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A review of decision support systems in the internet of things and supply chain and logistics using web content mining

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ABSTRACT

The Internet of Things (IoT) has attracted the attention of researchers and practitioners in supply chains and logistics (LSCs). IoT improves the monitoring, controlling, optimizing, and planning of LSCs. Several researchers have reviewed the IoT-based LSCs publications indexed by academic journals focusing on decision-making. Decision support systems (DSS) are in the infancy stage in IoT-based LSCs. This paper reviews the IoT-LSCs from the DSS perspective. We propose a new framework for helping decision-makers implement IoT based on the decisions that need to be made by describing a transition scheme from simple, if-then decisions to analytical decision-making approaches in IoT-LSCs. The IoT Adopter II is an extension of the IoT Adopter framework, in which a new layer called 'decision' has been added to enable decision-makers implementing IoT to improve the list of predefined decision-making processes in LSCs. Although academic literature review analysis provides valuable insights, a wide range of related information is available online. This study also utilizes a web content mining approach for the first time to analyze the IoT-LSCs in the decision-making context. The results show that the IoT-LSC field involves two emerging themes, blockchain supply chains and supply chain 5.0, and two mainstream themes, i.e., big data analytics and supply chain management.

Introduction and motivations

Supply chains are becoming significantly more complex nowadays and are also vulnerable to global risks since they extend over broad geographical areas. Furthermore, due to economic, social, and natural factors, the external environment of supply chains is very dynamic, and having the flexibility to deal with these constant changes is necessary to remain competitive [10]. Current and traditional supply chains cannot meet future business requirements. While processes in traditional supply chains are discrete and separate, digital supply chains (DSCs) break the walls in between, creating an integrated and continuous system. This growing evolution of supply chains through digital transformations can be attributed to the fourth industrial revolution or Industry 4.0 (M. [64]).

Industry 4.0 follows solutions for connecting traditional industries internally and digitalizing effectively [73,72]. It is a complete transformation of the manufacturing industry through the introduction of digitization along with the Internet. The result of this is a significant and revolutionary improvement in the manufacturing processes of products and systems [82]. Such improvement is supported by equipping factories with cutting-edge technologies such as the Internet of Things (IoT), Cyber-physical Systems (CPSs), and Cloud Computing (CC) [7, 97]. Following the transformations that Industry 4.0 has brought to supply chains, the term Supply Chain 4.0 has recently become a common term in academia and the industry [6], another term being Digital Supply Chain (DSC) [56]. Both researchers and practitioners believe IoT is a key technology for digitalizing supply chains and logistics, and IoT is a crucial component for transforming traditional supply chains into DCSs [7].

The development and spread of IoT offer new possibilities for innovation in modern supply chains. Supply chain operations can be improved by using technologies, devices, and sensors that are connected to IoT [78]. IoT is a data-driven technology comprising a set of interconnected objects, enabling logistics and supply chains (LSCs) to sense and monitor the environment remotely [7,66]. Management can dynamically optimize supply chains, monitor logistics processes

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remotely, and execute plans via the IoT [53]. Fig. 1 shows an overview of IoT-based LSCs tasks.

With the adoption of the IoT, firms can upgrade their operational efficiencies, do activities more conveniently, and better keep up with their competitors [65]. Digital supply chain technologies are divided into three main categories: *data-driven*, *knowledge-based*, and *decision-oriented*. Data-driven technologies such as IoT and CPS collect related data, store it in a physical (e.g., databases) or virtual place (e.g., clouds), and then exchange it between involved objects. The generated data is meaningless and cannot be used without knowing it. Knowledge-based technologies receive the data and analyze it to extract useful knowledge. Although the extracted knowledge can be useful for helping managers to make appropriate decisions, decision-oriented technologies (e.g., decision support systems (DSSs)) can be designed to optimize the decision-making approaches in supply chains [24,7]. To the best of the authors' knowledge, there is no serious effort to investigate these decision-oriented approaches in IoT-LSCs. In this paper, we provide a comprehensive literature review of the decision-oriented viewpoint of IoT technology in LSCs and then propose an integrated framework for handling decision-making processes. Also, due to the lack of academic publications, we use a text-mining approach to analyze the web content and extract insights from hidden knowledge of related websites and blogs. The main contributions of this paper could be summarized as follows:

i) One of the very first attempts to review the role of decision-making in the IoT-LSCs.
ii) Discussing the role of DSS in the IoT-LSCs domain.
iii) Describing the transition scheme from simple if-then decisions to analytical decision-making approaches in IoT-LSCs.
iv) Developing the newly proposed framework named *IoT Adopter* for embedding DSS technologies in IoT-LSCs.
v) Employing a text mining approach for analyzing the IoT LSCs from the viewpoint of decision-making based on the crawled web contents.

Methodology

In this paper, a systematic literature review is conducted to analyze IoT-based LSCs from the perspective of DSSs. Google Scholar is the most comprehensive academic search engine [31], and therefore, we used it to collect related publications. The initial list of keywords is divided into three classes: the first category relates to the 'supply chains and logistics' area, the second group refers to the 'IoT' area, and the third one refers to 'decision-making' approaches.

We applied a related search query for extracting the most relevant academic publications from the Google Scholar database as follows: *(TS=(internet of things) OR TS=(IoT)) AND (TS=(supply chain*) OR TS=(SCM) OR TS=(logistics) OR TS=(LSCM)) AND (TS=(decision support system*) OR TS=(DSS) OR TS=(decision*))*. The research gap investigated in this research is shown with grey lines in Fig. 2.

We searched in such a way that there was at least one keyword from each group in the abstract, title, or keywords of the indexed publications. Searching was conducted only between the titles, abstracts, and keywords in the English language for collecting the most relevant publications during the last five years until October 15, 2022. A total of 38 articles with the most topical relevance were selected. The number of

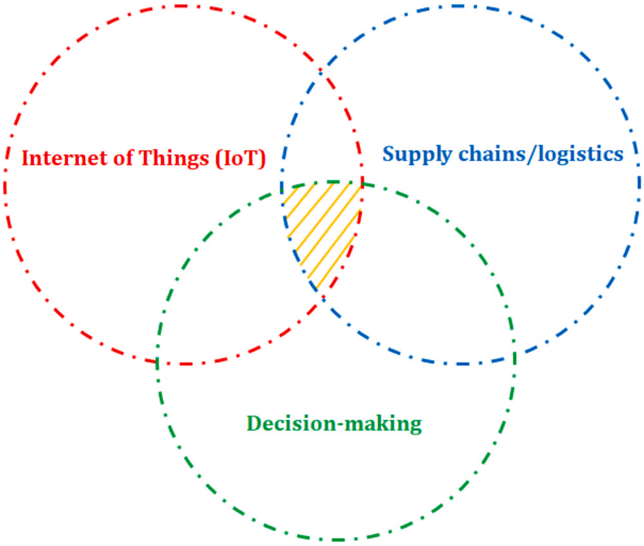

Fig. 2. The investigated research gap of the current study (the shaded area).

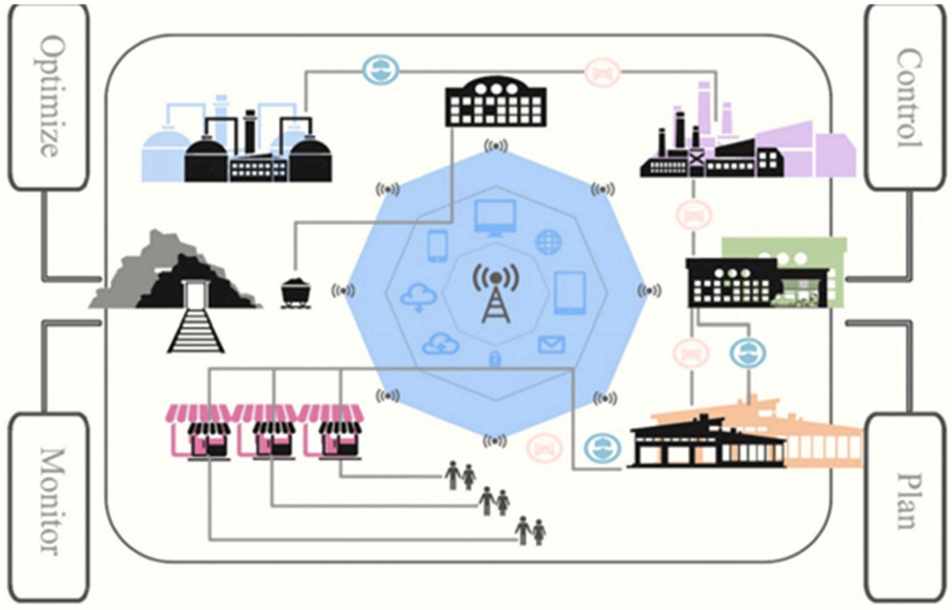

Fig. 1. An overview of IoT-based LSCs (Baziyad, Kayvanfar, en Kinra 2022).

related publications from 2008 to 2022 is presented in Fig. 3. The number of printed articles is increasing on average, and it could be expected that this field will receive the attention of more researchers in the coming years.

Based on the list of keywords provided by the authors, the most frequently used are listed in Table 1. As can be seen, the Internet of Things (IoT), Decision Support Systems (DSS), big data, Cyber-Physical Systems (CPS), and Industry 4.0 are the five most frequent keywords. To better understand, the word cloud of the keywords has been illustrated in Fig. 4.

In the provided word cloud picture, the more frequent keywords have been indicated bigger than the less frequent ones. For example, the term Internet of Things has been depicted as bigger than other keywords. With a glance at the word cloud, a wide range of keywords related to industry 4.0 and digital supply chains are shown, such as big data, digital twins, cloud computing, and cyber-physical systems. It could be interpreted as decision support in digital supply chains depending upon novel technologies.

The most active journals in publishing in the field of decision support in the era of IoT-based supply chains and logistics are listed in Table 2. The table shows the publishers, Impact Factor (IF), and h-index of various journals based on the Scimago Journal Rank (SJR). The journal Sustainability, with three papers, is the most active journal. Also, five journals with two publications lie in second place: Sensors, International Journal of Production Economics (IJPE), Future Generation Computer Systems (FGCS), Applied Sciences, and IEEE Access. Since this field is in its infancy, the number of publications in different journals could be higher. So, one may expect that the journals will focus on this area more in the near future.

Taxonomy of IoT-LSCs in the context of decision-making

The primary component of DSSs is decision-making [39]. Therefore, understanding the way a decision is made in IoT-LSCs is the prelude of DSSs. This section concentrates on the concepts of decision, decision support, and decision support systems. A brief taxonomy of investigated publications can be seen in Fig. 6.

Pre-implementation evaluation

Before implementing IoT in LSCs, an analysis of the possibility of applying IoT is needed. The current publications related to implementation evaluation are divided into four classes: technology adoption, profitability analysis, business model designing, and architecture designing.

Table 1
The most frequent keywords.

Row	Keywords	Frequency
1	Internet of Things (IoT)	26
2	Decision Support Systems (DSS)	9
3	Big Data	7
4	Cyber-Physical Systems (CPS)	6
5	Industry 4.0	6
6	Supply Chains	5
7	Digital twins	5
8	Digital Supply Chains	5
9	Cloud Computing	4
10	Radio Frequency Identification (RFID)	4
11	Industrial Internet of Things (IIoT)	3
12	Supply Chain Management (SCM)	3
13	IoT Supply Chains	3
14	Healthcare	3

Technology adoption

For more than three decades, technology adoption has been considered one of the main areas of Information Systems (IS) [84,85]. In technology adoption, researchers seek to discover, describe, and predict variables that affect adoption behavior regarding accepting technology innovations at both the organizational and individual levels [25].

Among technology adoption as decision-making about the adoption or rejection of IoT in LSCs, a wide range of factors such as trust, social influence, and technology readiness should be analyzed. However, some publications only concentrated on requirements [11,32]. Therefore, to make a comprehensive decision about IoT adoption in LSCs, key factors and enablers of IoT should be identified and analyzed.

Yadav et al. [92] proposed a framework for discovering the key enablers of effective coordination development in IoT-based agri-food supply chains (AFSC). Also, using an interpretive structure model (ISM), the framework was developed to analyze the interrelationships between the 30 enablers under seven categories in strategic and operational decision-making goals. They found that top management support has the most influence on adopting IoT to improve coordination in the AFSC for operational and strategic decision-making processes. Although identifying the IoT enablers in LSCs helps related managers make better decisions about adopting the technology, without prioritization, managers may be confused when conflicting enablers exist. Therefore, utilizing appropriate methods for ranking the enablers helps managers decide about considering the enablers for IoT adoption based on their degree of importance. Pimsakul et al. [61] used a two-phase approach for analyzing the IoT key enablers in the sustainable supply chain management (SSCM) context. The first phase, focuses on identifying the enablers, and in the second phase using grey relational analysis, the

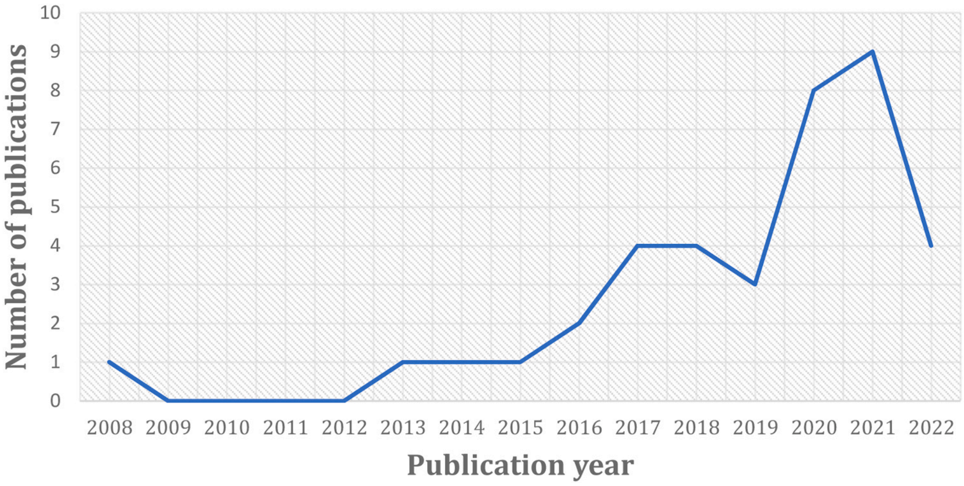

Fig. 3. Number of papers published in years from 2008 to 2022.

Fig. 4. Word cloud of the involved

Table 2

The most active journals in the field of decision support in the era of IoT-based supply chains and logistics.

Row	Journal	Publisher	IF	H-index	No. of publications
1	Sustainability	MDPI	4.39	136	3
2	Sensors	MDPI	4.417	219	2
3	International Journal of Production Economics (IJPE)	Elsevier	13.494	214	2
4	Future Generation Computer Systems (FGCS)	Elsevier	9.166	151	2
5	Applied Sciences	MDPI	3.095	101	2
6	IEEE Access	IEEE	4.825	204	2

Among the most active journals, MDPI, with seven publications, is on the front line of decision support in IoT supply chains and logistics. Indeed, MDPI covers 54% of the most active journals. Elsevier and IEEE, with 31% and 15% place second and third, respectively. Briefly, the mentioned statistics are shown in Fig. 5.

identified enablers are prioritized. They found that system integration and IoT infrastructure are the most influential factors for adopting IoT in SSCM.

Profitability

Technology adoption publications focused on discovering the influential factors of implementing IoT technologies in LSCs. However, introduced technology adoption approaches do not consider the possibility of implementation from costs and benefits. Therefore, introducing methods for the estimation of costs and benefits is required. Decker et al. [19] developed a quantification cost model for evaluating smart items, such as IoT components, from suppliers', customers', and shippers' perspectives. The proposed method considers cost-related parameters such as technology prices, fixed costs, and benefits such as utility. Finally, due to the real applicability of the model, some guidelines have been proposed for estimating the cost-benefit parameters.

Business model

After finding that IoT can be used in a logistics or supply chain, a transparent business model is needed for future implementation. The business model refers to the firm's logical roadmap for work to create value [51,52] designed an ontological business model for circular supply chain management enabled by IoT. Then, based on the designed business model, a DSS was built to make the resource economy more efficient. The embedded DSS was used to suggest repairing, remanufacturing, recycling, and reusing decisions.

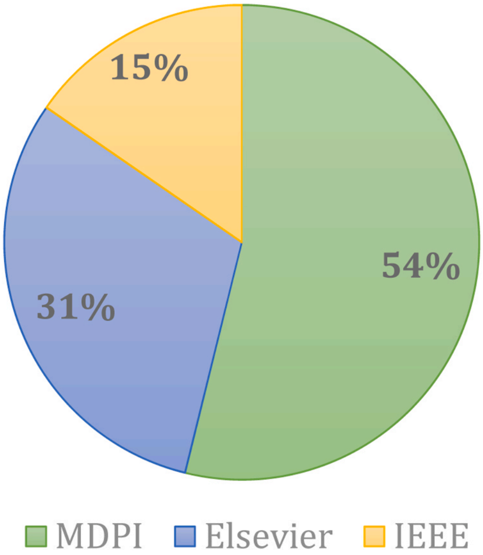

Fig. 5. Most active publishers among the most active journals.

Architectures

Although business models provide a logical road map for working, they cannot specify the technical specifications of an IoT platform in LSCs; therefore, designing architecture is required. An architecture determines the IoT platforms' layers and the way that layers interact with each other. Primary architectures, such as three-layer, four-layer, and five-layer, do not support complex decision-making processes [7]. Accordingly, designing architectures enabled by a separate decision

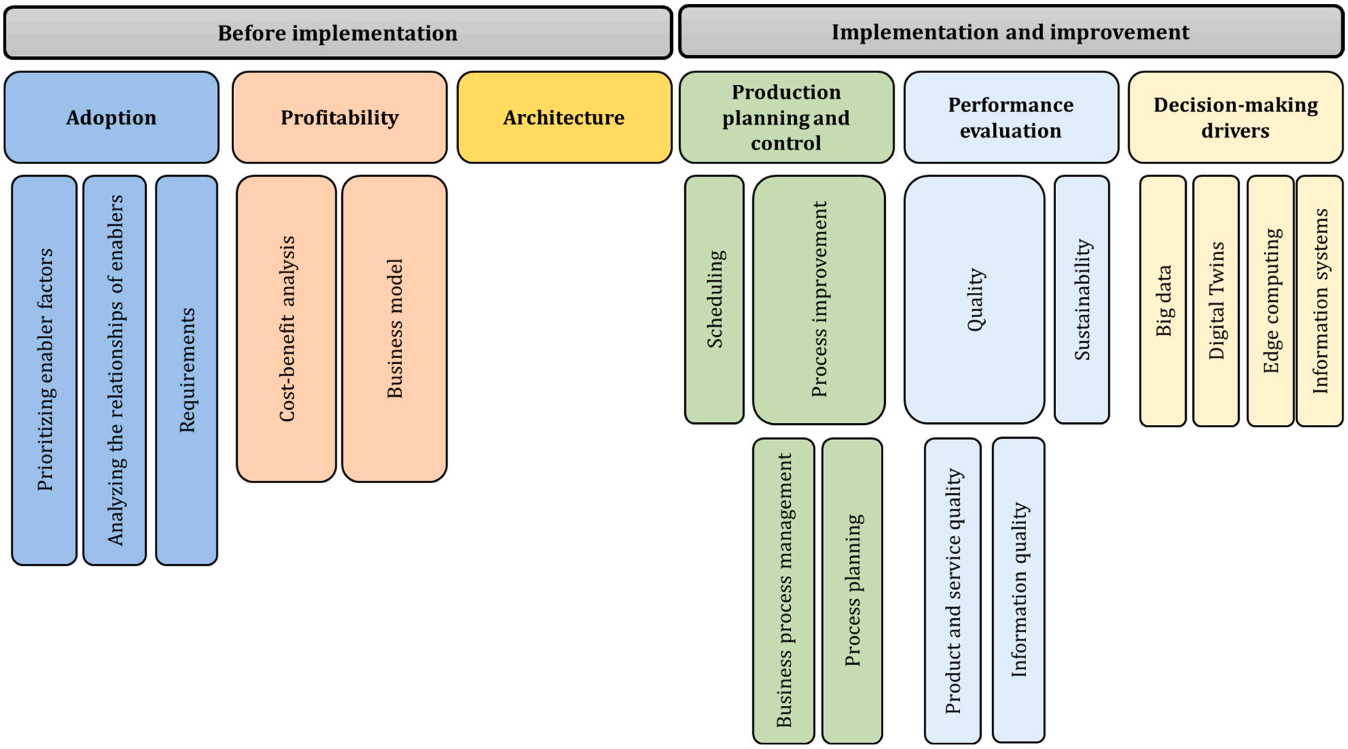

Fig. 6. A taxonomy of IoT-LSC publications in the era of decision-making.

layer may be helpful for handling complex decision-making approaches in IoT-LSCs. However, for complex decision-making processes in IoT-LSCs, the current architectures are divided into two groups: a) the primary architectures try to embed decision-making approaches [55], and b) new architectures that add decision layers [67,86].

Implementation and improvement

Performance evaluation

Here, performance evaluation helps managers find the status of IoT-LSCs in terms of some parameters and then plan to improve them. According to the existing publications in the literature, the current performance metrics of IoT-LSCs are divided into three main categories: quality, security, and sustainability.

Quality (Products/ services, and information quality). By tracing quality-related metrics in supply chains, appropriate decisions can be made, particularly in supply chains with perishable goods [22] such as vaccines [40,41], and foods [89]. For instance, when temperature measuring sensors of a food container show a warm temperature, a signal is sent to the driver, who decides to turn the fan on. Therefore, temperature violations will be controlled, and customer satisfaction will be improved with the food received. Such systems, called food safety pre-warning systems, help managers discover food safety risks and make appropriate decisions for maintaining the products' quality and safety [88]. However, pre-warning food safety systems cannot predict the future of perishable products in supply chains. Predicting the future status of products may lead to better planning and decision-making. Bogataj et al. [13] introduced a system for estimating the remaining shelf life in IoT supply chains. The introduced system matches the remaining shelf life with a dynamic real-time routing to minimize the risk of perishable products. However, most current publications focused on quality-related metrics, while some secondary factors, such as data flow and security, may influence safety and quality.

An appropriate data flow helps IoT supply chains and logistics to be more integrated, effective, and responsive in complex environments [48]. Having reviewed the related publications, Xu [90] found that an appropriate information architecture is required for effective quality management in IoT SCM. Inaccurate and unreliable information in LSCs is another challenge that leads to wrong analytical outputs and misleads managers about product quality and, finally, decision-making. Therefore, utilizing approaches for dealing with data counterfeiting is essential. To solve the counterfeit data problem in perishable products of IoT-LSCs, Tsang et al. [83] introduced a blockchain—IoT-based food tractability system (BIFTS). They found that BIFTS is essential in providing reliable and accurate data and analysis in IoT LSCs, enabling related managers to make reliable decisions. Recently, researchers have found that incorporating blockchain and IoT brings many benefits to digital supply chains, such as transparency, visibility, and trust [96,59].

Sustainability. Here, environmental quality refers to the quality of environments affected by production in supply chains or delivery through logistics networks. Based on the publications, waste generation, and gas emissions are the two factors influencing the environmental quality of LSCs. Waste management includes the collection, processing, transportation, and disposal of waste. Traditional waste management approaches were costly and inefficient [71]. Today, waste management has been regarded as one of the main goals of supply chains. Because of the growing population, waste generation has increased remarkably, leading to socioeconomic side effects [43]. Employing IoT technologies enables supply chains to collect waste-related data from supply chains in real-time. Analyzing the collected data helps managers make appropriate decisions [29]. Analyzing the data collected from IoT sensors in supply chains can be used to minimize waste or process non-reusable and non-recyclable wastes to generate energy for supply chains and logistics [87]. Environmental pollution from LSCs is not limited to waste generation. With the increased workload of factories and machines, toxic gas (e.g., CO_2) emissions in supply chains and logistics are also increased. Accordingly, the polluted air in workshops injures workers' health. They presented a smart closed-loop system in which air quality measures were collected from CO_2 sensors and visualized after their analysis using big data techniques. Managers could select an appropriate strategy for keeping workers safe by monitoring air conditions [54].

Production planning and control (PPC)

Schedule optimization. The PPC-related reviewed publications mainly focused on the scheduling task. Yao et al. [93] presented a DSS for adjusting the autonomous guided vehicles (AGVs) and machine schedules alongside the support of shop-floor decision-making. In their proposed DSS, near-optimal production schedules are found using non-linear mixed integer programming (NLMIP). They presented a decision support tool for delivery schedule optimization. The proposed system could reduce the managers' workload and improve the use of vehicles by up to 10% [1]. In a comprehensive approach, a logistics network can benefit from scheduling decision-making tasks, which improves average delivery speed, shortens the average transportation distance, and minimizes the transmission process's time consumption [46].

Process improvement. Supply-demand management is a key task in various supply chains [38,37,74]. The embedded sensor in IoT-LSCs collects data from different sectors and provides more visibility for existing processes. For instance, an analytical tool can be used for demand forecasting after demand data collection. Balancing production lines can be optimized by employing an effective process configuration method that considers the forecasted demands [16]. However, in some cases, real data may not be accessible. In such cases, simulation approaches are helpful. Tamas et al. [80] proposed a decision-support simulation method for process configuration in logistics in which changes in processes are tested and evaluated. Therefore, unnecessary planning failures are found and disposed of from the possible solutions. The Colored Petri Net (CPN) is one of the simulating modeling approaches successfully used by [23] for the process configuration of cotton transportation. Decision support tools can be designed to construct and evaluate different process models and guide managers in selecting the best one for implementation in LSCs [44,49]. Process management is a continuous task, and one cannot expect that when processes are configured, LSCs do not need more improvement in their processes. Therefore, process re-engineering is essential in modeling, evaluating, and finally changing the processes for improvement goals [17].

Decision-making drivers

Previously, embedded sensors in the IoT-LSCs collected related data and sent them to the processor to check the conditions and make a simple decision. Such decisions are called If-This-Then-That (IFTT). For example, if the processor finds out that the received temperature exceeds 32 Celsius, it orders the conditioner to turn on [27]. In IFTT decisions, processors decide based on limited constant rules that may not work under complex environments. Because in a complex environment, a wide range of variables influences the final decisions that, in many cases, conflict with each other. Therefore, utilizing new analysis approaches such as big data, data mining, and machine learning have emerged. We call them analysis-based decision-making drivers, enabling IoT-LSCs to make appropriate decisions in complex environments. The transition from IFTT decisions to analysis-based decisions in IoT-LSCs is shown in Fig. 7.

Big data analysis. Big data refers to the massive amount of data that is becoming impossible to store, process, and analyze with traditional database mechanisms [75]. Big data is described based on ten basic elements, namely *volume* (data size), *variety* (diversity of different data types), *velocity* (data generation speed), *veracity* (data understandability), *value* (benefits provided by big data), *validity* (data precise and accuracy), *variability* (context of data), *viscosity* (latency or lag of data transmitting between source and destination), *virility* (data transmission speed between multiple sources), and *visualization* (data interpretation by symbolizing data in a complete view way) [26,50]. After checking the elements, if it is determined that generated data in an IoT-LSC follows big data characteristics, data mining, and machine learning approaches cannot be used for analyzing the data, and big data techniques should be employed. Indeed, the utilized big data technique must meet the mentioned 10Vs.

Increasing digitalization between involved actors and constantly changing logistics locations are some big data generation sources that recent publications concentrated on. [15] developed an integrated DSS using big data technologies to determine underground logistics system (ULS) hub locations in complicated logistics environments. Their proposed DSS works on a big data platform with six layers: the data source, data pipeline, data processing, data storage, data application, and data service layers. According to the proposed platform, data is collected from sensors, QR codes, and GPS. Then, passing from a high-performance pipeline technology (e.g., Kafka), collected data are sent to big data processing technologies such as Spark and Hadoop. Here, Hadoop is utilized for processing a large amount of static data collected and stored over time, while Spark is embedded to process the dynamic data for real-time reaction to receiving data. Indeed, Hadoop was used for analyzing historical data analysis goals such as ULS hub location selection. Spark is employed for dynamic analysis applications such as route optimization for driving vehicles. Finally, the static and dynamic analysis outputs are transferred to corresponding applications for users' utilization.

Communicating with involved actors in a supply chain or logistics network requires a successful digital transformation. Digital transformation suffers from two critical issues: incompatibility within different data layers of the production value chain and a significant increase in data processes. In order to deal with the issues, Sorger et al. [77] developed the Reference Architecture Model Industry 4.0 framework (RAMI 4.0; a standardizing technical communication tool) for connecting the supply chain stakeholders in a big data environment. In this case, big data was used to optimize the digital transformation within

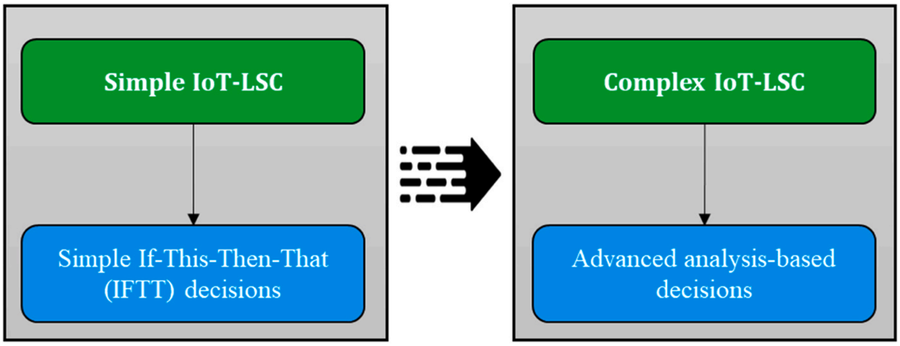

Fig. 7. Transition from simple decision-making to complex decision-making.

and between the actors involved in IoT supply chains and, consequently, enhance the real-time decision-making processes.

Edge computing (ED) is a new technology that, rather than processing data directly on the cloud, preprocesses the collected data from IoT devices at the broader of the network before sending them to the remote centralized or distributed servers deployed in the cloud [76]. Indeed, ED architectures utilize the capabilities of local processors embedded in the physical layer of the IoT for some primary preprocessing tasks, which leads to a decrease in the processes of centralized and decentralized servers. Therefore, employing ED architectures in IoT systems minimizes latency and reduces bandwidth costs and energy consumption [76]. ED is an alternative to processing big data from massive IoT sensors [69]. Dobrescu et al. [20] introduced an architecture for implementing ED technology in manufacturing supply chains, proving dual communication on both vertical (between the network layers) and horizontal (between similar devices deployed at the same Edge level) levels. The local processing idea behind the ED architecture facilitated real-time processing, leading to faster decision-making.

The existing software has not been designed to process big data from a wide range of IoT sensors, and software should be equipped with complex event processing (CEP) engines to process such big data. Therefore, designing CEP-based software is another solution used by IoT-LSCs for dealing with big data processing, particularly in dynamic environments where data are generated in real-time [47,57,70]. Briefly, solutions for handling big data processing in decision-making in IoT-LSCs are shown in Fig. 8.

Information systems (IS). Information systems (ISs) are formal, socio-technical organizational systems responsible for collecting, processing, storing, and distributing information [60]. Successful management of supply chains requires operational and performance analysis of provided information of different processes such as inventory and delivery schedules and lead times [18,42]. Therefore, to provide helpful information about the assessment of specific goals in supply chains, adopting an information system is needed [63]. Indeed, an information system is the prerequisite of analytical and decision-making processes in the supply chain because IS provides the required information for analytical and decision-making models in supply chains and logistics. Chen [14] introduced a new supply chain information system based on IoT technology. The designed supply chain information system shares relative information with an operational decision model for an appropriate decision about a specific issue. Finally, web service technology is utilized to improve the interpretability between Internet applications.

Digital twins (DT). Digital Twins (DT) refer to the dynamic virtual representation of a real system by describing and simulating physical entities' attributes, behaviors, and rules [94,28]. Briefly, DT replicates the physical objects or processes over a period of time by virtual representation [2]. The collected data from IoT sensors are fed to the DT simulator platform, and based on the embedded virtual model, a digital copy of physical entities is provided. Finally, an analytical approach, such as machine learning techniques, is used to analyze the digital copy and then make appropriate decision-making [81]. Supporting decision-making in different processes of IoT-LSCs is one of the earlier goals of DT-based IoT-LSCs [58]. Hauge et al. [33] discussed the role of DT in supporting decision-making processes of the proper component selection for a specific task in production logistics operations. They explained the requirements of implementing DT to support decision-making processes under two applications: workstation designing and automatic guided vehicle route planning. In order to support decision-making processes in DT-based IoT-LSCs, a decision model is embedded in the provided DT platform.

Before embedding a decision layer in DT-based IoT-LSCs, a comprehensive understanding of how a DT can connect decision-making in IoT-LSCs is essential. Therefore, some types of architectures have been introduced: *technical architectures* [30,35], *process architectures* [35,4], and *hardware architectures* [28,5]. Here, technical architectures have holistic approaches explaining the relationships between different layers of the technology. However, technical architectures do not pay attention to the details of the processes. Therefore, process architectures for the structural design of processes are required. Finally, in order to implement the technology, hardware specifications must be determined through a hardware architecture. Three main DT architectures supporting decision-making tasks in IoT-LSCs are shown in Fig. 9.

IoT Adopter II: a new framework for implementing decision-driven IoT-LSCs

Although IoT-LSCs support decision-making, most focus is on simple If-Then decision-making. At the same time, large data generated by embedded sensors in different locations need more sophisticated analytical approaches. The concentration of existing publications is on simple decision-making that does not need state-of-the-art analytical tools and techniques. Also, different data analysis techniques have been

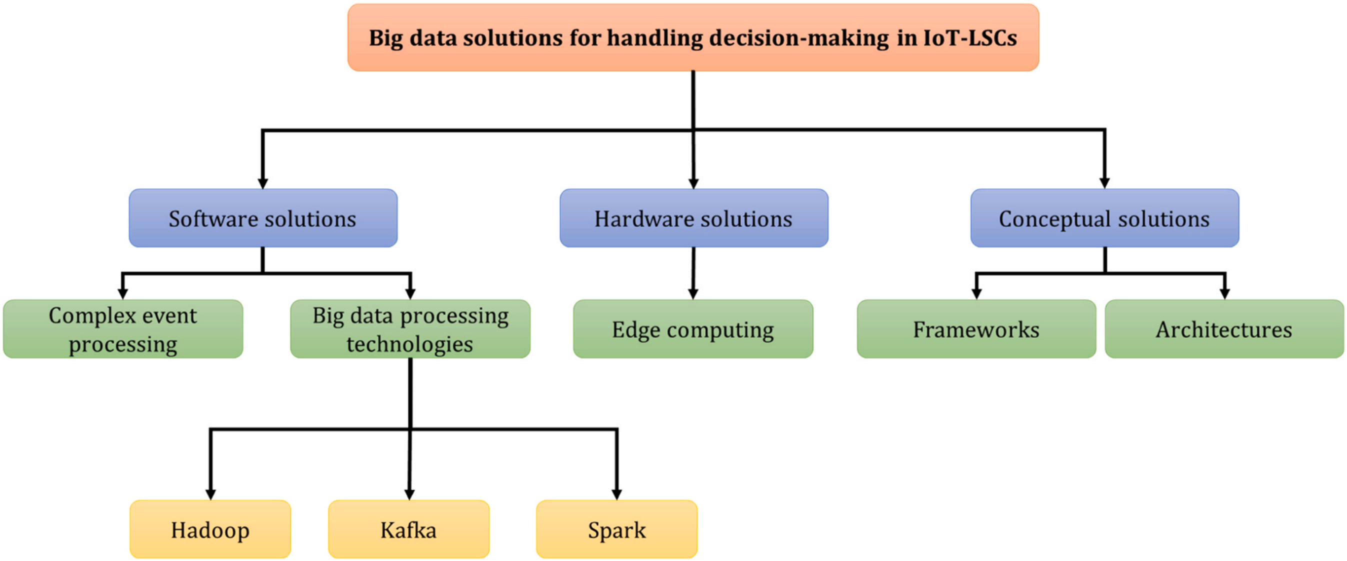

Fig. 8. Big data solutions for handling decision-making in IoT-LSCs.

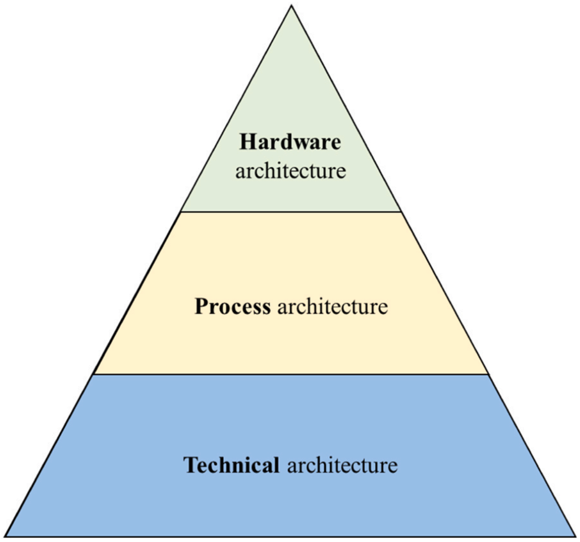

Fig. 9. Digital Twin-based IoT-LSCs architectures.

introduced recently, and some specific ones may be appropriate for guiding managers about each decision-making. Therefore, introducing a framework for decision-driven IoT implementation in LSCs is essential. Although the IoT Adopter introduced by Baziyad et al. [7] guides users in implementing IoT in supply chains, it does not consider decision-making processes. So, in this paper, we propose a new framework —the *IoT Adopter II*— that enables users to implement IoT technology in logistics and supply chains alongside the decision-making processes. The proposed IoT Adopter II is presented in Fig. 10.

According to the proposed framework, a list of decisions that can be made in LSC is provided. After that, the importance of decisions should be determined from the point of view of LSC experts. The less important ones are removed. By consulting with the related experts, those decisions that cannot be supported by IoT technology are removed. For those decisions that IoT can support, a process is built. Now, we deal with the decision-making process rather than a simple decision. By choosing an appropriate technology adoption model, influential factors on acceptance of IoT for designed decision-making processes are gained. A quantitative model is used to calculate the IoT adoption rate (AR) by knowing the effectiveness level of discovered factors. If the AR is lower than the experts' expectancy level (TH), the decision-making process should be redesigned; otherwise, the profitability of the process is calculated. If employing IoT for the related decision-making process is found profitable, some architectures are designed, and the best one is selected for implementing IoT technology. If the implemented IoT system improves the decision-making processes of the LSC, practically, we find that the IoT is useful; otherwise, the decision-making process should be redesigned. The *IoT Adopter* evaluated the IoT implementation without considering its applications in the LSC. At the same time, *IoT Adopter II* tries to investigate IoT technology in a specific context determined by decisions.

Discussion

Based on the reviewed papers and the *IoT Adopter* framework, we designed *IoT Adopter II* to help logistics and supply chain decision-makers evaluate the IoT implementation based on the specific decision-making goals that must be considered. We discuss IoT Adopter II's managerial, theoretical, and practical implementations as follows.

Managerial implications

The IoT Adopter II can be used as a road map for managers wanting to implement IoT in their supply chains and logistics. Indeed, IoT Adopter II provides some guidelines, making the path clearer for managers and related decision-makers. The IoT-Adopter II also prevents the

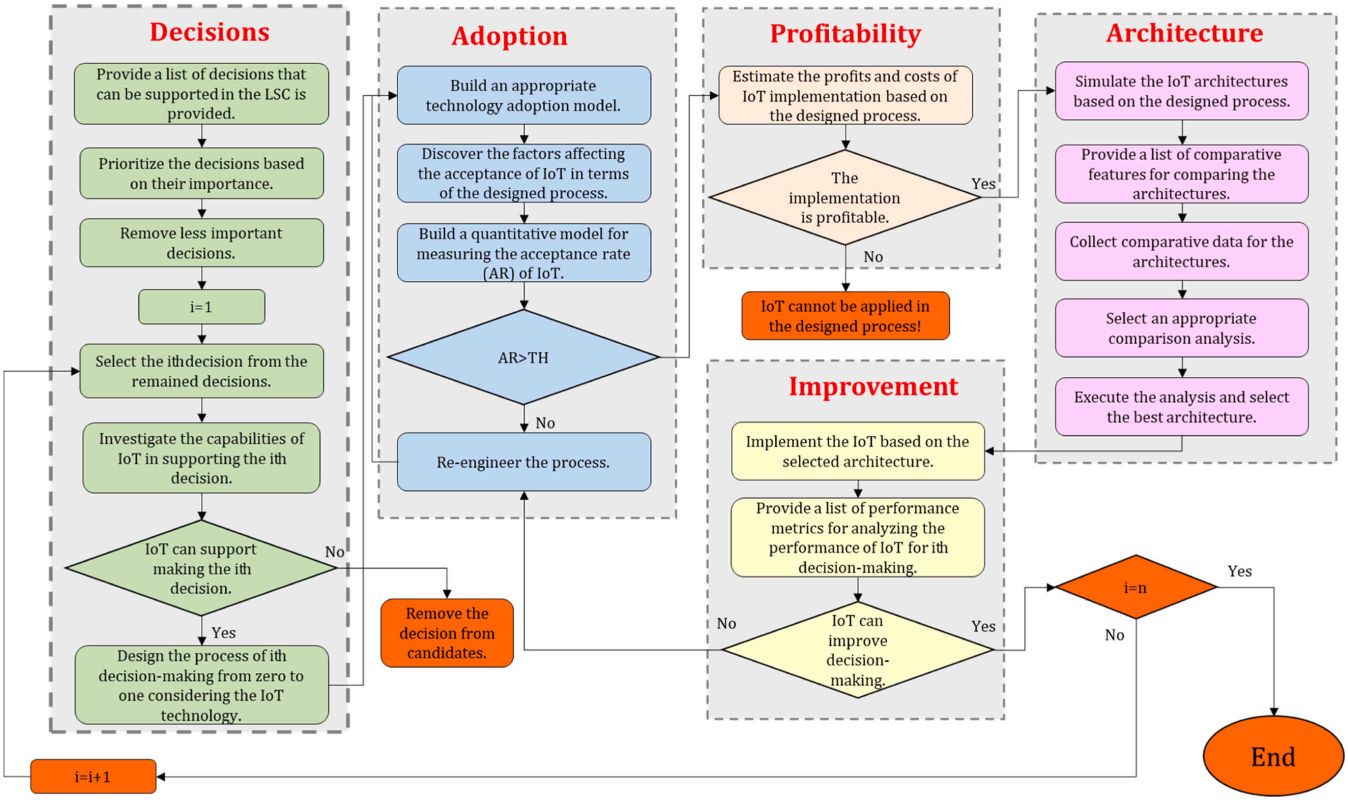

Fig. 10. IoT Adopter II: a proposal for decision-oriented IoT implementation in LSCs.

implementation of projects that fail and subsequently prevents the loss of companies. Moreover, in cases where the designed process for utilizing IoT for a specific decision may not be implementable, the proposed framework guides managers in redesigning the process.

Theoretical implications

DSSs revolve around the decisions that must be made. Before implementing a DSS, it should be clear what decisions should be supported and what decisions can be supported. Responding to these questions paves the way for designing a DSS.

However, there must be a framework for guiding IoT implementation in LSCs under decisions that must be made. Therefore, this paper develops the IoT Adopter to IoT Adopter II for adding a decision-clarifying layer. The new layer not only lists the possible decisions that can be made in LSCs but also removes those that the IoT cannot support. Also, in comparison to the previous version, IoT Adopter II takes more details into account. The third important change is related to considering the process of re-engineering. Indeed, the IoT Adopter II assumes that when the acceptance rate for IoT implication is low, rejecting the IoT implementation is not a good solution, and the decision-making process should be redesigned.

Practical implications

Although the IoT Adopter II framework has been designed to guide managers in implementing IoT in LSCs, it can be customized for utilization in further scopes. From a practical point of view, the IoT Adopter II forces technical teams to design the best probable architecture they can.

It provides a solution for simulating different architectures and comparing them to select the best one. By the embedded architecture, IoT Adopter II prevents implementing an IoT platform with poor technical characteristics. As a result, redesigned costs are decreased.

Analyzing the decision making in the context of IoT-LSCs through web content mining

Web content mining can help discover the topics, themes, sentiments, and trends of web data and classify, cluster, and summarize web pages according to their contents.

In previous sections, we reviewed and classified the academic publications related to decision-making in IoT-LSCs. In contrast, a huge amount of information is available on websites. Also, due to the time-consuming review process, academic publications are less up-to-date than web content [8]. Besides, due to the vast textual data on the web, traditional reviewing is not possible in a reasonable time. We adopt a web content mining approach, which helps us discover the topics and themes of web data.

Here, we use a text-mining approach to analyze the related web content. First, according to the FeedSpot ranking, the six best LSC blogs and websites with the most related content in the era of IoT-LSCs have been selected. Then, related textual data, including decision-making and IoT concepts, are screened and crawled. The statistics of collected data are shown in Table 3. Overall, 168 links were collected, and after manual scanning, we found 128 of them relevant to our research goals.

Table 3
Statistics of collected data from websites and blogs.

Row	Web address	Total number of links	Total number of related links
1	https://www.supplychainbrain.com	110	80
2	https://www.logisticsbureau.com	13	7
3	https://letstalksupplychain.com	5	2
4	https://www.allthingssupplychain.com	10	9
5	https://www.chainalytics.com	10	6
6	https://www.supplychain247.com	20	17
7	Total	168	121

Co-word analysis is one of the practical techniques for analyzing textual data and extracting valuable insights. However, most co-word analysis approaches work based on documents, including pre-defined keywords. While analyzing the website information, we need another step to extract the keywords. In this context, the Rapid Automatic Keyword Extraction (RAKE, [68]) is used. The RAKE algorithm is suitable for individual document analysis rather than corpus analysis and does not require any prior knowledge or training data. Then, extracted keywords are preprocessed based on the introduced steps by Hosseini et al. [36] and Pourhatami et al. [62]: 1) standardization of singular and plural forms (e.g., supply chain and supply chains), 2) combination of acronyms (e.g., supply chain management and SCM), and 3) elimination of general keywords (e.g., computers).

To construct a co-word network, two steps are performed: First, a dictionary that counts the number of co-occurrences of each pair of keywords is created. The keywords are selected from a feature selection phase, which identifies the most relevant words for the topic of interest. Then, a co-occurrence matrix that shows the frequency of co-occurrence of each pair of keywords in the dictionary is generated. The co-occurrence matrix is input into the Gephi 0.9.2 software, and a co-word network is generated. The nodes represent the keywords, and the edges indicate the frequency of co-occurrence of each pair of keywords.

Then, Louvain community detection [12] is executed to disclose the involved themes. Community detection is a fundamental problem in network analysis that aims to find groups of nodes that are more similar to each other than to the others. Finally, the given co-word network is visualized by the Gephi 0.9.2 software (see Fig. 11), in which nodes in a specific cluster have the same color.

The constructed co-word network comprises four main themes that we label based on their most weighted degree centrality: SCM (red theme), Supply Chain 5.0 (yellow theme), Big Data Analytics (green theme), and Blockchain Supply Chains (purple theme). Here, the weighted degree centrality of a given keyword K refers to the summation of frequencies that the keyword K appears in a website link with other network words. Keywords with the most weighted degree centralities are listed in Table 4.

Cluster 1 (SCM)

In the context of IoT, SCM is the process of using interconnected devices and sensors to monitor, control, and optimize the flow of materials, information, and services from the source to the customer. SCM in IoT can improve the visibility, efficiency, and responsiveness of the supply chain, as well as enable new capabilities and opportunities, such as real-time tracking, quality management, automation, and sustainability.

Cluster 2 (Supply chain 5.0)

Supply Chain 5.0 is a term that refers to the integration of human creativity and machine efficiency in supply chain management. Supply Chain 5.0 aims to cater to the hyper-personalization and hyper-customization of customer needs, which requires the use of technologies such as collaborative robots, artificial intelligence, big data analytics, and edge computing. Supply Chain 5.0 also seeks to balance the economic, social, and environmental aspects of the supply chain by enhancing transparency, traceability, automation, and sustainability.

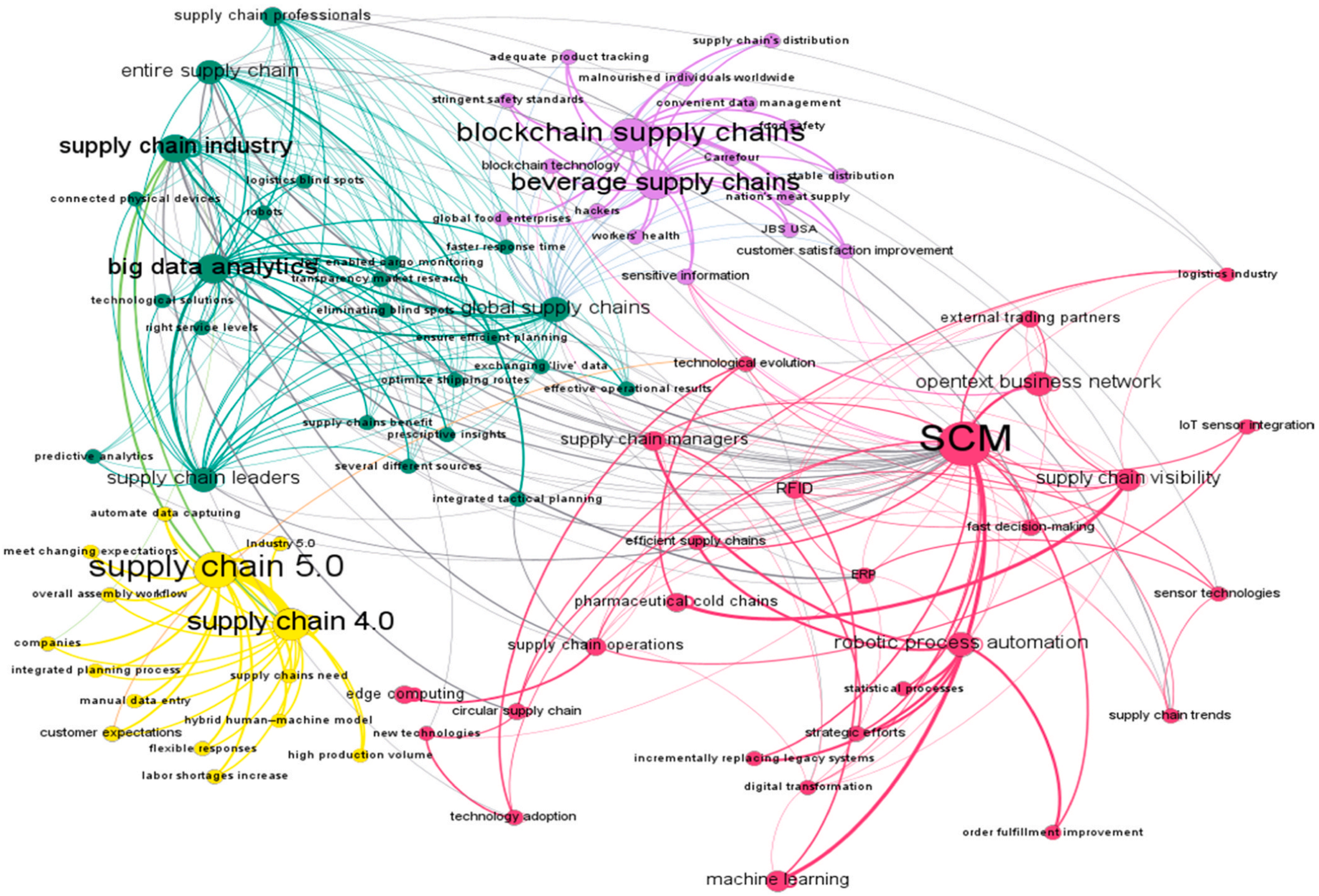

Fig. 11. The co-word network of web contents.

Table 4
Keywords with the most weighted degree centrality.

Row	Word	Weighted degree	Row	Word	Weighted degree
1	supply chain 5.0	110	**7**	supply chain industry	69
2	SCM	108	**8**	global supply chains	55
3	blockchain supply chains	95	**9**	supply chain leaders	51
4	supply chain 4.0	88	**10**	entire supply chain	45
5	beverage supply chains	81	**11**	robotic process automation	45
6	big data analytics	74	**12**	supply chain visibility	30

Cluster 3 (Big data analytics)

Big data can provide valuable insights into the patterns, trends, and behaviors of the supply chain actors, such as suppliers, customers, and logistics providers. Big data can enable data-driven and evidence-based decisions that can improve the performance, efficiency, and resilience of the supply chain. Big data can help to monitor and track the status and location of the products, assets, and vehicles in real-time, analyze and predict the demand and supply of the products, optimize and automate the production, distribution, and delivery of the products, and enhance and innovate the products, services, and business models.

Cluster 4 (Blockchain supply chains)

Blockchain supply chains are the application of blockchain technology to the management of the flow of materials, information, and services from the source to the customer. Blockchain supply chains can increase the transparency, traceability, and security of the transactions and data among the supply chain partners, such as suppliers, customers, carriers, and banks.

Co-word analysis outputs disclose the themes of the documents involved without providing information about the status of the disclosed themes. Thus, a strategic diagram is applied to investigate the status of themes from the context of development and applicability. A strategic diagram utilizes two criteria called centrality and density. Centrality is an external validator criterion that measures a theme's relationships with other themes; in contrast, density is an internal validator that measures the coherence of words' relationships in a specific theme. A high-density score for theme T indicates that T has developed theoretically well. Also, the high centrality score for them, T, indicates that T has connected strongly with other themes and has good potential for providing new applications.

According to the density and centrality measures, a strategic diagram is divided into four quadrants: Themes of Quadrant I (QI) have high centrality and density; therefore, they have theoretically developed well and have been applied successfully in other involved themes. Here, supply chain management and big data analytics lie in QI. Indeed, in the era of decision-making of IoT LSCs, SCM and big data could be developed from theoretical and practical points of view. In contrast, themes of QIII have low density and low centrality. The involved themes in QIII are emerging themes or declining themes. Here, blockchain supply chains and supply chain 5.0 lie in QIII are emerging themes that must be improved from the context of theory and application. The current strategic diagram is depicted in Fig. 12.

Conclusions, limitations, and future research

A Decision support system (DSS) is a computer-based decision-making system equipped with a knowledge-based model extracted from analyzing the received data and is used for discovering and analyzing a problem in a specific area of information and management system [79]. DSSs have been applied in different areas such as transportation [34], drug [97], and task-technology fit [23]. However, traditional DSSs did not utilize data mining approaches; therefore, they could not disclose the hidden knowledge of data. Indeed, traditional DSSs could only process and summarize the original data without the ability to convert raw data to practical knowledge (Y. [30]). By reviewing the collected publications, we found that although IoT-LSCs tried to improve decision-making processes, they needed to concentrate on DSS concepts. Also, there is little evidence about utilizing advanced analytical approaches for shifting from traditional DSSs to advanced ones in IoT-LSCs. Therefore, embedding state-of-the-art analytical approaches in DSSs of IoT-LSCs is required from a *theoretical implication*. Consequently, from *practical implications*, developing DSSs in the form of web applications and software is another gap in the reviewed publications that should be considered in future works. From *managerial implications*, a web-based DSS can enable managers to trace and track the supply chain and logistics in real-time and make appropriate decisions based on the situation.

This paper makes the following original contributions to the literature: (i) it provides one of the first comprehensive reviews of the role of decision-making in the IoT-LSCs context; (ii) it explores the potential and challenges of applying decision support systems (DSSs) to support various aspects of IoT-LSCs management and optimization; (iii) it proposes a transition scheme that guides the evolution of decision-making processes in IoT-LSCs from simple rule-based methods to more sophisticated analytical techniques: (iv) it introduces a novel framework called IoT Adopter II that integrates DSS technologies into IoT-LSCs design and implementation; (v) it demonstrates a text mining approach that extracts and analyzes decision-making insights from web contents related to IoT-LSCs.

We found that decision-making in big data environments is one of the challenges in IoT-LSCs. The extremely high data generation speed and the complex nature of the data coming from heterogeneous IoT sensors are one of the most critical dilemmas that DSSs may face, particularly when real-time decision-making is needed [79]. In such cases, applying big data techniques is a good solution for enabling DSSs to process massive amounts of data and extract knowledge for decision-making in a short time [45]. Employing local processing technologies such as edge computing (ED) can enable DSSs for real-time data processing collected from IoT-LSCs sensors. However, a comprehensive review of potential solutions for designing big data-based DSSs for IoT-LSCs is still needed. Additionally, designing a decision support framework for analyzing the different solutions for managing the big data generated in IoT-LSCs DSSs and recommending the best solutions can reduce DSS designers' challenges when building their DSS.

Although reviewing methodology provides insights into the publications, it cannot disclose the hidden knowledge of publications [62,9]. Additionally, the literature on IoT and its related domains grows continuously; therefore, more human effort is needed to cover many publications in a feasible time horizon. Accordingly, text mining approaches such as topic modeling [3], Natural Language Processing (NLP; [95]), and co-word analysis [8] are useful to overcome the mentioned challenges. Despite the lack of academic publications in the era of decision-making in IoT LSCs, a wide range of textual data is available on the web. Thus, we used a text mining approach to extract hidden knowledge from related websites and blogs and provide deeper insights. We found that IoT LSC, from the context of decision-making, comprises two emerging themes: Big Data Analytics and SCM, as well as two mainstream themes: Big Data Analytics and Supply Chain 5.0.

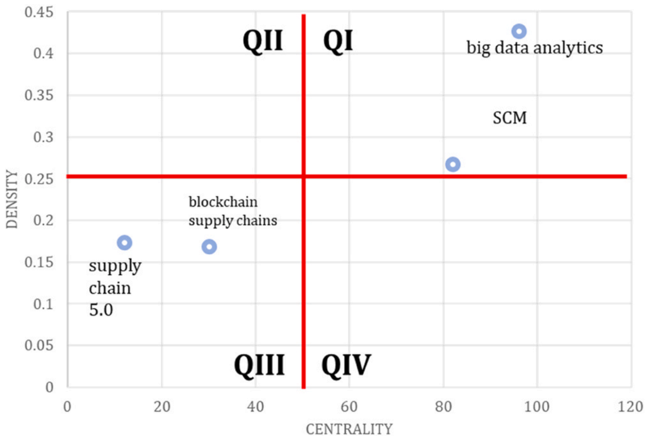

Fig. 12. Strategic diagram.

Both review analysis and the utilized co-word analysis analyzed the decision-making in the current state of IoT LSCs. Both approaches focus on descriptive analysis and do not provide predictive insights. Therefore, employing a predictive analysis helps researchers to determine the future state of a field. Link prediction is one of the predictive approaches that can be utilized to investigate the future status of IoT LSCs from the context of decision-making. Link prediction calculates the probability that two specific keywords will be used in the same paper. Indeed, it can be used to determine what sciences and different areas will converge in the future. Overall, employing link prediction can explain how the disclosed four themes can converge with each other in the future, and therefore, researchers can find ideas for work efficiently.

CRediT authorship contribution statement

Vahid Kayvanfar: Conceptualization, Data curation, Methodology, Project administration, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Adel Elomri:** Conceptualization, Investigation, Supervision. **Laoucine Kerbache:** Supervision, Validation. **Abdelfatteh El Omri:** Investigation, Resources. **Hadi Rezaei Vandchali:** Resources, Validation, Writing – review & editing.

Declaration of Competing Interest

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

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