intelligence”; “data mining”; “machine learning”; “smart”; " blockchain”; “cloud computing”; “digital/digitalization”.

Group 2: Words related to SC management: “supply chain”; “logistics”; “supplier”; “inventory”.

In Step 2, the articles whose abstracts contain the combined keywords are collected from two data sources. Data source 1 refers to the core database of the "Web of Science" (WOS), which provides extensive coverage of peer-reviewed scientific literature (Diaz-Balteiro et al., 2017; Wang et al., 2019). Data source 2 represents journals with star ratings above 1 on the Association of Business School list, which are not included in the WOS, in the categories of Operations and Technology Management and Operations Research and Management Science. In this step, 14,847 results were obtained from the two databases.

In Step 3, the articles are examined and eliminated using three criteria. Firstly, the abstract of the articles was examined for related content, namely, papers that failed to address SC optimization with OR methods were excluded. Thus, review and conceptual papers were also removed. Secondly, since the revolutionized impact of I4.0 depends on the value extraction from real-time data and big data, the papers that focus on the foundational value of the information technologies, such as accuracy improvement using RFID or seniors, were excluded. Thirdly, articles confined to AI algorithms, such as artificial bee colony algorithms, fuzzy sets, and artificial neural networks (ANN), were also removed. Finally, we identified 212 highly related papers for further analysis.

3.2 Literature evaluation with content analysis

The content analysis ensures that the classification is trustworthy and thorough. The literature was classified and reviewed with content analysis following the literature evaluation framework in Fig. 2. Both inductive and deductive approaches in content analysis were employed to classify the articles into a set of categories so that their characteristics and contributions are identified and analyzed. In the deductive approach, the categories are defined in advance

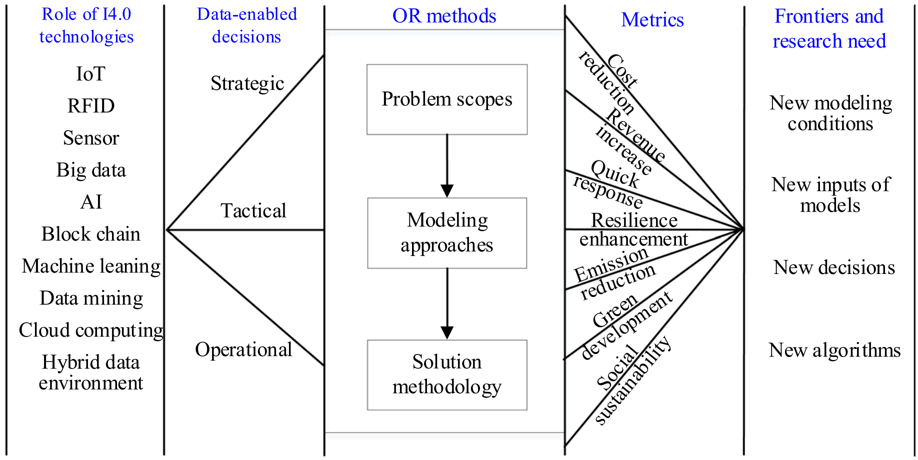

Fig. 2 Literature evaluation framework

before analyzing the contents, whereas in the inductive approach, they are identified by analyzing the sample (Abedinnia et al., 2017). The first three groups along with their sub-groups are produced with a deductive approach based on the previous review articles in the literature representing the characteristics of SC optimization I4.0:

1. I4.0 technologies: A group of keywords was used to represent the data enablers in I4.0; however, not all technologies were included in the final paper database, as shown in Fig. 2. Most of the papers addressing sensors, digital twins, or I4.0 were conceptual analyses and failed to fit the criteria for further analysis. Hybrid indicates the occurrence of an industrial problem involving two or more I4.0 technologies.
2. SC optimization levels: The sample was grouped into three categories according to the duration of the impact of the decisions on SC operations: strategic, tactical, and operational decisions, which were distinguished based on the time duration of their impacts on the SC and were separately evaluated by years, months, weeks, or days (Barbosa-Póvoa et al., 2018). Because low-level decisions are often synchronized with high-level decisions, such as logistics flows and facility location in SC network design, the papers about strategic decisions were grouped at the strategic level. Papers focusing on operational decisions separately were classified into the operational category.
3. OR methods: The publications were classified based on the problem scopes, modeling approaches, and the solution approach to solve the SC problem. The linkage among the I4.0 technologies, SC decisions, and OR methods was identified.

The following two groups along with their sub-groups are generated using the inductive method, the contents of the sample articles were analyzed thoroughly to identify the benefits of the adoption of the I4.0 in SC and indicate research frontiers and opportunities for future study.

4. Metrics: The metrics in papers indicate the objectives that can be achieved by the organizations by connecting the I4.0 technologies and OR methods.
5. Challenges and opportunities: The challenges in terms of four new modeling components and the future research agenda were presented.

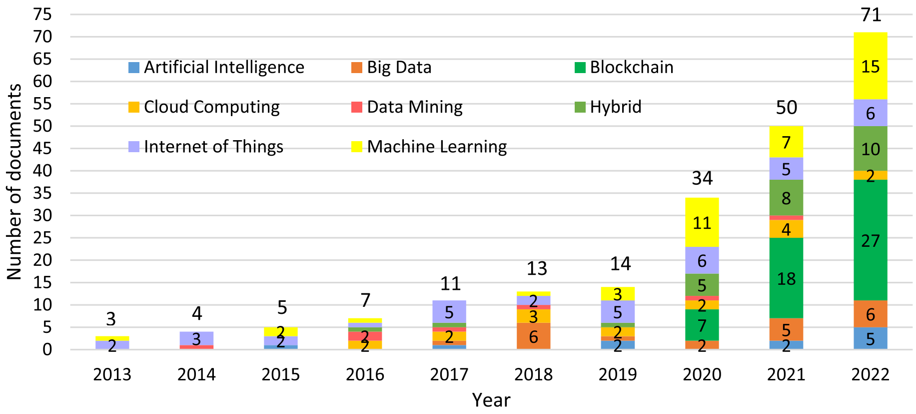

Fig. 3 Thematic categorization of selected papers

4 Publication meta-analyses

To illustrate the distribution of the reviewed articles, we have tailed the collection in the function of publication time, epitomized the contributing journals, compiled the decision levels, and timed the I4.0 technologies and modeling techniques.

4.1 Thematic categorization

Figure 3 shows the chronological development of the collections and their thematic scopes. The different blocks in the figure document the allocation to the eight main I4.0 categories that have been adopted to convey SC optimization with OR methods. The number of studies in this domain has been continuously increasing since 2013. Specifically, the number of articles almost tripled in 2020. Blockchain, IoT and ML are among the top three groups that have been addressed mostly by the selected papers.

4.2 Industrial 4.0 technologies categorization

The implementation of I4.0 in the SC optimization was quite diverse (Fig. 4), and the technology spectrum is still expanding and evolving. To avoid any misunderstanding, we coupled an article with an I4.0 technology only when the paper specified this technology with identified algorithms. For instance, a study investigating data mining was not tagged as a paper with AI. Articles were grouped according to the exact algorithms if more than one I4.0 technology have been mentioned. For instance, both AI and ML are addressed by Euchi et al., (2020), however, it was marked as an ML paper because the proposed solution is mainly based on the k-means clustering method (Gambella et al., 2021). A detailed analysis of the technical terms in I4.0 is available in Dalenogare et al., (2018) and Koh et al., (2019).

Figure 4 shows that 40.1% of the I4.0 technologies were deployed in strategic decision-making. The decisions on the investment in blockchain and IoT are the main contributors to this category. In a similar vein, the two data technologies are also among the mainstreams of the articles at the tactical level. Operational decisions, such as scheduling and delivery, occupied 29.2% of the sample and mainly benefitted from ML.

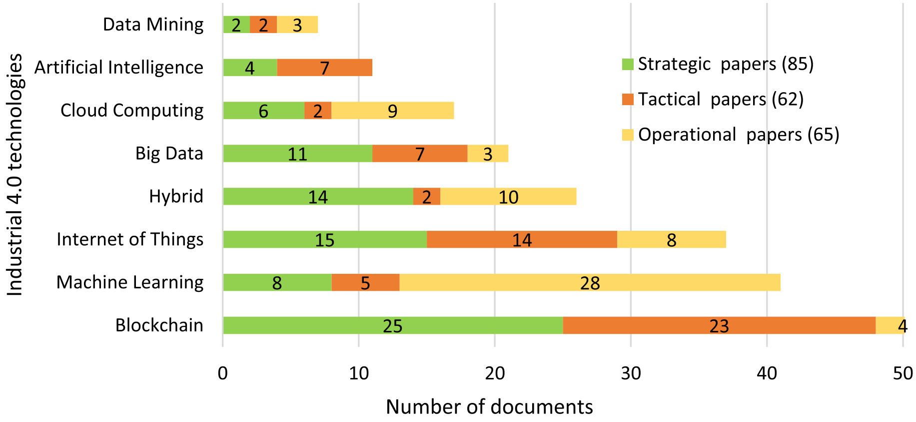

Fig. 4 Industrial 4.0 categorization of selected papers

4.3 Journals categorization

A total of 212 papers, for further analysis, were collected from 53 journals, 11 of which contributed more than five papers (See Fig. 5), and 28 journals encompassed one related paper each. All the top three contributing journals, including the International Journal of Production Research, Computers & Industrial Engineering, and Annals of Operations Research, fall into the Management Science and Operations research spectrum (See Fig. 5). After a thorough scrutinization, it is surprising to observe that some of the leading journals only have limited articles in this crossing domain. For instance, Decision Sciences and Journal of Operations Management, the former has one qualified article (Cai et al., 2020) and no article is detected in the latter. The detailed journal categorization of the selected 212 articles is reported in Appendix 2.

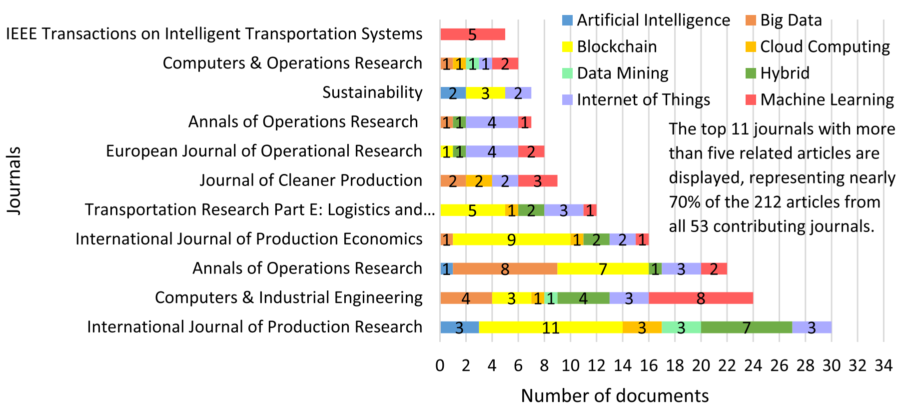

Fig. 5 Journals categorization of selected papers

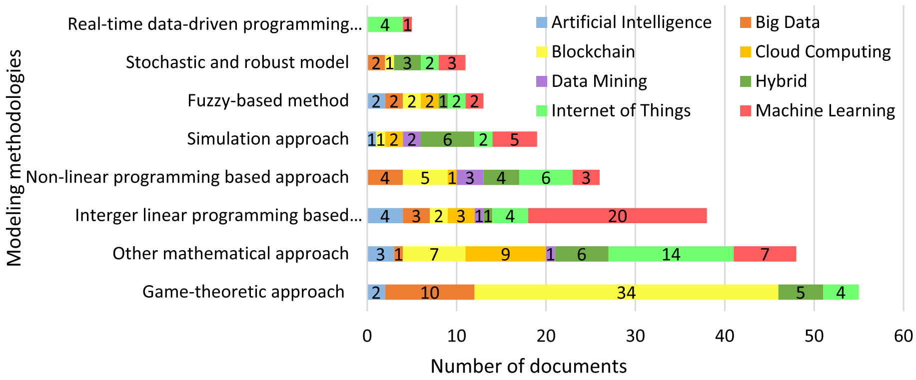

Fig. 6 Modeling methodological categorization of selected papers

4.4 Modeling methodological categorization

The OR methods used in the reviewed articles are illustrated in Fig. 6. Although such classifications can overlap, attempts were made to place all the articles into appropriate groups. Among these categories, the game-theoretic (GT) approach is the most frequently applied method for assessing the cost and benefit of I4.0. Integer linear programming (ILP)- and fuzzy-based approaches are popular methods. The former is common in vehicle routing problems (VRP) (Chen et al., 2013; Moradi, 2020), whereas the latter is often employed in supplier selection (Chen et al., 2020; Liou et al., 2021) and network design (Abbasi et al., 2020; Hajipour et al., 2019). In this study, we identified a new modeling method, the real-time data-driven programming (RDP) approach, in five articles. Moreover, 47 papers, accounting for 22.3% of the reviewed articles, developed mathematical models that cannot be categorized into one of the well-known modeling methodologies. This implies that the SC optimization becomes more intricate in I4.0, and it is difficult to establish models following the standard programming structure. Thus, innovation in OR approaches is required to respond to the new SC arena.

5 Summary of review findings

5.1 Role of industrial 4.0 technologies in supply chain optimization

Internet of Things IoT is a system of objects equipped with electronics, such as RFID and sensors, with the capability of collecting and sharing data (time, location, quantity, etc.). The IoT allows the items to be sensed and identified remotely across the SC network, creating opportunities for optimizing inventory levels, parcel delivery schedules, and vehicle routes in SC. The most recent industrial advances are related to decreasing product losses and lead time of transportation (Hajipour et al., 2019), detecting anomalies in logistics (Cao et al., 2019; Mejjaouli & Babiceanu, 2015; Sun et al., 2020), monitoring risks in cold chains(Tsang et al., 2018), tracking spare parts (Karatas & Kutanoglu, 2020), screening the perishable inventory level (Liou et al., 2021; Stefánsdóttir et al., 2022; Yang et al., 2019), and dispatching and picking up orders of online services (Liu et al., 2019a, 2019b; Sun & Ji, 2022; Wang et al., 2020).

Artificial intelligence AI is a data-learning system with the ability to discover and reveal hidden rules and patterns in business. Popular AI algorithms comprise bio-inspired algorithms, such as neural networks, swarm intelligence, and algorithms for unstructured data analysis, such as natural languages and cognitive computing. AI is competitive in dealing with sophisticated decision-making problems, where the optimal or exact solutions are either too expensive or difficult to be produced (Preil & Krapp, 2022). It has been integrated with OR methods in demand management (Duan et al., 2019; Liu et al., 2022a, 2022b), inventory control (Preil & Krapp, 2022; Tsang et al., 2020), supplier selection (Kuo et al., 2015), and SC design (Cai et al., 2022; Zhang et al., 2017).

Machine learning Among the AI spectrum, ML techniques have recently gained attention because of their high efficiency in analyzing real-time data. The widely used ML algorithms in SC are supervised, unsupervised, and reinforcement learning (Riahi et al., 2021). Studies have adopted ML to forecast customer demands (Ren et al., 2020; Zhu et al., 2021), analyze production feasibility in SC design (Bhosekar & Ierapetritou, 2021), and generate vehicle routes for product delivery (Jun & Lee, 2022; Ren et al., 2022). ML has also been combined with the heuristic algorithm to solve OR problems (Chobar et al., 2022; Gumte et al., 2021; Moradi, 2020).

Block chain Blockchain technology changes the power relationships in SC by allowing organizations to manage their data in a decentralized manner via consensus-based validation protocols and cryptographic signatures, rather than in a centralized legacy system. It is often mentioned as a transparent, secure, efficient, confident, and immutable solution for tracking, tracing, and verifying transactions across the SC (Chang et al., 2021; De Giovanni, 2020). The recent progress in blockchain includes intelligent contracting (Choi et al., 2020; Zheng et al., 2020), risk management (Choi, 2020; Lohmer et al., 2020; Niu et al., 2022), quality verification (Shen et al., 2021; Yang et al., 2022a, 2022b), cryptocurrency payment (Yuze Li et al., 2021), and information recording and sharing (Maity et al., 2021; Niu et al., 2021a, 2021b; Wang et al., 2021) in SC.

Data mining DM is the extraction of unexpected valuable knowledge or patterns from large datasets. Its applications have been directed at rule mining, like dispatching rule in logistics (W. Chen et al., 2013), purchase patterns for anticipatory shipping (Lee, 2017; Viet et al., 2020), and rule selection for reducing the inventory level (Dev et al., 2016). Another interesting research stream has used the DM method to preprocess the input data of the parameters in OR models (Gumte et al., 2021; Li, 2019). In addition, it has also been adopted to extract knowledge from historical data for supplier evaluation (Liou et al., 2021).

Big data analytics BD is often referred to as vast volumes and diverse datasets with complex relations. BD has been labeled with 3 V features, namely high volume, variety, and velocity (Lamba & Singh, 2017; Mishra & Singh, 2022) or 5 V features by adding veracity and value (Ivanov et al., 2019). Thus, the term BD analytics is used by academia to interpret the value extraction process (Arunachalam et al., 2018; Gholizadeh et al., 2020; Ying et al., 2022). BD analytics serves the OR approaches by preprocessing the values of parameters, such as customer demands (Gholizadeh et al., 2020; Mishra & Singh, 2022; Wu et al., 2020a, 2020b) and cost values (Gholizadeh et al., 2020; Peng et al., 2022) in SC optimization.

Cloud computing CC represents the on-demand computing services offered to customers via a network in a self-service fashion, independent of the physical location of the hardware and software. CC enhances SC collaboration (Ivanov et al., 2022; Yu et al., 2017) and visibility (Kochan et al., 2018) via information sharing. It also has been used for low-carbon supplier selection by collecting the emission information (A. Singh et al., 2018a, 2018b) and SC design by gathering the cost information (Ali et al., 2021).

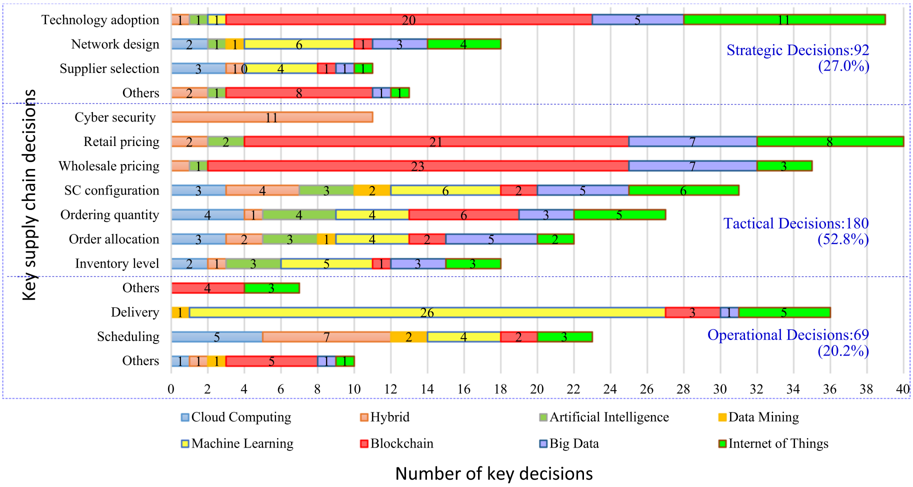

Fig. 7 Key supply chain decisions assisted by I4.0 technologies

Other data enables Leading digital technologies also include additive manufacturing, digital twins, robotics, augmented reality, and other emerging I4.0 technologies that interact with different businesses in SC. However, in current literature, these technologies are mostly addressed concerning production lines, flow shops, or stock management rather than from the SC perspective.

5.2 Data-enabled decisions at different supply chain levels

5.2.1 General overview

Figure 7 shows that strategic decisions, tactical decisions and operational decisions occupy 27.0%, 52.8% and 20.0% of all the decisions respectively. Among the strategic decisions, technology adoption has been investigated more explicitly. At the tactical level, the decisions are diverse and share similar occurrences. The product/service delivery (also mentioned as vehicle routing) optimization using ML is the predominant decision-making operational decision.

5.2.2 Strategic decisions

The most recent strategic decision-making studies also involve some tactical or operational decisions, except for the articles dedicated to partner selection (Chen et al., 2020; Liou et al., 2021), technology adoption (Manupati et al., 2022), or cyber security investment (Yanhui Li & Xu, 2021; Sawik, 2022; Schmidt et al., 2021). From a detailed content-wise classification standpoint, we analyzed the strategy-level articles by concentrating on I4.0 and its roles, main decisions, and OR methods, as listed in Table 2. The details of the OR aspects of the papers are analyzed in the following subsections.

Network design SC network design often deals with facility locations with a fixed cost consideration. Facility location using ML algorithms in forward SC was the main concern of

Table 2 Strategic decisions of supply chain optimization in Industrial 4.0

Authors and year	I4.0 technologies	Role of data enablers	Main decisions	OR approaches	Algorithms
A. K. Singh et al., (2018a, 2018b)	Big Data	Parameters estimation	Facility location and allocation	MILP model	CPLEX
Hajipour et al., (2019)	RFID	Product tracking	Facility Location, quantity of forward and backward products	Stochastic MINLP model	A multi-objective vibration damping-based algorithm
Vijaya K Manupati et al., (2020)	Blockchain	Cost and emission tracking	Network design, technology adoption, and logistics flows	MINLP	NSGA-II
Wan and Qie (2020)	Hybrid	Reducing cooperative risk	Government subsidy for smart platform	Evolutionary game method	/
Medina-González et al., (2020)	Machine Learning	Ordinary Kriging technique in model solving	Supplier selection, Facility selection, Order allocation, Inventory level	MILP model	CPLEX through GAMS
Y. He et al., (2021)	Blockchain	Quality monitoring of perishable product	Blockchain adoption	GT approach	/
Ali et al., (2021)	Cloud Computing	Real-time cost information	Supplier selection and logistics flows	MILP model	GA
Bhosekar and Ierapetritou (2021)	Machine Learning	SVM for production feasibility analysis	Facility location, production line selection, process design	MINLP model	CPLEX through GAMS
Gumte et al., (2021)	Machine Learning	Fuzzy C-means clustering in model solving	Facility selection, logistics flows, supplier inventory, and carbon emissions	Robust MILP model	CPLEX through GAMS

Table 2 (continued)

Authors and year	I4.0 technologies	Role of data enablers	Main decisions	OR approaches	Algorithms
Mishra and Singh (2022)	Big Data	Parameter dataset with 3 V characteristics	Location and capacities of facility, production–distribution of products	Stochastic model	LINGO
Rajput and Singh (2022)	IoT	Real-time production data	Machine selections with different precision, logistics flows	MIP model	LINGO
(Sawik, 2022), Schmidt et al., (2021)	Hybrid	Cyber security	Investment and selection of security controls	Stochastic MILP	MATLAB, Gurobi through Python
Xiao et al., (2022)	Machine Learning	ML-aided metaheuristic algorithm	Facility selection and logistics flows	ILP-based model	Gurobi
W. Yang et al., (2022a, 2022b)	Blockchain	SC finance	Blockchain adoption	MINLP	Customized heuristic
J. Liu et al., (2022a, 2022b)	Artificial Intelligence	Customer demands prediction	Facility selection and logistics flows	ILP-based model	Two-stage heuristic

the authors. Gumte et al., (2021) optimized the numbers and locations of suppliers and manufacturers in biowaste SC. Similarly, for the bio-based energy SC design, the ordinary kriging technique was used by Medina-González et al., (2020). The textual data were transformed into inputs of the location–allocation mixed-integer linear programming (MILP) model by Singh et al., (2018a, 2018b) for cold chain design. However, the 3 V features of big data were absent in this study. Mishra and Singh (2022) have analyzed network configurations in reverse SC with 3 V parameters. An ML-aided metaheuristic framework was developed by Xiao et al., (2022) for a production/distribution system design. Liu et al., (2022a, 2022b) established a MILP model where the ANN was adopted to predict customer demands for E-logistics distribution network design.

Partner selection Most studies have investigated sustainable partner evaluation problems (Chen et al., 2020; Singh et al., 2018a, 2018b). ML was embraced by Wu et al., (2020a, 2020b) to classify partners into strategic, preference, leverage, and routine suppliers. The SVM was exploited by Liou et al., (2021) to extract core criteria from historical data for supplier performance evaluation. Singh et al., (2018a, 2018b) surveyed the low-carbon supplier selection problem in beef SC in a big data context; however, the data analytic approach was absent in this study. The blockchain service platform provider selection problem was studied by Bai et al., (2021).

Technologies adoption The implementation of I4.0 is expensive and needs to be explicitly assessed. The investment in blockchain can be separately assessed (Liu et al., 2021; Yang et al., 2022a, 2022b) or coupled with other SC decisions (Manupati et al., 2022). The cost allocation of the IoT among the SC was addressed coupled with the environmental concern by Nativi and Lee (2012) and the social welfare consideration by Zhang and Liu (2021). Moreover, Blockchain and IoT adoption problems are often scrutinized in two-echelon SC, while the implementation of BD is common in three-echelon SC. Above all, the potential barriers to I4.0 implementation have not been elaborated explicitly, with the exception of Kazancoglu et al., (2021) and Hosseini Dehshiri et al., (2022).

Cyber security control Cyber security aims at protecting critical data facilities, such as servers and databases, in multi-tier SC with the constraint of investment (Cheung & Bell, 2021; Sawik, 2022; Schmidt et al., 2021). Studies have focused on proactive actions by developing robust cyber-layer networks to enhance the risk-mitigating capabilities of SC. Popular decisions regarding cybersecurity protection include the preferred security level (Cheung & Bell, 2021; Sawik, 2022), safeguard selection (Schmidt et al., 2021), and defense expenditures (Cheung & Bell, 2021; Prajapati et al., 2022).

5.2.3 Tactical decisions

Unlike decision-making at the strategic level, the tactical decisions are rarely considered with a lower level of operational decision. In a general sense, the articles can be classified into six groups based on their main decision variables in the models: wholesale and retail pricing, ordering quantity, inventory level, and SC configuration coupled with order allocation. With similar strategic-level literature scrutinizing schemas, Table 3 documents the tactical decision-making elements.

Wholesale and retail pricing Wholesale and retail pricing can be optimized simultaneously or separately. The first stream of literature studies the pricing decisions of wholesalers and retailers, accompanied by order quantity. Niu et al., (2021a, 2021b) focused on the pricing policies of medicines with blockchain for information transparency and quality trust. The pricing rules of green products in the big data environment are explored by Liu and Zhang (2022) and Li et al., (2022) separately. The second stream of literature includes pricing chilled

Table 3 Tactical decisions of supply chain optimization in Industrial 4.0

Authors and year	I4.0 technologies	Role of Data enablers	Tactical decisions	OR approaches	Algorithms
R. Kuo et al., (2015)	AI	Rule mining and artificial immune network in model solving	Supplier selection and order quantity allocation	ILP-based approach	Artificial immune network with PSO
Dev et al., (2016)	Machine Learning	Decision tree learning for real-time decision	Distribution network configuration, inventory level	Simulation approach	/
Liu and Yi (2017)	Big Data	BD targeted advertising	Retail and wholesale prices and the green degree of products	Stackelberg game and Nash Equilibrium game model	/
D. Li and Wang (2017)	IoT	Quality monitoring	Pricing the products based on shelf-life information	RDP approach	/
Viet et al., (2020), C. Lee (2017)	Machine Learning	Rule mining for anticipatory shipping	Product and cross-docking selection, logistics flows	Multi-agent simulation	/
Abbasi et al., (2020)	Machine Learning	Model solving	Order quantity of each hospital and the transshipment quantities between hospitals	Two-stage stochastic model	ML-based method
Gholizadeh et al., (2020)	Big Data	Avoid information fraud	Order allocation among several suppliers, inventory level, and vehicle selection	Robust fuzzy stochastic model	/

Table 3 (continued)

Authors and year	I4.0 technologies	Role of Data enablers	Tactical decisions	OR approaches	Algorithms
Maity et al., (2021)	Blockchain	Food quality trans-parency and security	Logistics flows	Stochastic model	L-Shaped algorithm
Xing et al., (2021)	Blockchain	Information sharing and smart contract design	Level of efforts of inventors	Principal-agent theory	/
Niu et al., (2021a, 2021b)	Block chain	Medicine quality tracking	Retail price	GT approach	/
M. Li and Li (2022)	AI	Ordering automation of the retailer	Whole pricing and ordering quantity	Newsvendor model	Customized algorithm
Ma and Hu (2022)	Blockchain	Product recycling enhance-ment	Retail and wholesale prices	Stackelberg differential game	/
Peng et al., (2022)	Big Data	Dealing with the uncer-tainties of parameters	Network con-figuration, retail, and wholesale prices	ILP-based approach	LINGO

food with sensor data (Hu et al., 2022; Li & Wang, 2017) and products on the online platform where the quality information is disclosed by blockchain (Ma & Hu, 2022; Xu & He, 2021).

Inventory level The inventory level was optimized isolatedly in this group. Considering the IoT-based forecast updating demand, T.-C. Kuo et al., (2021) analyzed parts inventory allocation policy in manufacturing SC. F. Wang and Lin (2021) addressed the optimum replenishment path, covering inventory level and ordering quantity, for understocked spare parts distributors. Ekren et al., (2021) discussed the re-order and up-to-inventory levels in a lateral inventory share-based system in E-commerce food SC.

SC configuration The SC configuration covers process design and facility incorporation decisions without considering the fixed costs. SC configuration is often determined by order allocation among suppliers (Kaur & Singh, 2018; Kuo et al., 2015; Lin et al., 2022), third-party logistics providers (Kaur & Singh, 2018; Ren et al., 2020), and flexible production facilities (Bhosekar & Ierapetritou, 2021; Rajput & Singh, 2022). This decision often occurs in the context of the manufacturing industry (Dev et al., 2016; Ivanov et al., 2022; Maity et al., 2021), sustainable SC (Kaur & Singh, 2018; Peng et al., 2022; Rajput & Singh, 2022), e-commerce (S. Ren et al., 2020), logistics service procurement (Kong et al., 2021), anticipatory shipping (C. Lee, 2017; Viet et al., 2020), and hospital SC (Kochan et al., 2018). Referring to the I4.0 technologies, all of them have been used with almost the same frequency in SC configuration.

Ordering The occurrence of the ordering decision was verified in both product inventory control and service outsourcing on the cloud platform. The order quantity and re-order point were studied by Yang et al., (2019) and Liou et al., (2021) in perishable and vendor-managed inventories, respectively. The order quantity of hospitals and the transshipment quantities between them were optimized by Abbasi et al., (2020) for blood SC management. Some authors have explored the third-party logistics service provider and customer matching problem (Aghamohammadzadeh et al., 2020; Ran & Liu, 2020) and the optimum order quantity generation in multi-echelon SC on a cloud platform (Y. Yu et al., 2017).

5.2.4 Operational decisions

In addition to articles that have addressed strategic or tactical decisions, several prior studies have also focused on SC optimization at the operational level. The main operational decisions in logistics consist of the scheduling and delivery of products. Those decisions have been made both in manufacturing SC (Ivanov et al., 2016; Jamrus et al., 2020; Zeng et al., 2022) and service SC, such as logistics services (Ran & Liu, 2020; Weaver et al., 2022) and medical services (Euchi et al., 2020). Table 4 lists some of the main elements of the selected literature at the tactical level.

Scheduling Recent articles on scheduling in SC not only have fallen into the manufacturing category but also the service division (Euchi et al., 2020; Weaver et al., 2022; Zahedi et al., 2021). DM is the dominant I4.0 technology that has been implemented to refine the input parameters of the OR models (Smith & Ehmke, 2016) and cluster the customers (M. Wu et al., 2019). A few studies investigated the scheduling problem in the production–distribution system (P. He et al., 2022; R. S. Kumar et al., 2016; Liao & Wang, 2019; Zeynivand et al., 2021). The short-term scheduling in CPS-enabled SC was investigated by Ivanov et al., (2016). Kang et al., (2019) addressed the real-time new order assignments in crowdsourced parcel delivery. J. Sun et al., (2020) constructed a model to determine the optimal switching point in an intelligent production network. P. He et al., (2022) investigated the integrated production and transportation scheduling problem in 3D-printing spare parts SC.

Delivery Product delivery management is often addressed as the VRP in literature but we only focus on those who have addressed I4.0 technologies. In this domain, the articles can be classified into two clusters based on whether they have specific applications. The first cluster aimed at developing innovative algorithms to solve the classical VRP problem by introducing ML (W. Chen et al., 2013; Ghiani et al., 2022; Moradi, 2020; Qin et al., 2021). The second cluster focused on the routing or rerouting the vehicles with distinct applications, such as drone-based routing (X. Chen et al., 2022; Salama & Srinivas, 2020) and real-time rerouting under disruptions (S. Liu et al., 2019a, 2019b; Mejjaouli & Babiceanu, 2018; J. Wang et al., 2020; K. Zhang et al., 2022a, 2022b).

5.3 Operational research methods for supply chain optimization in industrial 4.0

5.3.1 Modeling approaches

Game-theoretic approach The implementation of I4.0 requires cooperation between the players in the SC to share the cost and the benefit. GT models address these advances by creating coordination between players, hence obtaining optimum behaviors in the new data environment. The Stackelberg game model is the most popular method, while the bargaining game model (H. Yang & Chen, 2020), evolutionary game model (W. Liu et al., 2022a,

Table 4 Operational decisions of supply chain optimization in Industrial 4.0

Authors and year	I4.0 technologies	Role of Data enablers	Operational decisions	OR approaches	Algorithms
Mejjaouli and Babiceanu (2015)	IoT	Quality monitoring	When and how much products should be delivered	RDP approach	/
Ivanov et al., (2016)	Hybrid	Real-time data collection	Production scheduling	Other mathematical approach	Krylov–Chernousko method
C. Lee (2017)	Data Mining	discover the purchase pattern and predict future purchase	Anticipatory shipping	Other mathematical approach	Cluster-based association rule mining and GA
Mejjaouli and Babiceanu (2018)	IoT	Real-time data in logistics	Stopping transportation and/or rerouting the shipments to a closer location	ILP-based approach	CPLEX
Kochan et al., (2018)	Cloud Computing	Information sharing	Order allocation and inventory level	Systems dynamics simulation	/
Kang et al., (2019)	Machine Learning	Model solving	New order assignment and vehicle rerouting	RDP approach	Reinforcement learning based algorithm
Aghamohammadzadeh et al., (2020)	Cloud Computing	Cloud service matching	Logistics customers and providers matching	NLP-based approach	NSGA-II
J. Sun et al., (2020)	IoT	Real-time data in factory	Switching point of manufacturing tasks among factories	Other mathematical approach	/
Salama and Srinivas (2020)	Machine Learning	Model solving	Truck-drone routing	ILP-based and MILP-based approaches	ML-based algorithms and heuristics
Jamrus et al., (2020)	Hybrid	Real-time scheduling	Plant selection for operation and its completion time	Fuzzy-based approach	Hybrid PSO and GA

Table 4 (continued)

Authors and year	I4.0 technologies	Role of Data enablers	Operational decisions	OR approaches	Algorithms
Z. Wang et al., (2021)	Blockchain	Data exchange	Data pricing	Other mathematical approach	Other customized algorithm
Zahedi et al., (2021)	IoT	Gathers information from suspected Covid-19 cases	Routing of ambulance	MINLP and MILP model	Hybrid meta-heuristics
Feng et al., (2022)	Machine Learning	New algorithms for model solving	Vehicle routing for delivery	ILP-based approach	Machine learning based algorithm
Yankai Wang et al., (2022)	Cloud Computing	cloud manufacturing	Service composition exception handling	NLP-based approach	Ant colony algorithm
Ahmadi and Ghasemi (2022)	Artificial Intelligence	Demand forecasting	Hotel pricing	GT approach and ILP-based approach	/

2022b; W. Liu et al., 2021; Wan & Qie, 2020), differential game model (Ma et al., 2021; M. Xu et al., 2022), and Nash game model (Choi, 2020; Liu & Yi, 2017; Zheng et al., 2020) are also utilized. However, current studies are confined to static games where players make side payments or form coalitions.

More than half of the reviewed papers in this arena have evaluated the investment in IoT (Ben-Daya et al., 2022; X. Li, 2020; H. Yang & Chen, 2020), BD (Liu & Yi, 2018a; H. Song et al., 2022a, 2022b), and blockchain (Choi, 2020; M. Liu et al., 2021; Niu et al., 2021a, 2021b). There is a huge scope to study the investment involving the remaining I4.0 technologies using the GT approach.

The coordination in two-echelon SC has been analyzed explicitly, but is limited to manufacturers and retailers, such as stated by Choi (2020); De Giovanni (2020); Liu and Yi (2018a, 2018b); Ma and Hu (2022), with no mention of manufacturer-supplier SC. A few studies have extended the discussion to multi-player games in two-echelon SC. Liu and Yi (2018a) established a Stackelberg game model, in which a data company is the game leader and sells the BD of consumer preferences to the manufacturer. X.-Y. Wu et al., (2021) defined a Stackelberg game, in which the manufacturer decides the wholesale prices of the fresh product and a third-party logistics provider decides the service price afterward. Only one article considers a multi-echelon SC, where a supplier, manufacturer, and retailer are in a Stackelberg game (Fan et al., 2022).

The multiplayer platform SC is a new application area of game theory. Wan and Qie (2020) analyzed cooperative games between cooperatives and smart SC platforms. W. Liu et al., (2021) defined a three-party evolutionary game to investigate BD discriminatory pricing behavior in platform SC. X. Li (2020) designed a Stackelberg game where the platform SC acts as a connector between manufacturers and consumers in agency selling practices. W. Liu et al., (2022a, 2022b) adopted the evolutionary game theory to analyze smart logistics ecological cooperation with data sharing and platform empowerment. A Stackelberg differential game model is developed by Ma and Hu (2022) to optimize the combination of “blockchain & sales format” in closed-loop SC. This study shows that platform recycling can be improved by building consumer trust with the adoption of blockchain.

Integer linear programming-based approaches The ILP-based approach represents a set of optimization methods, in which both the objective and constraints are integral and linear. The MILP model is the most well-known and widely used ILP-based approach for SC design and VRP problems. ILP-based methods are the main modeling techniques for VRP problems with time windows (Euchi et al., 2020; Moradi, 2020; Yong Wang et al., 2018; Worawattawechai et al., 2022). Most recent studies in this domain aim at deriving efficient algorithms, whereas only a few of them are conducted in a real-world context. The routes of synchronized home healthcare visits were investigated by Euchi et al., (2020) using the MILP technique. Zahedi et al., (2021) established two models for transferring the suspected COVID-19 cases in IoT-enabled relief SC. The first NLP-based model aims at promising an earlier visit to the suspected case with the lowest priority, whereas the second ILP-based model aims at minimizing the total response time. A MILP model was established by Gopalakrishnan et al., (2021) to optimize the quantity of solid waste traded between supplier and consumer companies in a blockchain-based waste recycling SC.

ILP-based models are also used to maximize profit (Gopalakrishnan et al., 2021; Rahmanzadeh et al., 2022) or minimize costs (Euchi et al., 2020; Rajput & Singh, 2022; A. K. Singh et al., 2018a, 2018b; Xiao et al., 2022) of a SC. However, only a few studies have extended the single-objective problem to multi-objective optimization. Medina-González et al., (2020) considered the three objectives of net present value and environmental and social aspects to design a bio-based energy SC. The fleet size and total traveling distance were simultaneously optimized by Moradi (2020) for the VRP problem with time windows. The environmental and economic objectives are considered by Chobar et al., (2022) to design a hub-spoke network of perishable tourism products.

Non-linear programming-based approaches NLP-based approaches contain nonlinear terms in the objectives or constraints. The intricate relations among the variables and parameters are common in SC optimization. In this subsection, we only analyze articles with NLP-based models that failed to be grouped into other modeling techniques, such as stochastic programming or fuzzy-based methods. A two-objective NLP-based model was developed by H. Lee et al., (2018) to minimize the fuel cost and maximize the service level by optimizing the vessel speed using a weather archive BD.

If the decision variables are confined to the integer values, the NLP-based approach is also mentioned as mixed integer nonlinear programming (MINLP). Vijaya K Manupati et al., (2020) developed a MINLP model to design a blockchain-based SC to minimize cost and emissions. Similarly, a MINLP model was established by Hajipour et al., (2021) to maximize the number of undamaged delivered items in an IoT-enabled relief SC design. Bhosekar and Ierapetritou (2021) also adopted the MINLP approach to analyze the feasibility of configuring a modular manufacturing system. The MINLP method was borrowed by Prajapati et al., (2022) to determine the optimum configuration of the blockchain and IoT-embedded closed-loop SC network in E-commerce. Similarly, the network configuration of an E-commerce SC is investigated by Rahmanzadeh et al., (2022) to maximize the total net profit.

Stochastic and robust programming Ignoring the uncertainties in SC optimization leads to less realistic results. The availability of real-time and big data contributes to foreseeability but can not eliminate all the impacts of unforeseen events. Three modeling techniques—stochastic programming, robust optimization, and fuzzy programming—are widely used to deal with uncertain parameters in this domain.

In stochastic programming, uncertain events are assumed to occur with known probabilities, which is practical in strategic decision-making in SC. Hajipour et al., (2019) established a stochastic MINLP model to optimize the configuration of a traceable closed-loop SC network. Flores and Villalobos (2020) provided a two-stage stochastic framework to optimize the schedule of agricultural production. In this study, the farming technologies were selected for each identified region, and operational decisions were made under various discretized yield and market scenarios. The main ambiguous sources of cybersecurity risks are the occurrence of cyber attacks and the effectiveness of alternative controls. Thus, another application of stochastic programming is to obtain optimal investments in SC by selecting a portfolio of cybersecurity safeguards (Sawik, 2020, 2022; Schmidt et al., 2021). Considering the uncertain demand of customers, two-stage stochastic mathematical models were used by Maity et al., (2021) and Abbasi et al., (2020) to separately allocate the inventory along the SCs. The former aims at determining the quantities of raw materials used in the facilities (first stage) and logistics flows (second stage) in a blockchain-enabled food SC. The latter investigates the transshipment of the blood among the healthy centers by minimizing the cost of the medical SC.

Robust optimization seeks premium results in the worst case when the probabilities of the uncertain parameters are undisclosed. As a popular ambiguity-averse method in SC optimization, it has been undertaken within a limited scope in the context of I4.0, with only a few exceptions. Gumte et al., (2021) considered the worst-case realizations of the uncertain demand and the supply of biomass feed in a biowaste SC network design. Polo et al.,

(2019) employed the hybrid robust fuzzy stochastic method to generate optimal sustainable procurement and transportation decisions. Z. Cai et al., (2022) adopted the graph theory to design a robust logistics network by building a multi-objective robustness function, including relative robustness, betweenness robustness, edge robustness, and closeness robustness.

Fuzzy-based approach Fuzzy-based approaches represent quantitative models where the fuzzy set theory provides details of vague information in the decision-making process. Triangular fuzzy numbers are the dominant methods to assess the best alternatives (A. Singh et al., 2018a, 2018b; C. Wu et al., 2020a, 2020b) and capture the uncertainties in mathematical programming (Coppolino et al., 2021; Jamrus et al., 2020).

Fuzzy numbers are often integrated with the rough method (Z. Chen et al., 2020) or analytic hierarchy process (AHP) (A. Singh et al., 2018a, 2018b) to mitigate internal and external uncertainties. C. Wu et al., (2020a, 2020b) defined a fuzzy ensemble learning model to classify sustainable partners by considering both qualitative and quantitative inputs. Belhadi et al., (2021) established an AI-based decision framework to identify patterns in the SC resilience strategies. Y. Tsang et al., (2020) adopted the fuzzy triangular method to describe the ambiguous inputs and outputs of the dynamic routing model. Fuzzy trapezoidal numbers were used by Jamrus et al., (2020) to represent the epistemic makespan of the coordinated scheduling in smart production.

Simulation approach Many complex systems cannot be represented using accurate and convenient mathematical models. The advantage of a simulation method is that it mimics the behaviors and intricate inactions of the individuals in the business while avoiding sophisticated problem breakdown or algorithm development. Compared with the models in other categories, the results of simulation-based optimization are built on the assumptions and simulation framework (Illgen & Höck, 2019). Thus, it is essential to validate the findings by repeating the experiments independently several times under various situations (i.e., parameter combinations). However, only a few studies have verified the reliability of simulation results by statistical analysis (L.-M. Chen & Chang, 2021; Nativi & Lee, 2012; Weißhuhn & Hoberg, 2021) or sensitivity analysis (Alqahtani et al., 2022; Dev et al., 2016; Kong et al., 2021).

The discrete-event (DE) simulation has been the mainstay of the simulation community to derive the optimum replenishment policies (Weißhuhn & Hoberg, 2021) and cyber risk mitigations (L.-M. Chen & Chang, 2021; Shi et al., 2021). The ARENA simulation software package with the OptQuest optimizer was used by Ekren et al., (2021) and Nativi and Lee (2012) to conduct DE simulation-based optimization in IoT-empowered SC.

Multi-agent systems (MAS) contain decision-making entities with autonomous behaviors. The cooperation of the agents within a MAS enables it to deal with the uncertainties and dynamics in SC optimization (Dev et al., 2016; Kong et al., 2021; F. Wang & Lin, 2021; X. Xu et al., 2021; Y. Yu et al., 2017). Studies have used the ML technique, such as decision tree learning (Dev et al., 2016; Jelen et al., 2022), Q-learning algorithm (F. Wang & Lin, 2021), and reinforcement learning (Alqahtani et al., 2022), to derive the rules of agent behavior in the MAS.

Real-time data-driven programming Some structural models that share the following characteristics are observed in SC optimization in I4.0: (1) they follow the mathematical programming regimen, for instance, optimization objectives are subject to a set of constraints, but difficult to be grouped into a well-known modeling technique exactly; (2) they have time-dependent decision variables and real-time inputs; and (3) the state of the model is dynamic, similar to the model solving process. Thus, the term RDP technique was used to refer to this approach in this review.

The RDP model is mainly used in VRP problems with real-time data generated by the IoT. S. Liu et al., (2019a, 2019b) developed an RDP model to optimize the costs of task delivery of smart vehicles. A multi-objective RDP model was established by J. Wang et al., (2020) to coordinate customers, order-picking robots, and cloud technology dynamically. Mejjaouli and Babiceanu (2015) constructed an RDP model to determine whether the producer should deliver fresh products to retailers when the spoilage of products is reported by the IoT during transportation. D. Li and Wang (2017) analyzed dynamic pricing policies in light of the identified quality features of the on-shelf products with sensors.

Other mathematical approach The permeation of the I4.0 technologies into SC optimization requires decision-makers to deconstruct the problems in a new pattern and form unstructured analytical models. The modeling process does not follow any fixed rules but serves specific optimized objectives, for example, BC-empowered data sharing (Z. Wang et al., 2021; Q. Xu & He, 2021) and anticipatory shipping with data mining (C. Lee, 2017) in SC. In addition, three recent studies have been dedicated to the newsvendor model in inventory optimization with blockchain (Chang et al., 2021), AI (M. Li & Li, 2022), and deep learning (S. Ren et al., 2020).

5.3.2 Solution methodologies

Common observations The solution methodologies were deployed based on modeling techniques. For instance, the primary models of the simulation approaches, fuzzy-based approaches, and GT models are the analysis and precision. Exact solution generation is often synchronized with state updating in the RDP model. For exact solutions, commercial solvers, such as CPLEX, Gurobi, and LINGO, are also utilized. Nevertheless, heuristic algorithms are efficient in generating a reasonably good solution of the ILP- and NLP-based models for large-scale problems. Surprisingly, ML-based algorithms are becoming popular in solving ILP-based models, but not in NLP-based problems, as they open a completely unexplored research avenue. Another fast-growing aspect of the solution methodologies is the use of Python as the programming environment for Genetic algorithm (GA) (Y. Tsang et al., 2020), ML-based algorithms (Furian et al., 2021; Salama & Srinivas, 2020; Xiao et al., 2022), and Gurobi solver calling (de Carvalho et al., 2022; Schmidt et al., 2021), because it can be extended easily with new functions and data types.

Commercial solvers For small- or medium-scale problems, a commercial solver can generate an optimal or near-optimal exact solution within a reasonable computation time. The literature shows that the Gurobi is preferred to find the portfolio of the cybersecurity mitigations in SC (Sawik, 2022; Schmidt et al., 2021), while the CPLEX works at all three SC decision levels. In contrast, LINGO was only applied to solve the ILP-based models (Mishra & Singh, 2022; Rajput & Singh, 2022) and NLP-based models (Pitakaso et al., 2022; Prajapati et al., 2022). Although some optimization solvers, such as CPLEX and Gurobi, are capable of dealing with the integer quadratic programming model, they have been observed only in one study by Karatas and Kutanoglu (2020).

Remarkably, most commercial solvers are directly exploited for ILP-based models. Only a few studies have deployed commercial solvers to deal with NLP-based models after linearization, for instance, stochastic models (Mishra & Singh, 2022; Sawik, 2022). To avoid nonlinearity in the objective function, new variables and constraints were introduced by

Bhosekar and Ierapetritou (2021) and Sawik and Sawik (2022). For the nonlinear terms in the constraints, the binary equivalents and first-order Taylor series approximation were used by Mishra and Singh (2022) and Sawik (2022), respectively. However, the linearization of LP-base models relies on the nature of the objective and constraint expressions, as well as the structure of the optimization problem. As a vital step to use commercial solvers to solve the NLP-based models, linearization approaches need to be investigated in future studies.

Heuristic algorithms For large-scale and complex problems, we cannot expect to obtain the optimal solution within a limited CPU time. Therefore, the authors have exploited heuristic algorithms like GA (Ali et al., 2021; V. K. Manupati et al., 2022; Y. Yang et al., 2019), particle swarm algorithm (PSO)(R. S. Kumar et al., 2016; H. Lee et al., 2018), and physarum-based algorithm (Z. Cai et al., 2022; X. Zhang et al., 2017), to derive reasonably good solutions. Since the heuristic algorithms are diverse and evolving, they should be selected and adapted based on the characteristics of the models. Different heuristic algorithms can be used separately or in combination to exploit their search strengths in solution generation.

GA is one of the most adaptive heuristic algorithms and is preferred by the authors to solve mathematical models individually. Y. Tsang et al., (2020) developed a two-phase multi-objective GA to solve a fuzzy-based programming model where the dynamic delivery schedules are optimized. Using a cluster-based association for purchase pattern mining, C. Lee (2017) modified the GA to optimize anticipatory shipping plans. The neuro-fuzzy C-means clustering method was adopted by Gumte et al., (2021) to convert a large problem to a small one to more efficiently solve the input data of the MILP roust model by the GA. The GA-based approach is adopted by V. K. Manupati et al., (2022) to derive the optimal recovery strategies for a disrupted SC network.

PSO-based hybrid heuristic algorithms have been used in recent studies to solve complex large-scale problems. Hajipour et al., (2019) combined the PSO algorithm and the greedy randomized adaptive search procedure to solve an NLP-based model. The PSO algorithm is integrated with the ANN by R. Kuo et al., (2015) to allocate the order quantity. Initialed by heuristics procedures, the Krylov–Chernousko method of successive approximation approach was exploited by Ivanov et al., (2016) to optimize short-term scheduling in smart SC. The robustness of a logistics network design is analyzed by Z. Cai et al., (2022) with the help of the artificial physarum swarm algorithm. Zahedi et al., (2021) compared the performances of different combinations of the simulated annealing (SA) algorithm, PSO, and social engineering optimization (SEO). Their analysis shows that the hybrid SA and SEO outperforms others in solving a MINLP model in relief SC design. However, studies evaluating the efficiency and effectiveness of individual or hybrid heuristics are scarce and should be explored more explicitly in the future.

Machine learning-based algorithms ML has been recognized as a computational counterpart to decision-makers in identifying patterns based on experience (Furian et al., 2021). Although both supervised and unsupervised learning algorithms are leveraged, they are unable to directly construct solutions for mathematical models and are often integrated with other algorithms, such as heuristic algorithms (Abbasi et al., 2020; Chobar et al., 2022), branch and price algorithms (Furian et al., 2021), and the cutting plane algorithm (Flores & Villalobos, 2020).

Some authors have employed the reinforcement learning (RL) technique to develop an end-to-end solution to the VRP problems with real-time data. To reduce the CPU time to build the solutions, a deep RL algorithm was used by J. J. Q. Yu et al., (2019) to tailor the parameters of an offline neural network model. The RL with a function approximation was utilized by Kang et al., (2019) to determine the admission of new order requests and dynamic routes of vehicles. The ANN, random forest, classification, and regression tree (CART), and multilayer perceptron (MLP) techniques were adopted by Abbasi et al., (2020) to disclose the relations between the input parameters and decision variables in a stochastic model. Their analysis shows that the MLP model outperforms the other ML techniques in terms of the efficiency of obtaining the optimum order quantities in the blood SC. L. Ren et al., (2022) developed a multi-agent RL approach to optimize the route length and the vehicle's arrival time for VRP problems. In order to extract scalable heuristics from the best feasible solutions, Jun and Lee (2022) proposed an ML-based approach to improve the heuristics by an evolutionary neural network for pickup-and-delivery problems.

The ML-based algorithms have contributed to the generation of programming-based mathematical solutions by integrating them with various heuristics. The k-means clustering has been adopted to derive high-quality initial solutions by decomposing the space into smaller zones in the VRP (Euchi et al., 2020; Salama & Srinivas, 2020). To govern the evolutionary process in the decision tree, the non-Darwinian-type operators were introduced by Moradi (2020). Their analysis shows that the multi-objective discreet learnable evolution model with the new heuristic operators outperforms classical and meta-heuristics. The MLP classifier was embedded by Gutierrez-Rodríguez et al., (2019) to select the best meta-heuristic for the VRP with time windows. Similarly, as the high-level selection strategy, the RL was adopted by Qin et al., (2021) to select meta-heuristics at the low level. Five supervised learning algorithms, including CART, Gaussian Naive Bayes, and SVM, were applied by Dauer and de Athayde Prata (2021) to reduce the size of the time–space network in variable fixing heuristics by predicting the arcs that a vehicle will be allocated to in multiple depot VRP problems. A learning enhanced golden ball algorithm was used by Worawattawechai et al., (2022) for VRP problems with backhauls.

Random forest classifiers were used by Furian et al., (2021) to predict the values of the binary decision variables and branching scores for fractional variables in a reliability-based branching algorithm. The SVM was adopted and coupled with the cutting plane algorithm by Flores and Villalobos (2020) to identify the relationship between first-stage solutions and yield scenarios in the second stage of the agricultural SC design.

6 Frontiers and research needed for SC optimization in I4.0

6.1 Research frontiers by mapping the new modeling components

The recent advance in the OR methods for SC optimization in I4.0 can be summarized as four new modeling components: new modeling conditions, new inputs of models, new decisions, and new algorithms for model solving, as mapped graphically and numerically in Fig. 8. The four components connect I4.0 technologies and OR modeling approaches at all SC optimization levels. The main streams of the literature and under-examined areas are analyzed in the following subsections.

6.1.1 New modeling conditions

Almost one-third of the articles have treated I4.0 as the modeling condition, for instance, one of the main streams of literature starts from the blockchain and covers GT models at the strategic level (See Fig. 8). These studies assume that the utilization of blockchain would

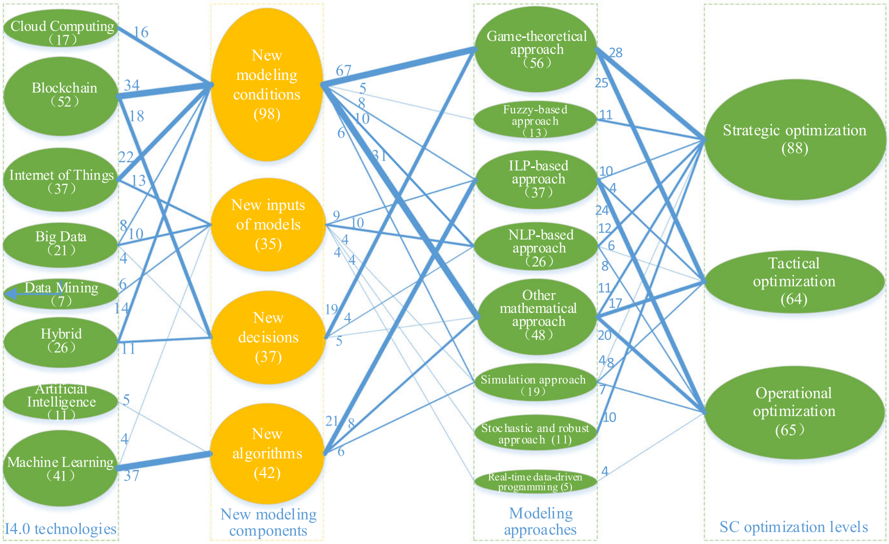

Fig. 8 Research frontiers by mapping the new modeling components

build a new data-sharing SC where the competition or cooperation of the firms would be impacted by the quality monitoring (Chang et al., 2021; He et al., 2021; Shen et al., 2022) or cost tracking (Vijaya K Manupati et al., 2020), but failed to address the process of achieving data sharing using blockchain. Similar observations were also observed in other studies in the context of IoT, BD, AI, or CC.

6.1.2 New inputs

Figure 8 shows the main literature streams related to the new inputs that comprise the IoT, BD, and DM, and serve various OR models except those with GT approaches. The I4.0 reforms the inputs of the OR models by introducing the real-time data, BD, and the shared data as well as preprocessing those data to adapt to the mathematical methods.

The real-time updating inputs enabled by IoT require the OR models to run dynamically to obtain time-dependent solutions. Unfortunately, real-time data are used for periodic decision-making (Ekren et al., 2021; Yang et al., 2019; Zahedi et al., 2021), rather than for data-driven decision-making processes in literature.

BD is well known for its 3 V or 5 V features. However, only a few studies have elaborated on the adaption of parameters with 3 V or 5 V characteristics. Most of the reviewed articles claimed to have conducted the study in a BD environment or considered big data parameters without addressing these significant features. Fast-growing digitalization provides massive amounts of random data that can be used for SC optimization. However, most of the data are unstructured or semi-structured. Despite the widespread acceptance of BD analytics as a knowledge extraction technique, its implementation is still scarce in SC optimization.

6.1.3 New decisions

The adoption of I4.0 is expensive and requires an initial investment and incurs variable costs, such as the blockchain (Chang et al., 2021; De Giovanni, 2020; Y. Song et al., 2022a, 2022b) and BD (Liu & Yi, 2017; Liu & Zhang, 2022). Only a few studies have evaluated firms' decisions to invest in data technologies.

In addition to the direct investment of I4.0, exploiting these techniques can lead to other new decision-making problems, such as cybersecurity mitigations (Sawik & Sawik, 2022), blockchain-enabled data-sharing strategies (Z. Wang et al., 2021; M. Xu et al., 2022), and data technology provider selection (Bai et al., 2021; Coppolino et al., 2021). More recent papers have focused on optimizing investments in I4.0 and cybersecurity. However, the integration of the two decisions in SC optimization is still under-examined.

6.1.4 New algorithms

Organizations have rich experience in daily practices in SC. The knowledge in the historical data can be extracted by DM, ML, or AI to serve as a basis for initially achieving optimal/near-optimal solutions (W. Chen et al., 2013). Moreover, the solution generation procedures of many algorithms, for example, heuristic algorithms, are also data generation processes that can be guided by these data analytical techniques. However, only limited articles have exploited these techniques in solution generation.

The ML-based algorithms are competitive in terms of computation time, convergence rate, and solution quality. However, most of the ML-based algorithms are problem-specific and substantially focused on ILP-based models, and more innovations are needed to solve the sophisticated models, for instance, the stochastic MINLP model (Flores & Villalobos, 2020). As an emerging and evolving algorithm, ML-based algorithms are not perfect and exhibit a few shortcomings, such as the risk of missing the optimal solution (Flores & Villalobos, 2020) and the dependence on the knowledge of the domain (Moradi, 2020). Furthermore, it is worthwhile to compare the performance of the hybrid algorithms with the exact approaches, heuristic methods, or individual ML algorithms.

6.2 Future research agenda

6.2.1 Incorporating new decisions relevant to data-enabled SC optimization

Joint decisions: The development of the data collection and value extraction capability of an organization requires long-term investment in hardware, software, and technicians. Simultaneously, the benefits brought by I4.0 are manifold, rather than limited to SC integration (T.-C. Kuo et al., 2021; J. Sun et al., 2020) or any other individual aspect. Thus, future research should evaluate the investment in I4.0 along the multi-tier SC in terms of costs, benefits, and cyber risk.

*Decisions related to data center*s Data centers offering cloud computing services and data management are a vital part of an SC network (Ali et al., 2021). More effort is required to address the process configuration, data backup scheduling, and network design in this area.

Service vendor selection The evaluations of professional service providers and cloud service vendor platforms for data utilization, such as cloud service vendor platforms and professional service providers for AI and BD analytics, are still absent and should be explored in the future.

Risk management The global SC is under severe strain not only owing to COVID-19, military conflicts between Russia and Ukraine, and their secondary disruption but also due to direct and indirect cyber-related attacks. It is difficult to decouple the physical flow from cyber flow (Shi et al., 2021). The scientific community should assist the decision-makers in identifying and evaluating the risks and optimizing the preparations in the global SC.

Decentralized scheduling One of the main shortcomings of centralized and hierarchical scheduling is its complementary response to disturbances (Y. Liu et al., 2019a, 2019b; J. Sun et al., 2020). Future research can examine decentralized scheduling to realize flexible and real-time decision-making in smart SC.

Spare parts SC with 3D printing Additive manufacturing has shown great potential in spare parts offering because constructing a new manufacturing facility with 3D printers is much more efficient than adding conventional production lines (Muhammad et al., 2022; Tosello et al., 2019). Thus, the dynamic optimization of the spare part inventory and the associated SC configurations can be further studied.

6.2.2 Developing data-enabled modeling approaches

Modeling automation The adoption of I4.0 technologies creates fragmented SC optimization scenarios with specific settings, as the organizations are required to construct customized models. To save the resources (money, machines, energy) of the SC optimization and shorten the customization process, more efforts are needed to acclimate the general OR modeling approaches, for example, MILP, to fit customized operational requirements by learning the rules of mathematical representations to support the automatic decision making in SC. The scholars are encouraged to achieve the OR Modeling automation by taking advantage of the Large Language Models, like the Chat Generative Pre-trained Transformer (ChatGPT) model and the Pathways Language Model (PaLM) model.

Self-tuning models Future OR models should be capable of coping with the dynamics by learning from the BD and the real-time data in the background. The self-tuning capability allows the models to reconstruct quantitative relations between the variables and parameters in objectives and constraints to adapt to the changing decision-making environment, for example, moving from single objective to multi-objective optimization.

Real-time data-driven programming One of the main challenges of SC optimization in I4.0 is building and leveraging dynamic interactions between customers, robots, and systems with real-time data-driven processes. It is necessary to continuously run the model to generate real-time decisions by updating input data (Speranza, 2018). The RDP technique needs to be extended and implemented not only in the VRP problem but also in other SC decision-making scenarios, such as scheduling.

Modeling uncertainties The I4.0 technologies are useful in reducing uncertainties, but they cannot be eliminated, especially at the strategic and tactical SC levels. Future studies should concentrate on robust and stochastic approaches when making new decisions, such as data center network design.

Data-related service vendors Professional data-related service vendors, such as the CC platform (Coppolino et al., 2021) and blockchain platform (Y. Cao et al., 2022), have become the pivotal players of the SC. The GT models can be extended by incorporating the dynamic behaviors of data-related service vendors into games in the analysis.

6.2.3 Preprocessing of parameters

Adapting the parameters of big data The classical OR methods have shown weaknesses in dealing with 3 V or 5 V big data, in terms of computational time and solution generation (Gholizadeh et al., 2020; Kaur & Singh, 2018). In future studies, it is essential to convert the huge and unstructured information into a small volume and refined but high-value dataset by BD analytics, like ML and DM, so that it can be adapted to the OR methods to better support SC optimization.

Uncertainty alleviation and elimination Constrained by the availability of the inputs, many previous studies have been built on delicate assumptions, such as estimating customer demands with optimistic and pessimistic outlooks. The data-rich environment creates an opportunity to eliminate or alleviate the uncertainties in SC optimization, such as customer demand (Liu & Yi, 2018b; Peng et al., 2022). It is imperative to utilize data analytical techniques to alleviate and eliminate the uncertainties of parameters of the OR models by predicting their precise changes.

6.2.4 Developing data-enabled algorithms

Self-adaptive and evolutionary algorithms I4.0 allows decision-makers to construct more realistic models, which also complicates their solution generation. The scientific community should develop self-adaptive and evolutionary algorithms by integrating ML, AI, and DM techniques into the meta- and hyper-heuristics.

Learning-based heuristics Future studies should explore both online and offline learning processes to obtain near-optimal solutions from historical data and ongoing data. To improve the efficiency and the effectiveness of the traditional heuristic algorithms, it is advisable to be integrated with ML by guiding the parameters selection of the heuristics, for example, the mutation and crossover rates in GA, and by developing the operators, for example, neighborhood search strategies.

Hybrid exact algorithms The combination of the data analytical techniques and the exact algorithms, such as the branch-and-price, branch-and-bound, and column generation algorithms, is another worthy research direction.

7 Conclusions

7.1 Main contributions

The contribution of this investigation is trifold: methodological, theoretical, and practical. For the methodological contribution, our proposed SLR methodology integrated with the content analysis as well as the literature evaluation framework are scalable and adaptable, which means it can be tailored for future review research concerning the multi-discipline, multi-topic, and multi-method article collections. In addition, the graphical and numerical mapping approach for the new modeling components provides a way to quantify the innovations and the complicated relations among various elements when deconstructing high-quality articles.

From theoretical perspective, it contributes to the literature by identifying the four OR innovations to typify the recent advances in SC optimization: new modeling conditions, new inputs, new decisions, and new algorithms. OR professionals have long been at the forefront of solving SC problems by using mathematical models. The four new modeling components are supposed to serve as a foundation for building new OR methods. Furthermore, four potential future research avenues are recommended for SC optimization in I4.0: (1) incorporating new decisions relevant to data-enabled SC optimization, both in I4.0 adoption and SC decision aspects; (2) developing data-enabled modeling approaches, such as modeling automation, self-tuning models, and RDP models; (3) preprocessing of parameters, including adapting the parameters of big data and uncertainty elimination and alleviation; and (4) developing data-enabled algorithms, such as self-adaptive and evolutionary algorithms, learning-based heuristics, and hybrid exact algorithms. The set of directions elaborated in the thematic analysis is a starting point to guide the development of upcoming research works and provide directions for further literature reviews to be produced.

From practical perspective, this study contributes to a better understanding of the role of OR approaches for SC practitioners who are struggling to find new solution approaches for business success in their own domains. The description of the new operations models and the rich context in which the models are adapted will guide practitioners to select appropriate OR methods to incorporate a variety of decision-making dimensions at different SC levels. The identification of the exciting opportunities that fuse and cross the boundaries of SC and I4.0 paves the way for managers to achieve a decisive competitive advantage by developing more realistic models.

7.2 Concluding remarks

The growing implementation of I4.0 equips the SC as a data-driven system to deliver products and services in a more accessible and affordable manner. It is believed that I4.0 will revolutionize the SC management. The potential benefits of integrating I4.0 and OR methods have been widely reported by both academics and practitioners. However, due to the fragmentation of the results and the lack of a review perspective on OR methodologies, a clear and systemic analysis of the SC optimization in I4.0 is still missing. In this study, the existing literature was systematically reviewed to survey the recent advances in SC optimization in I4.0. More than 14,000 articles were refined and 212 were examined, classified, and analyzed in terms of the: (1) role of I4.0 technologies, (2) SC decisions, (3) modeling approaches, and (4) solution methodologies. The research frontiers, gaps, and promising future perspectives in different domains of SC optimization in I4.0 are presented.

It is observed that AI, blockchain, ML, and IoT are the most addressed I4.0 technologies in current studies. The OR methods have been implemented innovatively in four aspects for SC optimization in I4.0. GT methods are the most popular, whereas robust and stochastic methods are still under investigation. A new modeling form, the RDP model, was identified and elaborated in this analysis. Future research should take advantage of the big data and real-time data offered by I4.0 to enhance the performance of the SC. The deep analysis of the OR methods and the rich I4.0 context would provide valuable insights to the academic community and industry in exploiting the value of the data generated along the SC. Scholars can take this investigation as a means to ignite collaborative research that tackles the emerging problems in business, whereas practitioners can glean a better understanding of how to employ their OR experts to support digital SC decision-making.

Although the methodology adopted was carefully structured, this study has several limitations that we outline here. The findings of this review are applicable based on the limitations of the data sources, which is the core database of WOS. The combinations of the few keywords are used to collect published papers, which may lead to missing of some publications due to the choice of the keywords. In addition, the analysis of the selected papers is based on our interpretation and thus dependent upon our perceptions and categorizations of the collected documents.

Funding Open Access funding provided by the Qatar National Library. This work was supported by the Key Project of Philosophy and Social Sciences Research in Jiangsu Universities (Grant No. 2023SJZD127), and the Fundamental Research Funds for the Central Universities (Grant No. ND2023006).

Data availability The data that support the findings of this study are available from the corresponding author Dr. Adel Elomri and the first author Dr. Zhitao Xu, upon reasonable request.

Declarations

Conflict of interest The author declares that have no conflict of interest.

Appendix 1. Abbreviation

No.	Abbreviation	Description
1	AHP	Analytic hierarchy process
2	AI	Artificial intelligence
3	ANN	Artificial neural network
4	BD	Big data
5	CART	Classification and regression tree
6	CPS	Cyber-physical systems
7	DE	Discrete-event
8	DM	Data mining
9	GA	Genetic algorithm
10	GT	Game theory
11	I4.0	Industrial 4.0
29	ILP	Integer linear programming
14	IoT	Internet of Things
15	LP	Linear programming
16	MILP	Mixed integer linear programming

No.	Abbreviation	Description
17	MINLP	Mixed integer nonlinear programming
18	ML	Machine learning
19	MLP	Multilayer perceptron
20	OR	Operation research
21	PSO	Particle swarm algorithm
22	RDP	Real-time data-driven programming
23	RFID	Radio frequency identification
24	RL	Reinforce learning
25	SA	Simulated annealing
26	SC	Supply chain
27	SEO	Social engineering optimization
28	SLR	Systematic literature review
29	SVM	Support vector machines
30	VRP	Vehicle routing problem
31	WOS	Web of science

Appendix 2. Journals categorization of the articles

No.	Journals	Number of articles
1	International Journal of Production Research	30
2	Computers & Industrial Engineering	24
3	Annals of Operations Research	22
4	International Journal of Production Economics	16
5	Transportation Research Part E: Logistics and Transportation Review	12
6	Journal of Cleaner Production	9
7	European Journal of Operational Research	8
8	Sustainability	7
9	Computers & Operations Research	6
10	IEEE Transactions on Intelligent Transportation Systems	5

No.	Journals	Number of articles
11	Production and Operations Management	5
12	Applied Soft Computing	4
13	Expert Systems with Applications	4
14	Soft Computing	4
15	Transportation Research Part C: Emerging Technologies	4
16	IEEE Transactions on Engineering Management	3
17	Industrial Management & Data Systems	3
18	International Journal of Logistics Research and Applications	3
19	Journal of Manufacturing Systems	3
20	Applied Mathematical Modelling	2
21	Computers & Chemical Engineering	2
22	Discrete Dynamics in Nature and Society	2
23	Manufacturing & Service Operations Management	2
24	OR Spectrum	2
25	Reliability Engineering & System Safety	2
26	Applied Mathematics and Computation	1
27	Arabian journal for science and engineering	1
28	Computers in Industry	1
29	Decision Sciences	1
30	Engineering Applications of Artificial Intelligence	1
31	EURO Journal on Transportation and Logistics	1
32	IEEE Transactions on Industrial Informatics	1
33	IISE Transactions	1
34	Information Sciences	1
35	INFORMS Journal on Computing	1
36	International Journal of Computer Integrated Manufacturing	1
37	Journal of Computational and Applied Mathematics	1
38	Journal of Computing and Information Science in Engineering	1
39	Journal of Industrial and Management Optimization	1
40	Journal of Industrial Information Integration	1
41	Journal of Intelligent Manufacturing	1
42	Kybernetes	1
43	Mathematics	1

No.	Journals	Number of articles
44	Omega	1
45	Operational Research	1
46	Optimization Letters	1
47	RAIRO-Operations Research	1
48	Resources, Conservation and Recycling	1
49	Socio-Economic Planning Sciences	1
50	Soft Computing volume	1
51	Technological Forecasting and Social Change	1
52	Technology Analysis & Strategic Management	1
53	Waste Management	1

References

Abbasi, B., Babaei, T., Hosseinifard, Z., Smith-Miles, K., & Dehghani, M. (2020). Predicting solutions of large-scale optimization problems via machine learning: A case study in blood supply chain management. *Computers and Operations Research, 119*, 104941.

Abedinnia, H., Glock, C. H., & Schneider, M. D. (2017). Machine scheduling in production: A content analysis. *Applied Mathematical Modelling, 50*, 279–299.

Aghamohammadzadeh, E., Malek, M., & Valilai, O. F. (2020). A novel model for optimisation of logistics and manufacturing operation service composition in cloud manufacturing system focusing on cloud-entropy. *International Journal of Production Research, 58*(7), 1987–2015.

Agrawal, R., Surendra Yadav, V., Majumdar, A., Kumar, A., Luthra, S., & Arturo Garza-Reyes, J. (2023). Opportunities for disruptive digital technologies to ensure circularity in supply chain: A critical review of drivers, barriers and challenges. *Computers and Industrial Engineering, 178*, 109140.

Ahmadi, S. A., & Ghasemi, P. (2022). Pricing strategies for online hotel searching: A fuzzy inference system procedure. *Kybernetes*. https://doi.org/10.1108/K-03-2022-0427

Ali, S. I., Ali, A., AlKilabi, M., & Christie, M. (2021). Optimal supply chain design with product family: A cloud-based framework with real-time data consideration. *Computers and Operations Research, 126*, 105112.

Alqahtani, M., Scott, M. J., & Hu, M. (2022). Dynamic energy scheduling and routing of a large fleet of electric vehicles using multi-agent reinforcement learning. *Computers and Industrial Engineering, 169*, 108180.

Antônio Rufino Junior, C., Sanseverino, E. R., Gallo, P., Koch, D., Schweiger, H.-G., & Zanin, H. (2022). Blockchain review for battery supply chain monitoring and battery trading. *Renewable and Sustainable Energy Reviews, 157*, 112078.

Arunachalam, D., Kumar, N., & Kawalek, J. P. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges and implications for practice. *Transportation Research Part e: Logistics and Transportation Review, 114*, 416–436.

Bai, C., Zhu, Q., & Sarkis, J. (2021). Joint blockchain service vendor-platform selection using social network relationships: A multi-provider multi-user decision perspective. *International Journal of Production Economics, 238*, 108165.

Barbosa-Póvoa, A. P., da Silva, C., & Carvalho, A. (2018). Opportunities and challenges in sustainable supply chain: An operations research perspective. *European Journal of Operational Research, 268*(2), 399–431.

Belhadi, A., Kamble, S., Wamba, S. F., & Queiroz, M. M. (2021). Building supply-chain resilience: An artificial intelligence-based technique and decision-making framework. *International Journal of Production Research, 60*(14), 4487–4507.

Ben-Daya, M., Hassini, E., Bahroun, Z., & Saeed, H. (2022). Optimal pricing in the presence of IoT investment and quality-dependent demand. *Annals of Operations Research, 324*(1), 869–892.

Bhosekar, A., & Ierapetritou, M. (2021). A framework for supply chain optimization for modular manufacturing with production feasibility analysis. *Computers and Chemical Engineering, 145*, 107175.

Cai, Y.-J., Choi, T.-M., & Zhang, J. (2020). Platform supported supply chain operations in the blockchain era: Supply contracting and moral hazards. *Decision Sciences, 52*(4), 866–892.

Cai, Z., Yang, Y., Zhang, X., & Zhou, Y. (2022). Design a robust logistics network with an artificial physarum swarm algorithm. *Sustainability, 14*(22), 14930.

Cao, X., Li, T., & Wang, Q. (2019). RFID-based multi-attribute logistics information processing and anomaly mining in production logistics. *International Journal of Production Research, 57*(17), 5453–5466.

Cao, Y., Yi, C., Wan, G., Hu, H., Li, Q., & Wang, S. (2022). An analysis on the role of blockchain-based platforms in agricultural supply chains. *Transportation Research Part e: Logistics and Transportation Review, 163*, 102731.

Chang, J. A., Katehakis, M. N., Shi, J. J., & Yan, Z. (2021). Blockchain-empowered Newsvendor optimization. *International Journal of Production Economics, 238*, 108144.

Chen, L.-M., & Chang, W.-L. (2021). Supply- and cyber-related disruptions in cloud supply chain firms: Determining the best recovery speeds. *Transportation Research Part e: Logistics and Transportation Review, 151*, 102347.

Chen, W., Song, J., Shi, L., Pi, L., & Sun, P. (2013). Data mining-based dispatching system for solving the local pickup and delivery problem. *Annals of Operations Research, 203*(1), 351–370.

Chen, X., Ulmer, M. W., & Thomas, B. W. (2022). Deep Q-learning for same-day delivery with vehicles and drones. *European Journal of Operational Research, 298*(3), 939–952.

Chen, Z., Ming, X., Zhou, T., & Chang, Y. (2020). Sustainable supplier selection for smart supply chain considering internal and external uncertainty: An integrated rough-fuzzy approach. *Applied Soft Computing, 87*, 106004.

Cheung, K.-F., & Bell, M. G. H. (2021). Attacker–defender model against quantal response adversaries for cyber security in logistics management: An introductory study. *European Journal of Operational Research, 291*(2), 471–481.

Chobar, A. P., Adibi, M. A. & Kazemi, A. (2022). Multi-objective hub-spoke network design of perishable tourism products using combination machine learning and meta-heuristic algorithms. Environment, Development and Sustainability, published Online.

Choi, T. M. (2023). Supply chain financing using blockchain: Impacts on supply chains selling fashionable products. *Annals of Operations Research, 331*(1), 393–415.

Choi, T.-M., Guo, S., Liu, N., & Shi, X. (2020). Optimal pricing in on-demand-service-platform-operations with hired agents and risk-sensitive customers in the blockchain era. *European Journal of Operational Research, 284*(3), 1031–1042.

Coppolino, L., Romano, L., Scaletti, A., & Sgaglione, L. (2021). Fuzzy set theory-based comparative evaluation of cloud service offerings: An agro-food supply chain case study. *Technology Analysis and Strategic Management, 33*(8), 900–913.

Dalenogare, L.S., Benitez, G.B., Ayala, N.F. & Frank, A.G. (2018). The expected contribution of Industry 4.0 technologies for industrial performance. *International Journal of Production Economics, 204*, 383–394.

Dauer, A. T., & de Athayde Prata, B. (2021). Variable fixing heuristics for solving multiple depot vehicle scheduling problem with heterogeneous fleet and time windows. *Optimization Letters, 15*(1), 153–170.

de Carvalho, P. R. V., Naoum-Sawaya, J., & Elhedhli, S. (2022). Blockchain-enabled supply chains: An application in fresh-cut flowers. *Applied Mathematical Modelling, 110*, 841–858.

De Giovanni, P. (2020). Blockchain and smart contracts in supply chain management: A game theoretic model. *International Journal of Production Economics, 228*, 107855.

Deiva Ganesh, A., & Kalpana, P. (2022). Future of artificial intelligence and its influence on supply chain risk management: A systematic review. *Computers and Industrial Engineering, 169*, 108206.

Dev, N. K., Shankar, R., Gunasekaran, A., & Thakur, L. S. (2016). A hybrid adaptive decision system for supply chain reconfiguration. *International Journal of Production Research, 54*(23), 7100–7114.

Diaz-Balteiro, L., González-Pachón, J., & Romero, C. (2017). Measuring systems sustainability with multi-criteria methods: A critical review. *European Journal of Operational Research, 258*(2), 607–616.

Duan, C., Xiu, G., & Yao, F. (2019). Multi-period E-closed-loop supply chain network considering consumers' preference for products and ai-push. *Sustainability, 11*(7), 4571.

Ekren, B. Y., Mangla, S. K., Turhanlar, E. E., Kazancoglu, Y., & Li, G. (2021). Lateral inventory share-based models for IoT-enabled E-commerce sustainable food supply networks. *Computers and Operations Research, 130*, 105237.

Euchi, J., Zidi, S., & Laouamer, L. (2020). A hybrid approach to solve the vehicle routing problem with time windows and synchronized visits in-home health care. *Arabian Journal for Science and Engineering, 45*(12), 10637–10652.

Fan, Z.-P., Wu, X.-Y., & Cao, B.-B. (2022). Considering the traceability awareness of consumers: Should the supply chain adopt the blockchain technology? *Annals of Operations Research, 309*(2), 837–860.

Feng, L., Huang, Y., Tsang, I. W., Gupta, A., Tang, K., Tan, K. C., & Ong, Y.-S. (2022). Towards faster vehicle routing by transferring knowledge from customer representation. *IEEE Transactions on Intelligent Transportation Systems, 23*(2), 952–965.

Flores, H., & Villalobos, J. R. (2020). A stochastic planning framework for the discovery of complementary, agricultural systems. *European Journal of Operational Research, 280*(2), 707–729.

Furian, N., O'Sullivan, M., Walker, C., & Çela, E. (2021). A machine learning-based branch and price algorithm for a sampled vehicle routing problem. *Or Spectrum, 43*(3), 693–732.

Gambella, C., Ghaddar, B., & Naoum-Sawaya, J. (2021). Optimization problems for machine learning: A survey. *European Journal of Operational Research, 290*(3), 807–828.

Ghiani, G., Manni, A., & Manni, E. (2022). A scalable anticipatory policy for the dynamic pickup and delivery problem. *Computers and Operations Research, 147*, 105943.

Gholizadeh, H., Fazlollahtabar, H., & Khalilzadeh, M. (2020). A robust fuzzy stochastic programming for sustainable procurement and logistics under hybrid uncertainty using big data. *Journal of Cleaner Production, 258*, 120640.

Gopalakrishnan, P. K., Hall, J., & Behdad, S. (2021). Cost analysis and optimization of Blockchain-based solid waste management traceability system. *Waste Management, 120*, 594–607.

Gumte, K., Pantula, P. D., Miriyala, S. S., & Mitra, K. (2021). Achieving wealth from bio-waste in a nationwide supply chain setup under uncertain environment through data driven robust optimization approach. *Journal of Cleaner Production, 291*, 125702.

Gupta, S., Modgil, S., Bhattacharyya, S., & Bose, I. (2022a). Artificial intelligence for decision support systems in the field of operations research: Review and future scope of research. *Annals of Operations Research, 308*(1), 215–274.

Gutierrez-Rodríguez, A. E., Conant-Pablos, S. E., Ortiz-Bayliss, J. C., & Terashima-Marín, H. (2019). Selecting meta-heuristics for solving vehicle routing problems with time windows via meta-learning. *Expert Systems with Applications, 118*, 470–481.

Hajipour, V., Niaki, S. T. A., Akhgar, M., & Ansari, M. (2021). The healthcare supply chain network design with traceability: A novel algorithm. *Computers and Industrial Engineering, 161*, 107661.

Hajipour, V., Tavana, M., Di Caprio, D., Akhgar, M., & Jabbari, Y. (2019). An optimization model for traceable closed-loop supply chain networks. *Applied Mathematical Modelling, 71*, 673–699.

Han, Y., & Fang, X. (2023). Systematic review of adopting blockchain in supply chain management: Bibliometric analysis and theme discussion. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2236241

Hazen, B. T., Skipper, J. B., Boone, C. A., & Hill, R. R. (2018). Back in business: Operations research in support of big data analytics for operations and supply chain management. *Annals of Operations Research, 270*(1–2), 201–211.

He, P., Li, K., & Kumar, P. N. R. (2022). An enhanced branch-and-price algorithm for the integrated production and transportation scheduling problem. *International Journal of Production Research, 60*(6), 1874–1889.

He, Y., Chen, L., & Xu, Q. (2021). Optimal pricing decisions for a global fresh product supply chain in the blockchain technology era. *International Journal of Logistics Research and Applications*. https://doi.org/10.1080/13675567.2021.1981275

Hosseini Dehshiri, S. J., Emamat, M. S. M. M., & Amiri, M. (2022). A novel group BWM approach to evaluate the implementation criteria of blockchain technology in the automotive industry supply chain. *Expert Systems with Applications, 198*, 116826.

Hu, S., Huang, S., & Qin, X. (2022). Exploring blockchain-supported authentication based on online and offline business in organic agricultural supply chain. *Computers and Industrial Engineering, 173*, 108738.

Illgen, S., & Höck, M. (2019). Literature review of the vehicle relocation problem in one-way car sharing networks. *Transportation Research Part b: Methodological, 120*, 193–204.

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research, 57*(3), 829–846.

Ivanov, D., Dolgui, A., & Sokolov, B. (2022). Cloud supply chain: Integrating industry 4.0 and digital platforms in the "supply chain-as-a-service." *Transportation Research Part e: Logistics and Transportation Review, 160*, 102676.

Ivanov, D., Dolgui, A., Sokolov, B., Werner, F., & Ivanova, M. (2016). A dynamic model and an algorithm for short-term supply chain scheduling in the smart factory industry 4.0. *International Journal of Production Research, 54*(2), 386–402.

Jabbour, C. J. C., Fiorini, P. D. C., Ndubisi, N. O., Queiroz, M. M., & Piato, É. L. (2020). Digitally-enabled sustainable supply chains in the 21st century: A review and a research agenda. *Science of the Total Environment, 725*, 138177.

Jahani, H., Jain, R., & Ivanov, D. (2023). Data science and big data analytics: A systematic review of methodologies used in the supply chain and logistics research. *Annals of Operations Research*. https://doi.org/10.1007/s10479-023-05390-7

Jamrus, T., Wang, H.-K., & Chien, C.-F. (2020). Dynamic coordinated scheduling for supply chain under uncertain production time to empower smart production for Industry 3.5. *Computers and Industrial Engineering, 142*, 106375.

Jelen, G., Babic, J., & Podobnik, V. (2022). A multi-agent system for context-aware electric vehicle fleet routing: A step towards more sustainable urban operations. *Journal of Cleaner Production, 374*, 134047.

Jun, S., & Lee, S. (2022). Evolutionary neural network for learning of scalable heuristics for pickup and delivery problems with time windows. *Computers and Industrial Engineering, 169*, 108282.

Kang, Y., Lee, S., & Do Chung, B. (2019). Learning-based logistics planning and scheduling for crowdsourced parcel delivery. *Computers and Industrial Engineering, 132*, 271–279.

Karatas, M., & Kutanoglu, E. (2020). Joint optimization of location, inventory, and condition-based replacement decisions in service parts logistics. *IISE Transactions, 53*(2), 246–271.

Kaur, H., & Singh, S. P. (2018). Heuristic modeling for sustainable procurement and logistics in a supply chain using big data. *Computers and Operations Research, 98*, 301–321.

Kazancoglu, Y., Sagnak, M., Mangla, S. K., Sezer, M. D., & Pala, M. O. (2021). A fuzzy based hybrid decision framework to circularity in dairy supply chains through big data solutions. *Technological Forecasting and Social Change, 170*, 120927.

Kim, D.-Y., & Fortado, B. (2021). Outcomes of supply chain dependence asymmetry: A systematic review of the statistical evidence. *International Journal of Production Research, 59*(19), 5844–5866.

Kochan, C. G., Nowicki, D. R., Sauser, B., & Randall, W. S. (2018). Impact of cloud-based information sharing on hospital supply chain performance: A system dynamics framework. *International Journal of Production Economics, 195*, 168–185.

Koh, L., Orzes, G. & Jia, F. (2019). The fourth industrial revolution (Industry 4.0): technologies disruption on operations and supply chain management. *International Journal of Operations & Production Management, 39*(6/7/8), 817–828.

Kong, X. T. R., Kang, K., Zhong, R. Y., Luo, H., & Xu, S. X. (2021). Cyber physical system-enabled on-demand logistics trading. *International Journal of Production Economics, 233*, 108005.

Kumar, D., Singh, R. K., Mishra, R., & Vlachos, I. (2023). Big data analytics in supply chain decarbonisation: A systematic literature review and future research directions. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2179346

Kumar, R. S., Kondapaneni, K., Dixit, V., Goswami, A., Thakur, L. S., & Tiwari, M. K. (2016). Multi-objective modeling of production and pollution routing problem with time window: A self-learning particle swarm optimization approach. *Computers and Industrial Engineering, 99*, 29–40.

Kumari, S., Venkatesh, V. G., Tan, F. T. C., Bharathi, S. V., Ramasubramanian, M., & Shi, Y. (2023). Application of machine learning and artificial intelligence on agriculture supply chain: A comprehensive review and future research directions. *Annals of Operations Research*. https://doi.org/10.1007/s10479-023-05556-3

Kuo, R., Pai, C., Lin, R., & Chu, H. (2015). The integration of association rule mining and artificial immune network for supplier selection and order quantity allocation. *Applied Mathematics and Computation, 250*, 958–972.

Kuo, T.-C., Chen, K. J., Shiang, W.-J., Huang, P. B., Otieno, W., & Chiu, M.-C. (2021). A collaborative data-driven analytics of material resource management in smart supply chain by using a hybrid Industry 3.5 strategy. *Resources, Conservation and Recycling, 164*, 105160.

Lamba, K., & Singh, S. P. (2017). Big data in operations and supply chain management: Current trends and future perspectives. *Production Planning and Control, 28*(11–12), 877–890.

Lee, C. (2017). A GA-based optimisation model for big data analytics supporting anticipatory shipping in Retail 4.0. *International Journal of Production Research, 55*(2), 593–605.

Lee, H., Aydin, N., Choi, Y., Lekhavat, S., & Irani, Z. (2018). A decision support system for vessel speed decision in maritime logistics using weather archive big data. *Computers and Operations Research, 98*, 330–342.

Li, D., & Wang, X. (2017). Dynamic supply chain decisions based on networked sensor data: An application in the chilled food retail chain. *International Journal of Production Research, 55*(17), 5127–5141.

Li, J. (2019). Optimal design of transportation distance in logistics supply chain model based on data mining algorithm. *Cluster Computing, 22*(2), 3943–3952.

Li, M., & Li, T. (2022). AI automation and retailer regret in supply chains. *Production and Operations Management, 31*(1), 83–97.

Li, Q., Ma, M., Shi, T., & Zhu, C. (2022). Green investment in a sustainable supply chain: The role of blockchain and fairness. *Transportation Research Part e: Logistics and Transportation Review, 167*, 102908.

Li, X. (2020). Reducing channel costs by investing in smart supply chain technologies. *Transportation Research Part e: Logistics and Transportation Review, 137*, 101927.

Li, Y., Jiang, S., Shi, J., & Wei, Y. (2021). Pricing strategies for blockchain payment service under customer heterogeneity. *International Journal of Production Economics, 242*, 108282.

Li, Y., & Xu, L. (2021). Cybersecurity investments in a two-echelon supply chain with third-party risk propagation. *International Journal of Production Research, 59*(4), 1216–1238.

Liao, W., & Wang, T. (2019). A novel collaborative optimization model for job shop production-delivery considering time window and carbon emission. *Sustainability, 11*(10), 2781.

Lim, M. K., Li, Y., Wang, C., & Tseng, M.-L. (2021). A literature review of blockchain technology applications in supply chains: A comprehensive analysis of themes, methodologies and industries. *Computers and Industrial Engineering, 154*, 107133.

Lin, H., Lin, J., & Wang, F. (2022). An innovative machine learning model for supply chain management. *Journal of Innovation and Knowledge, 7*(4), 100276.

Liou, J. J. H., Chang, M.-H., Lo, H.-W., & Hsu, M.-H. (2021). Application of an MCDM model with data mining techniques for green supplier evaluation and selection. *Applied Soft Computing, 109*, 107534.

Liu, J., Chen, W., Yang, J., Xiong, H., & Chen, C. (2022a). Iterative prediction-and-optimization for E-logistics distribution network design. *INFORMS Journal on Computing, 34*(2), 769–789.

Liu, P., & Yi, S.-P. (2017). Pricing policies of green supply chain considering targeted advertising and product green degree in the big data environment. *Journal of Cleaner Production, 164*, 1614–1622.

Liu, P., & Yi, S.-P. (2018a). Investment decision-making and coordination of a three-stage supply chain considering data company in the big data era. *Annals of Operations Research, 270*(1), 255–271.

Liu, P., & Yi, S.-P. (2018b). A study on supply chain investment decision-making and coordination in the big data environment. *Annals of Operations Research, 270*(1), 235–253.

Liu, P., & Zhang, F.-J. (2022). Pricing strategies of dual-channel green supply chain considering big data information inputs. *Soft Computing, 26*(6), 2981–2999.

Liu, S., Zhang, Y., Liu, Y., Wang, L., & Wang, X. V. (2019a). An 'Internet of Things' enabled dynamic optimization method for smart vehicles and logistics tasks. *Journal of Cleaner Production, 215*, 806–820.

Liu, W., Long, S., Wei, S., Xie, D., Wang, J., & Liu, X. (2022b). Smart logistics ecological cooperation with data sharing and platform empowerment: An examination with evolutionary game model. *International Journal of Production Research, 60*(13), 4295–4315.

Liu, W., Long, S., Xie, D., Liang, Y., & Wang, J. (2021). How to govern the big data discriminatory pricing behavior in the platform service supply chain? An examination with a three-party evolutionary game model. *International Journal of Production Economics, 231*, 107910.

Liu, Y., Wang, L., Wang, X. V., Xu, X., & Zhang, L. (2019b). Scheduling in cloud manufacturing: State-of-the-art and research challenges. *International Journal of Production Research, 57*(15–16), 4854–4879.

Lohmer, J., Bugert, N., & Lasch, R. (2020). Analysis of resilience strategies and ripple effect in blockchain-coordinated supply chains: An agent-based simulation study. *International Journal of Production Economics, 228*, 107882.

Ma, D., & Hu, J. (2022). The optimal combination between blockchain and sales format in an internet platform-based closed-loop supply chain. *International Journal of Production Economics, 254*, 108633.

Ma, D., Hu, J., & Yao, F. (2021). Big data empowering low-carbon smart tourism study on low-carbon tourism O_2O supply chain considering consumer behaviors and corporate altruistic preferences. *Computers and Industrial Engineering, 153*, 107061.

Maity, M., Tolooie, A., Sinha, A. K., & Tiwari, M. K. (2021). Stochastic batch dispersion model to optimize traceability and enhance transparency using Blockchain. *Computers and Industrial Engineering, 154*, 107134.

Manupati, V. K., Schoenherr, T., Ramkumar, M., Panigrahi, S., Sharma, Y., & Mishra, P. (2022). Recovery strategies for a disrupted supply chain network: Leveraging blockchain technology in pre- and post-disruption scenarios. *International Journal of Production Economics, 245*, 108389.

Manupati, V. K., Schoenherr, T., Ramkumar, M., Wagner, S. M., Pabba, S. K., & Singh, I. R. (2020). A blockchain-based approach for a multi-echelon sustainable supply chain. *International Journal of Production Research, 58*(7), 2222–2241.

Medina-González, S., Shokry, A., Silvente, J., Lupera, G., & Espuña, A. (2020). Optimal management of bio-based energy supply chains under parametric uncertainty through a data-driven decision-support framework. *Computers and Industrial Engineering, 139*, 105561.

Mejjaouli, S., & Babiceanu, R. F. (2015). RFID-wireless sensor networks integration: Decision models and optimization of logistics systems operations. *Journal of Manufacturing Systems, 35*, 234–245.

Mejjaouli, S., & Babiceanu, R. F. (2018). Cold supply chain logistics: System optimization for real-time rerouting transportation solutions. *Computers in Industry, 95*, 68–80.
Mishra, S., & Singh, S. P. (2022). A stochastic disaster-resilient and sustainable reverse logistics model in big data environment. *Annals of Operations Research, 319*(1), 853–884.
Moradi, B. (2020). The new optimization algorithm for the vehicle routing problem with time windows using multi-objective discrete learnable evolution model. *Soft Computing, 24*(9), 6741–6769.
Muhammad, M. S., Kerbache, L., & Elomri, A. (2022). Potential of additive manufacturing for upstream automotive supply chains. *Supply Chain Forum: An International Journal, 23*(1), 1–19.
Nativi, J. J., & Lee, S. (2012). Impact of RFID information-sharing strategies on a decentralized supply chain with reverse logistics operations. *International Journal of Production Economics, 136*(2), 366–377.
Nayernia, H., Bahemia, H., & Papagiannidis, S. (2022). A systematic review of the implementation of industry 4.0 from the organisational perspective. *International Journal of Production Research, 60*(14), 4365–4396.
Nguyen, D. T., Adulyasak, Y., Cordeau, J.-F., & Ponce, S. I. (2022a). Data-driven operations and supply chain management: Established research clusters from 2000 to early 2020. *International Journal of Production Research, 60*(17), 5407–5431.
Nguyen, T., Duong, Q. H., Nguyen, T. V., Zhu, Y., & Zhou, L. (2022b). Knowledge mapping of digital twin and physical internet in supply chain management: A systematic literature review. *International Journal of Production Economics, 244*, 108381.
Niu, B., Dong, J., & Liu, Y. (2021a). Incentive alignment for blockchain adoption in medicine supply chains. *Transportation Research Part e: Logistics and Transportation Review, 152*, 102276.
Niu, B., Mu, Z., Cao, B., & Gao, J. (2021b). Should multinational firms implement blockchain to provide quality verification? *Transportation Research Part e: Logistics and Transportation Review, 145*, 102121.
Niu, B., Xu, H., & Chen, L. (2022). Creating all-win by blockchain in a remanufacturing supply chain with consumer risk-aversion and quality untrust. *Transportation Research Part e: Logistics and Transportation Review, 163*, 102778.
Olsen, T. L., & Tomlin, B. (2020). Industry 4.0: Opportunities and challenges for operations management. *Manufacturing and Service Operations Management, 22*(1), 113–122.
Peng, J., Chen, L., & Zhang, B. (2022). Transportation planning for sustainable supply chain network using big data technology. *Information Sciences, 609*, 781–798.
Pitakaso, R., Nanthasamroeng, N., Srichok, T., Khonjun, S., Weerayuth, N., Kotmongkol, T., Pornprasert, P., & Pranet, K. (2022). A novel artificial multiple intelligence system (AMIS) for agricultural product transborder logistics network design in the greater mekong subregion (GMS). *Computation, 10*(7), 126.
Polo, A., Peña, N., Muñoz, D., Cañón, A., & Escobar, J. W. (2019). Robust design of a closed-loop supply chain under uncertainty conditions integrating financial criteria. *Omega, 88*, 110–132.
Prajapati, D., Jauhar, S. K., Gunasekaran, A., Kamble, S. S., & Pratap, S. (2022). Blockchain and IoT embedded sustainable virtual closed-loop supply chain in E-commerce towards the circular economy. *Computers and Industrial Engineering, 172*, 108530.
Preil, D., & Krapp, M. (2022). Artificial intelligence-based inventory management: A Monte Carlo tree search approach. *Annals of Operations Research, 308*(1), 415–439.
Qin, W., Zhuang, Z., Huang, Z., & Huang, H. (2021). A novel reinforcement learning-based hyper-heuristic for heterogeneous vehicle routing problem. *Computers and Industrial Engineering, 156*, 107252.
Rahmanzadeh, S., Pishvaee, M. S., & Govindan, K. (2022). Emergence of open supply chain management: The role of open innovation in the future smart industry using digital twin network. *Annals of Operations Research, 329*(1), 979–1007.
Rajput, S., & Singh, S. P. (2022). Industry 4.0 model for integrated circular economy-reverse logistics network. *International Journal of Logistics Research and Applications, 25*(4–5), 837–877.
Ran, W., & Liu, H. (2020). Cloud service selection based on QoS-aware logistics. *Soft Computing, 24*(6), 4323–4332.
Ren, L., Fan, X., Cui, J., Shen, Z., Lv, Y., & Xiong, G. (2022). A multi-agent reinforcement learning method with route recorders for vehicle routing in supply chain management. *IEEE Transactions on Intelligent Transportation Systems, 23*(9), 16410–16420.
Ren, S., Choi, T.-M., Lee, K.-M., & Lin, L. (2020). Intelligent service capacity allocation for cross-border-E-commerce related third-party-forwarding logistics operations: A deep learning approach. *Transportation Research Part e: Logistics and Transportation Review, 134*, 101834.
Riahi, Y., Saikouk, T., Gunasekaran, A., & Badraoui, I. (2021). Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions. *Expert Systems with Applications, 173*, 114702.

Risso, L. A., Ganga, G. M. D., Godinho Filho, M., Santa-Eulalia, L. A. D., Chikhi, T., & Mosconi, E. (2023). Present and future perspectives of blockchain in supply chain management: A review of reviews and research agenda. *Computers and Industrial Engineering, 179*, 109195.

Sahoo, S., Kumar, A., Mishra, R., & Tripathi, P. (2022). Strengthening supply chain visibility with blockchain: A PRISMA-based review. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2022.3206109

Salama, M., & Srinivas, S. (2020). Joint optimization of customer location clustering and drone-based routing for last-mile deliveries. *Transportation Research Part c: Emerging Technologies, 114*, 620–642.

Sawik, T. (2020). A linear model for optimal cybersecurity investment in industry 4.0 supply chains. *International Journal of Production Research, 60*(4), 1368–1385.

Sawik, T. (2022). Balancing cybersecurity in a supply chain under direct and indirect cyber risks. *International Journal of Production Research, 60*(2), 766–782.

Sawik, T., & Sawik, B. (2022). A rough cut cybersecurity investment using portfolio of security controls with maximum cybersecurity value. *International Journal of Production Research, 60*(21), 6556–6572.

Schmidt, A., Albert, L. A., & Zheng, K. (2021). Risk management for cyber-infrastructure protection: A bi-objective integer programming approach. *Reliability Engineering and System Safety, 205*, 107093.

Seyedghorban, Z., Tahernejad, H., Meriton, R., & Graham, G. (2020). Supply chain digitalization: Past, present and future. *Production Planning and Control, 31*(2–3), 96–114.

Shen, B., Cheng, M., Dong, C., & Xiao, Y. (2021). Battling counterfeit masks during the COVID-19 outbreak: Quality inspection vs. blockchain adoption. *International Journal of Production Research, 60*(4), 1368–1385.

Shen, B., Dong, C., & Minner, S. (2022). Combating copycats in the supply chain with permissioned blockchain technology. *Production and Operations Management, 31*(1), 138–154.

Shi, X., Deng, D., Long, W., Li, Y., & Yu, X. (2021). Research on the robustness of interdependent supply networks with tunable parameters. *Computers and Industrial Engineering, 158*, 107431.

Singh, A., Kumari, S., Malekpoor, H., & Mishra, N. (2018a). Big data cloud computing framework for low carbon supplier selection in the beef supply chain. *Journal of Cleaner Production, 202*, 139–149.

Singh, A. K., Subramanian, N., Pawar, K. S., & Bai, R. (2018b). Cold chain configuration design: Location-allocation decision-making using coordination, value deterioration, and big data approximation. *Annals of Operations Research, 270*(1), 433–457.

Smith, L. D., & Ehmke, J. F. (2016). A mathematical programming technique for matching time-stamped records in logistics and transportation systems. *Transportation Research Part c: Emerging Technologies, 69*, 375–385.

Song, H., Shu, Y., Dai, Y., Zhou, L., & Li, H. (2022a). Big data service investment choices in a manufacturer-led dual-channel supply chain. *Computers & Industrial Engineering, 171*, 108423.

Song, Y., Liu, J., Zhang, W., & Li, J. (2022b). Blockchain's role in e-commerce sellers' decision-making on information disclosure under competition. *Annals of Operations Research, 329*(1), 1009–1048.

Speranza, M. G. (2018). Trends in transportation and logistics. *European Journal of Operational Research, 264*(3), 830–836.

Stefánsdóttir, B., Grunow, M., & Piramuthu, S. (2023). Dynamics of sensor-based information in supply chains with perishables substitutable by non-perishables. *Annals of Operations Research, 329*(1), 1357–1380.

Sun, C., & Ji, Y. (2022). For better or for worse: Impacts of IoT technology in e-commerce channel. *Production and Operations Management, 31*(3), 1353–1371.

Sun, J., Yamamoto, H., & Matsui, M. (2020). Horizontal integration management: An optimal switching model for parallel production system with multiple periods in smart supply chain environment. *International Journal of Production Economics, 221*, 107475.

Taddei, E., Sassanelli, C., Rosa, P., & Terzi, S. (2022). Circular supply chains in the era of Industry 4.0: A systematic literature review. *Computers and Industrial Engineering, 170*, 108268.

Talwar, S., Kaur, P., Fosso Wamba, S., & Dhir, A. (2021). Big data in operations and supply chain management: A systematic literature review and future research agenda. *International Journal of Production Research, 59*(11), 3509–3534.

Tosello, G., Charalambis, A., Kerbache, L., Mischkot, M., Pedersen, D. B., Calaon, M., & Hansen, H. N. (2019). Value chain and production cost optimization by integrating additive manufacturing in injection molding process chain. *The International Journal of Advanced Manufacturing Technology, 100*(1), 783–795.

Trevisan, C., & Formentini, M. (2023). Digital technologies for food loss and waste prevention and reduction in agri-food supply chains: A systematic literature review and research agenda. *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2023.3273110

Tsang, Y. P., Choy, K. L., Wu, C.-H., Ho, G. T., Lam, C. H., & Koo, P. (2018). An Internet of Things (IoT)-based risk monitoring system for managing cold supply chain risks. *Industrial Management and Data Systems, 118*(7), 1432–1462.

Tsang, Y., Wu, C., Lam, H., Choy, K., & Ho, G. (2020). Integrating Internet of Things and multi-temperature delivery planning for perishable food E-commerce logistics: A model and application. *International Journal of Production Research, 59*(5), 1534–1556.

Van Nguyen, T., Cong Pham, H., Nhat Nguyen, M., Zhou, L., & Akbari, M. (2023). Data-driven review of blockchain applications in supply chain management: Key research themes and future directions. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2023.2165190

Viet, N. Q., Behdani, B., & Bloemhof, J. (2020). Data-driven process redesign: Anticipatory shipping in agro-food supply chains. *International Journal of Production Research, 58*(5), 1302–1318.

Wan, X., & Qie, X. (2020). Poverty alleviation ecosystem evolutionary game on smart supply chain platform under the government financial platform incentive mechanism. *Journal of Computational and Applied Mathematics, 372*, 112595.

Wang, F., & Lin, L. (2021). Spare parts supply chain network modeling based on a novel scale-free network and replenishment path optimization with Q learning. *Computers and Industrial Engineering, 157*, 107312.

Wang, J., Lim, M. K., Zhan, Y., & Wang, X. (2020). An intelligent logistics service system for enhancing dispatching operations in an IoT environment. *Transportation Research Part e: Logistics and Transportation Review, 135*, 101886.

Wang, X., Leng, M., Song, J., Luo, C., & Hui, S. (2019). Managing a supply chain under the impact of customer reviews: A two-period game analysis. *European Journal of Operational Research, 277*(2), 454–468.

Wang, Y., Assogba, K., Liu, Y., Ma, X., Xu, M., & Wang, Y. (2018). Two-echelon location-routing optimization with time windows based on customer clustering. *Expert Systems with Applications, 104*, 244–260.

Wang, Y., Wang, S., Yang, B., Gao, B., & Wang, S. (2022). An effective adaptive adjustment method for service composition exception handling in cloud manufacturing. *Journal of Intelligent Manufacturing, 33*, 735–751.

Wang, Z., Zheng, Z., Jiang, W., & Tang, S. (2021). Blockchain-enabled data sharing in supply chains: model, operationalization, and tutorial. *Production and Operations Management, 30*(7), 1965–1985.

Weaver, G. A., Feddersen, B., Marla, L., Wei, D., Rose, A., & Van Moer, M. (2022). Estimating economic losses from cyber-attacks on shipping ports: An optimization-based approach. *Transportation Research Part c: Emerging Technologies, 137*, 103423.

Weißhuhn, S., & Hoberg, K. (2021). Designing smart replenishment systems: Internet-of-Things technology for vendor-managed inventory at end consumers. *European Journal of Operational Research, 295*(3), 949–964.

Worawattawechai, T., Intiyot, B., Jeenanunta, C., & Ferrell, W. G. (2022). A learning enhanced golden ball algorithm for the vehicle routing problem with backhauls and time windows. *Computers and Industrial Engineering, 168*, 108044.

Wu, C., Lin, C., Barnes, D., & Zhang, Y. (2020a). Partner selection in sustainable supply chains: A fuzzy ensemble learning model. *Journal of Cleaner Production, 275*, 123165.

Wu, M., Liu, K., & Yang, H. (2019). Supply chain production and delivery scheduling based on data mining. *Cluster Computing, 22*(4), 8541–8552.

Wu, X., Cao, Y., Xiao, Y., & Guo, J. (2020b). Finding of urban rainstorm and waterlogging disasters based on microblogging data and the location-routing problem model of urban emergency logistics. *Annals of Operations Research, 290*(1), 865–896.

Wu, X.-Y., Fan, Z.-P., & Cao, B.-B. (2021). An analysis of strategies for adopting blockchain technology in the fresh product supply chain. *International Journal of Production Research, 61*(11), 3717–3734.

Xiao, Z., Zhi, J., & Keskin, B. B. (2022). Towards a machine learning-aided metaheuristic framework for a production/distribution system design problem. *Computers and Operations Research, 146*, 105897.

Xie, S., Gong, Y., Kunc, M., Wen, Z., & Brown, S. (2023). The application of blockchain technology in the recycling chain: A state-of-the-art literature review and conceptual framework. *International Journal of Production Research, 61*(24), 8692–8718.

Xing, G., Duan, Z., Yan, W., & Baykal-Gürsoy, M. (2021). Evaluation of "innovation chain + supply chain" fusion driven by blockchain technology under typical scenario. *International Journal of Production Economics, 242*, 108284.

Xu, M., Ma, S., & Wang, G. (2022). Differential game model of information sharing among supply chain finance based on blockchain technology. *Sustainability, 14*(12), 7139.

Xu, Q., & He, Y. (2021). Optimal information disclosure strategies for a retail platform in the blockchain technology era. *International Journal of Production Research, 61*(11), 3781–3792.

Xu, X., Rodgers, M. D., & Guo, W. (2021). Hybrid simulation models for spare parts supply chain considering 3D printing capabilities. *Journal of Manufacturing Systems, 59*, 272–282.

Yang, H., & Chen, W. (2020). Game modes and investment cost locations in radio-frequency identification (RFID) adoption. *European Journal of Operational Research, 286*(3), 883–896.

Yang, L., Ni, Y., & Ng, C.-T. (2022a). Blockchain-enabled traceability and producer's incentive to outsource delivery. *International Journal of Production Research, 61*(11), 3811–3828.
Yang, W., Ziyang, W., Xiaohao, Z., & Jianming, Y. (2022b). The optimisation research of blockchain application in the financial institution-dominated supply chain finance system. *International Journal of Production Research, 61*(11), 3735–3755.
Yang, Y., Chi, H., Tang, O., Zhou, W., & Fan, T. (2019). Cross perishable effect on optimal inventory preservation control. *European Journal of Operational Research, 276*(3), 998–1012.
Ying, D., Yi, Z., Han, S., Lin, Z., & Haiyan, L. (2022). Investment decision-making of closed-loop supply chain driven by big data technology. *Journal of Industrial and Management Optimization, 19*(6), 4381–4409.
Yu, J. J. Q., Yu, W., & Gu, J. (2019). Online vehicle routing with neural combinatorial optimization and deep reinforcement learning. *IEEE Transactions on Intelligent Transportation Systems, 20*(10), 3806–3817.
Yu, Y., Cao, R. Q., & Schniederjans, D. (2017). Cloud computing and its impact on service level: A multi-agent simulation model. *International Journal of Production Research, 55*(15), 4341–4353.
Zahedi, A., Salehi-Amiri, A., Smith, N. R., & Hajiaghaei-Keshteli, M. (2021). Utilizing IoT to design a relief supply chain network for the SARS-COV-2 pandemic. *Applied Soft Computing, 104*, 107210.
Zeng, M., Sadeghzadeh, K., & Xiong, T. (2022). A three-echelon based sustainable supply chain scheduling decision-making framework under the blockchain environment. *International Journal of Production Research, 61*(14), 4951–4971.
Zeynivand, M., Ranjbar, H., Radmanesh, S.-A., & Fatahi Valilai, O. (2021). Alternative process routing and consolidated production-distribution planning with a destination oriented strategy in cloud manufacturing. *International Journal of Computer Integrated Manufacturing, 34*(11), 1162–1176.
Zhang, G., Yang, Y., & Yang, G. (2022a). Smart supply chain management in industry 4.0: The review, research agenda and strategies in North America. *Annals of Operations Research, 322*(2), 1075–1117.
Zhang, K., Lin, X., & Li, M. (2022b). Transformer-based reinforcement learning for pickup and delivery problems with late penalties. *IEEE Transactions on Intelligent Transportation Systems, 23*(12), 24649–24661.
Zhang, X., Chan, F. T., Adamatzky, A., Mahadevan, S., Yang, H., Zhang, Z., & Deng, Y. (2017). An intelligent physarum solver for supply chain network design under profit maximization and oligopolistic competition. *International Journal of Production Research, 55*(1), 244–263.
Zhang, Y., & Liu, N. (2021). Optimal Internet of Things technology adoption decisions and pricing strategies for high-traceability logistics services. *Sustainability, 13*(19), 10597.
Zheng, K., Zhang, Z., & Gauthier, J. (2020). Blockchain-based intelligent contract for factoring business in supply chains. *Annals of Operations Research, 308*(1), 777–797.
Zhu, X., Ninh, A., Zhao, H., & Liu, Z. (2021). Demand forecasting with supply-chain information and machine learning: Evidence in the pharmaceutical industry. *Production and Operations Management, 30*(9), 3231–3252.