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Artificial intelligence applications for supply chain risk management considering interconnectivity, external events exposures and transparency: a systematic literature review

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Abstract

Purpose – Supply chain risk management (SCRM) is a multi-stage process that handles the adverse impact of disruptions in the supply chain network (SCN), and various SCRM techniques have been widely developed in the literature. As artificial intelligence (AI) techniques advance, they are increasingly applied in SCRM to enhance risk management's capabilities.

Design/methodology/approach – In the current, systematic literature review (SLR), which is based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method, we analysed the existing literature on AI-based SCRM methods without any time limit to categorise the papers' focus in four stages of the SCRM (identification, assessment, mitigation and monitoring). Three research questions (RQs) consider different aspects of an SCRM method: interconnectivity, external events exposure and explainability.

Findings – For the PRISMA process, 715 journal and conference papers were first found from Scopus and Web of Science (WoS); then, by automatic filtering and screening of the found papers, 72 papers were shortlisted and read thoroughly, our review revealed research gaps, leading to five key recommendations for future studies: (1) Attention to considering the ripple effect of risks, (2) developing methods to explain the AI-based models, (3) capturing the external events impact on the SCN, (4) considering all stages of SCRM holistically and (5) designing user-friendly dashboards.

Originality/value – The current SLR found research gaps in AI-based SCRM and proposed directions for future studies.

Keywords Supply chain risk management, Artificial intelligence, Systematic literature review, PRISMA

Paper type Literature review

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1. Introduction

This section introduces the motivation for the current systematic literature review (SLR) paper, research directions and contributions. First, the background and motivation are discussed in Section 1.1. Second, research questions (RQs) and key directions are explained in Section 1.2. Finally, contribution statements and the paper's structure are discussed in Section 1.3.

1.1 Background and motivation

A supply chain network (SCN) connects multiple local or global partners (e.g. suppliers, receivers, consumers and connectors) to move products and provide services worldwide. In a multi-echelon SCN, all partners must collaborate to enhance efficiency. Each partner must proactively identify and mitigate disruptions to minimise risks affecting others. Therefore, the SCN inherently poses high complexity for three reasons: firstly, the diversity of the SCN in terms of structure, operation process and potential risk characteristics; secondly, because of the dynamic connection of components, which have influenced each other; and thirdly, because of the unexpected but hugely influential events (e.g. COVID-19 pandemic). Therefore, supply chain risk management (SCRM) methods should be updated according to the growing complexity of the SCNs and associated risks (Zhao *et al.*, 2020).

Scholars in the literature define four sequential stages of SCRM (Baryannis *et al.*, 2019b), namely *Identification (S1), Assessment (S2), Mitigation (S3)* and *Monitoring (S4)*. The first stage identifies disruption events that may negatively affect a partner's ability to achieve desired outcomes (Aboutorab *et al.*, 2022; Bui *et al.*, 2022). It leads to the second stage in which the probability and severity of the disruptions are determined (Wan *et al.*, 2019; Zhang *et al.*, 2020). The mitigation step is the third stage that prioritises the identified risks and develops strategies to mitigate their occurrence or impacts (Mostafa *et al.*, 2021; Gao *et al.*, 2019; Yılmaz *et al.*, 2023; Bag *et al.*, 2023). Risk monitoring is the last stage in which the SCN is constantly monitored to ensure that the system's operations are not impacted adversely (Tsang *et al.*, 2018). For SCRM to be effective in a multi-echelon supply chain, it is crucial to implement its stages from the perspective of the entire SCN rather than focusing solely on individual partners. This holistic approach is needed to account for the interdependencies, the complex network of connections and the snowball effects caused by various factors, such as geo-specific uncertainties impacting different parts of the supply chain. This point is underscored by (Xiao *et al.*, 2019), who highlighted the dependence of downstream partners on upstream ones. It is crucial to model the ripple effects of the upstream layer's disruptions as they impact other players in the SCN (Meyer *et al.*, 2021). Additionally, Rebs *et al.* (2019) emphasised the need to consider the geographical boundaries of different players and the associated uncertainties of external factors. Despite this, various recent incidents such as the Fukushima disaster in 2011 and the Suez Canal disruption in 2021 serve as recent examples where companies failed to fully grasp the intricacies of a multi-echelon supply chain in their SCRM strategies, resulting in consequences such as increased lead times, global trade disruptions, higher costs and financial losses.

Over the years, SCRM has seen a considerable shift in the analytical methods. With an ever-growing increase in the digitisation of supply chain operations and data processing techniques, SCRM methods have increasingly become data-focused. Because of the high velocity and volume of the collected data and the necessity of using intelligent methods, decision-makers (DMs) have widely used artificial intelligence (AI) models for agile and reliable risk management processes (Shah *et al.*, 2023; Xiao *et al.*, 2019). For example, AI-driven predictive methods can effectively identify risks such as delays (Brintrup *et al.*, 2020), price fluctuations (Sarode *et al.*, 2024) and demand fluctuations (Shahidzadeh *et al.*, 2022) allowing DMs to adjust their strategies proactively. The definition of AI is still controversial, and its primary focus may need to be clarified. As the focus of this paper, two aspects of AI are found in the literature; first, AI methods are data-driven (Brintrup *et al.*, 2024; Amjad *et al.*, 2023), and second, they are supposed to provide intelligent assistance to users (Angulo *et al.*, 2023; Mitchell *et al.*, 2022); therefore, we defined it as *"AI in SCRM are data-driven methods that assist DMs with intelligent assistance."* These include techniques such as machine learning, big data analysis, digitisation and data analytics applied on different platforms. For example, Cavalcante *et al.* (2019) designed a digital twin to identify risks in digital manufacturing for supplier selection and noticed a significant improvement in the resiliency of the supply chain. Oger *et al.*(2019) used Business Intelligence (BI) to identify and mitigate risks before recommending strategies to DMs. In another case, reinforcement learning has been applied to risk identification by continuously learning from textual data gained from news (Aboutorab *et al.*, 2022). Additionally, AI-powered risk assessment tools, such as those using natural language processing (NLP), can analyse news, text data and social media trends to detect emerging risks in supply chains (Makridis *et al.*, 2022; Chiu *et al.*, 2024). In the mentioned examples, AI is used as an intelligent data-driven assistant for the DMs to empower them more than traditional approaches.

Most of the proposed SCRM approaches address a single player's perspective. Although it helps achieve the goal of that particular player in risk management, the analysis should be integrated and considered in conjunction with other players of SCRM who also take their perspectives holistically. Considering other players' activities is crucial for capturing the complex network of interconnections across the SCN. Moreover, the nature of AI's decision-making process is complicated and complex for users, especially those with limited knowledge of AI. This problem is exacerbated when SCRM needs to be done from a multi-echelon perspective, in which the DM of a particular echelon may need to understand more of the uncertainties impacting it from other partners. Our objective in this paper is to systematically review the AI-based SCRM literature to determine if they consider (a) an AI-based methodology for SCN to capture the real intricacies and disruptions that impact an SCN operation and (b) develop risk management strategies by considering the sequential stages (i.e. S1–S4).

1.2 Research questions (RQs) and key findings

We defined three RQs, the factors that we want to determine whether the existing AI-based SCRM approaches have been addressed across the SCN for more efficient SCRM. The RQs are listed as follows:

RQ1. How do existing SCRM approaches consider the interconnections of the SCN' components?

RQ2. How do existing approaches consider the impact of external events on an SCN's operations

RQ3. How transparent and explainable are the existing SCRM AI-based models?

RQ1 considers how AI-driven methods consider the interconnectivity of the SCN components for risk management. The interconnectivity of the SCN components considers the correlation and collaboration of the internal factors and features in SCN's boundaries, which are capable of managing. For instance, the transportation of the products between manufacturers and customers, inventory capacity or workforce scheduling. The DMs manage the internal factors and are connected to each other. Each of their actions has some impact on the performance of other components. The SCRM should be done by linking and making sense of the different interdependencies present across the different partners of the SCN (Pournader *et al.*, 2020). In such an approach, the interdependencies across the SCN should be modelled as a cause-and-effect relationship that assists in modelling the impact of disruptions across the SCN (Gruchmann and Neukirchen, 2019; Pavlov *et al.*, 2022). However, modelling such interdependencies is quite a challenging task (Hosseini and Ivanov, 2022). The RQ1 questions how proposed AI methods consider and analyse the interconnections among different players of the SCN for a more effective SCRM.

Building on this, *RQ2* explores how AI methods incorporate the impact of external events alongside internal factors. External events are unmanageable influencing factors out of the boundaries of the SCN; some examples of external events are climatic catastrophes, political issues and natural disasters. All SCNs span different geographical locations, exposing them to external uncertainties outside the SCN boundaries. The current scenarios of COVID-related lockdowns on the semiconductor industries located in Taiwan and the impact it had on computing and car manufacturers highlight this scenario (Chien *et al.*, 2020). For the SCN's risk management process to be effective, identifying and capturing such external events and their impact is essential before determining their impact across different echelons (Aboutorab *et al.*, 2023). The question is how the behaviour of the external events and their impact on the SCN activities can be captured.

Figure 1 represents concepts regarding RQ1 (i.e. interconnectivity of the internal factors) and RQ2 (i.e. the influence of the external factors), which is done by defining the system's boundaries and identifying the players' network. This network should then be modelled by capturing the different parameters of a single player and its operations (e.g. interconnection of warehouse and production departments of a factory) and, secondly, the connection of the different echelons (e.g. between supplier and customer). Therefore, all the components and relations that are controllable and inside the boundaries of the SCN are considered in RQ1, and all other factors are considered in RQ2.

Finally, the main focus of the RQ3 is on the explainability of the proposed AI methods, which concerns clarifying the process and results of the AI models in decision-making (Nimmy *et al.*, 2022). As mentioned earlier, the nature of AI's decision-making process is complicated and complex for users, especially those with limited knowledge of AI. This problem is exacerbated when SCRM needs to be done from a multi-echelon perspective in which the DM of a particular echelon may have less or no understanding of the uncertainties impacting it from another partner. Moreover, the decision-making process of AI is often a

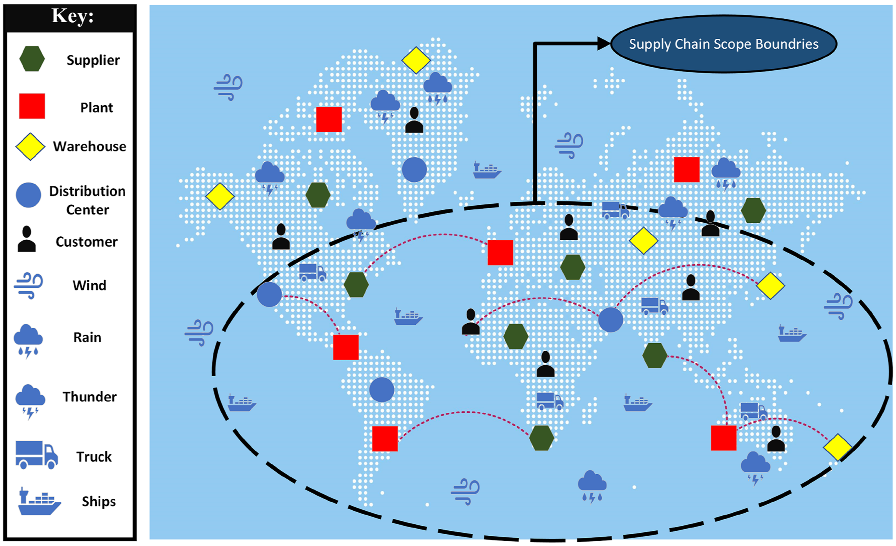

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Figure 1. Illustration of interconnection and external events exposure of an SCN (i.e. RQ1 and RQ2)

"black box". Researchers emphasise the need for transparency to ensure fairness and explainability in AI models (Schäfer, 2023; Nimmy *et al.*, 2022). Explainable Artificial Intelligence (XAI) methods are meant to improve the trustability of the AI-based decision-making models to address this issue (Melançon *et al.*, 2021). However, this needs to be done in the SCRM domain for the models to move from a black box model to a white box one, which can explain the decision-making process and the reasoning for the model's outputs. The question is if the proposed AI methods considered the models' transparency and explainability for SCRM in the literature.

Figure 2 shows at a high level how XAI methods try to clarify the black-box AI-based models by explaining the decision-making process, highlighting the important factors and finally justifying the output of the AI models.

1.3 Contribution statements and paper's structure

We acknowledge that many literature review papers already focused on how AI-based methods have been used in SCRM, as shown in Table 1. However, as shown, the three RQs are not the focus of the previous SLR papers comprehensively. This paper aims to review the current AI-based models for SCRM by focusing on the three questions to find which AI-based models are suitable for answering three RQs. Moreover, the four stages of SCRM (i.e. S1–S4) are distinguished based on the main focus of the articles in the literature. In summary, the main contributions of the current SLR in comparison with previous ones in Table 1, rather than focusing on the RQ1-RQ3, which are the main research directions of the current SLR, is to classify the main focus of the papers according to the four SCRM stages, which can be a guideline for researchers and practitioners to update their SCRM methods based on AI. Moreover, the whole literature, without time limits, is analysed thoroughly, which firstly helps to understand the progressive trend of AI in SCRM. Secondly, gaps and present areas for future work are presented.

The rest of this paper is structured as follows: Section 2 explains the paper selection process using the PRISMA method. Section 3 analyses the selected papers. Sections 4 and 5 discuss research gaps and future directions, while Section 6 concludes the paper by summarising key findings and limitations.

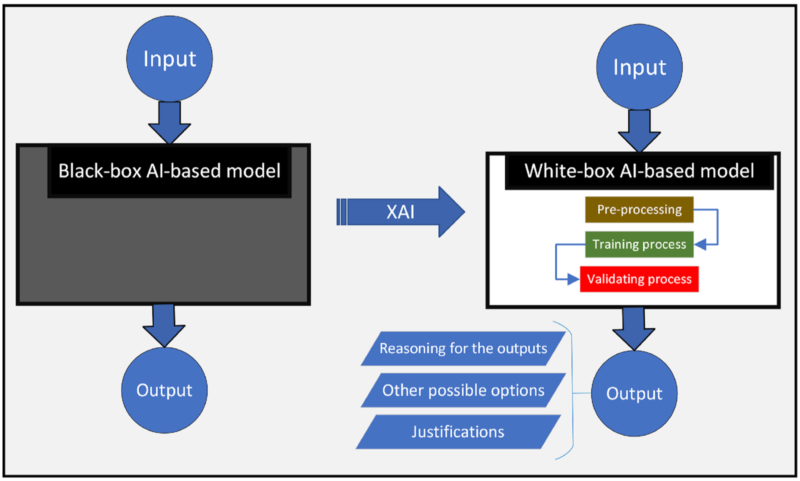

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Figure 2. Illustration of transparency and explainability of the analysis (RQ3)

Table 1. Recent related review papers based on considering SCRM stages and the research requirements

No	Authors	Year published	Time range of papers considered in the analysis	Does it consider all the SCRM stages?	RQ1	RQ2	RQ3
1	Mageto (2022)	2022	Last 22 years	No	No	No	No
2	Ganesh and Kalpana (2022a)	2022	Last 12 years	Yes	Yes	No	No
3	Nimmy *et al.* (2022)	2022	All time	No	Yes	No	Yes
4	Svoboda *et al.* (2021)	2021	Last 18 years	No	Yes	No	No
5	Tordecilla *et al.* (2021)	2021	Last 21 years	No	Yes	No	No
6	Shah *et al.* (2021)	2021	Last 13 years	No	Yes	No	No
7	Aboutorab *et al.* (2021)	2021	Last 41 years	No	No	Yes	No
8	Hosseini and Ivanov (2020)	2020	Last 13 years	No	Yes	No	No
9	Ghadge *et al.* (2020)	2020	Last 14 years	No	No	Yes	No
10	Hosseini *et al.* (2019)	2019	last 15 years	No	Yes	No	No
11	Baryannis *et al.* (2019 b)	2019	Last 41 years	No	Yes	No	No
12	Hamdi *et al.* (2018)	2018	Last 12 years	No	Yes	No	No
13	Yang *et al.* (2022)	2023	All time	Yes	Yes	Yes	No
14	Suryawanshi and Dutta (2022)	2022	All time	No	Yes	No	No
15	Shishehgarkhaneh *et al.* (2024)	2024	All time	Yes	Yes	No	No
16	This paper		All time	Yes	Yes	Yes	Yes

Source(s): Authors' own creation

2. Paper selection process

We used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach (Page *et al.*, 2021) to search the literature for articles on AI-based SCRM. In the following subsections, the search query applied to the databases, the selection process of the papers and the statistical analysis of selected papers are explained.

2.1 Search queries

This paper, similar to most review papers, used two well-known sources of scientific databases: SCOPUS and Web of Science (WoS). The search query contains the two main keywords as follows:

(1) ”Supply chain risk management” OR ”SCRM” OR (”Supply Chain” AND ”Risk”)

(2) ”Artificial Intelligence” OR ”AI”

These two sets of keywords were searched in the paper's title, abstract and keywords without any limit on the publication year. The first set of keywords ensured coverage of the SCRM domain, and the second set, while the second set focused on AI methods. Then, automatic filtering was applied using the inclusion and exclusion criteria in Table 2. For instance, duplicates in SCOPUS and WoS are removed by automatic tools. Moreover, the remaining papers are all in English, in the final publication stage and published as journals, conferences or book chapters.

Then, to ensure that the selected papers are relevant to the SLR's topic, the abstract of the papers was read by the authors in the screening phase to make sure that the methods used are data-driven and help the DMs by providing intelligent assistance, which is not possible or

Table 2. Automatic inclusion and exclusion criteria before screening the papers

No	Criteria	Description
1	Exclusion	Duplicate records should be deleted
2	Inclusion	Papers should be in the final stage of publishing
3	Inclusion	Papers should be in English
4	Inclusion	Journal, conference or book chapters

Source(s): Authors' own creation

applicable manually, as the main contribution of the AI. Moreover, the review and conceptual models are omitted. The selected papers should propose a method and be validated for a specific problem. The criteria for selecting articles in the screening phase are shown in Table 3. Those articles that did not meet the criteria were removed from further analysis.

2.2 Selection process of the papers

Figure 3 shows the PRISMA selection process statistics applied in this paper. Firstly, as of the end of June 2024, 715 articles were found. Secondly, after applying the automatic inclusion and exclusion criteria of Table 2, 526 records remained. Finally, the authors carefully read these shortlisted papers' abstracts, considering the screening criteria of Table 3. For marginal cases where inclusion/exclusion was uncertain, all authors independently reviewed and discussed the abstracts. Papers were included if a majority consensus was reached. The judgement criteria were explained in Table 3. Therefore, some studies with valuable scientific contributions were excluded because of their focus out of the selection criteria, such as Reyes *et al.* (2023) were excluded due to their focus on proposing a conceptual model without empirical experiments or Wang *et al.* (2023) was considered as they mentioned AI in the abstract as a future direction, while they focused more on the statistical and qualitative methods in the paper. Finally, 72 papers remained for comprehensive reading after the screening process.

2.3 Statistics of selected papers based on the SCRM stages

There are 72 shortlisted articles categorised into four SCRM stages (i.e. identification, assessment, mitigation and monitoring). The analysis showed that there has been a consistent increase in the application of AI-based techniques for SCRM. Most studies focused on risk

Table 3. Screening criteria for removing papers

No	Description
1	Review papers should be excluded
2	Conceptual frameworks, which are theoretical frameworks without mathematical models, numerical results, implementations, validation and comparison with previous literature, should be excluded
3	Papers should propose a method for at least one stage of SCRM (i.e. identification, assessment, mitigation or monitoring), papers which proposed AI-based models but their focus of application is not SCRM should be excluded
4	Proposed method should be validated using case studies, real-world scenarios, simulations and empirical experiments. Pure theoretical discussions without considering datasets or supply chain assumptions should be excluded
5	Proposed method should assist DMs by providing intelligent assistance enabled by AI, which is not attainable with traditional manual methods. For instance, articles that focus only on experts' opinions or surveys should be excluded

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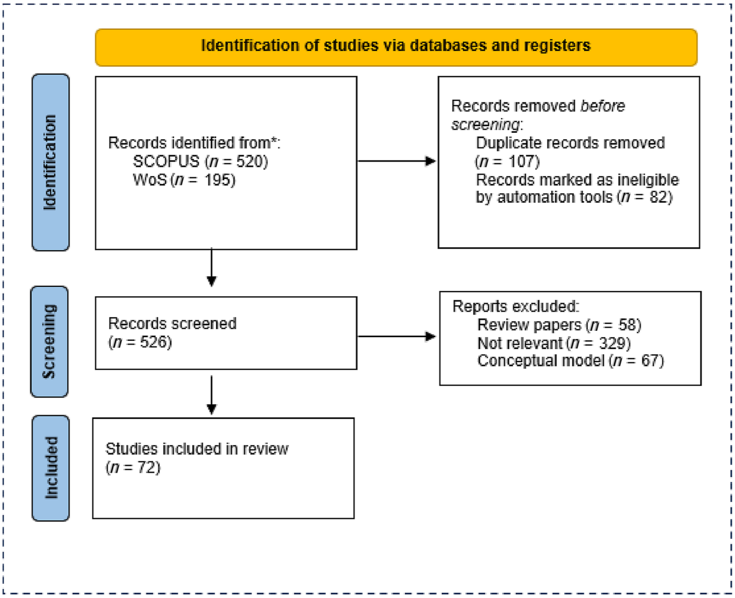

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Figure 3. PRISMA flowchart for the searching, screening and reading process

identification (i.e. 35 papers), followed by assessment (i.e. 13 papers), mitigation (i.e. 15 papers) and monitoring (i.e. 9 papers). Table 4 and Figure 4 illustrate the time series of the reviewed papers.

3. Analysis of the shortlisted papers in each stage of SCRM

In this section, the shortlisted papers are analysed by classifying them in each stage of SCRM. The discussion focuses on the broad category of AI methods used in each stage of SCRM and, depending on whether they meet RQ1-RQ3. This analysis is used in the next sections to discuss the gaps and future research areas.

3.1 Stage 1 – identification of risks

As mentioned earlier, identification is the first stage of SCRM. This stage aims to determine the presence of risks; scholars have used AI-driven techniques such as machine learning, text mining, NLP and time series methods to identify future risks and disruptions. Such techniques

Table 4. Time series of the reviewed SCRM literature

SCRM stage	Publication year 2018 or before	2019	2020	2021	2022	2023	2024
Identification	4	2	2	4	10	8	5
Assessment	1	0	3	1	2	3	3
Mitigation	4	4	1	0	3	2	1
Monitoring	4	0	1	1	0	1	2

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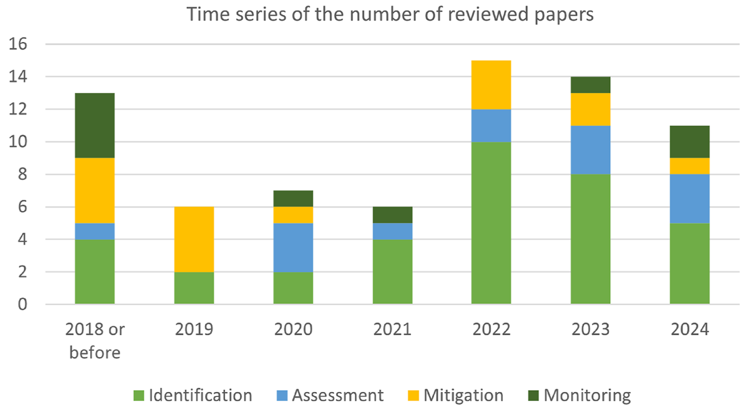

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Figure 4. Time series of the reviewed SCRM literature

primarily synthesise knowledge from data by determining patterns in them, although they may cause some errors such as false detection, overfitting and high computational complexities. Tables 5 and 5–7 compare papers in this stage. They evaluate whether these techniques focus solely on risk identification or address other SCRM stages (i.e. S2, S3 and S4). The tables also present the employed techniques and whether the papers meet RQ1, RQ2 and RQ3. Since the number of papers in this stage is higher than in other stages, they have been divided into three parts based on the publication date to represent progress over time; we divided the papers into three groups: those published in 2020 or earlier (3.1.1), those from 2021 to 2022 (3.1.2) and those from 2023 to 2024 (3.1.3).

3.1.1 Stage 1 – identification of risks (2003–2020). Scholars have applied AI-based predictive models for risk identification. In the early 2000s, Bruzzone and Orsoni (2003) proposed a methodology that combined three models: a mathematical model, a simulation model and an Artificial Neural Network (ANN) model. The ANN model identifies the

Table 5. Comparison of papers focused on identification stage (2003–2020)

Source	Year	Which SCRM stages are the area of focus? S1	S2	S3	S4	Which requirements are addressed? R1	R2	R3	Methods
Bruzzone and Orsoni (2003)	2003	Yes	No	No	No	Yes	No	No	ANN
Boonyanusith and Jittamai (2012)	2012	Yes	No	No	No	Yes	No	No	DT and ANN
Slimani *et al.* (2015)	2015	Yes	No	No	No	Yes	No	No	ANN
Zhu *et al.* (2017)	2017	Yes	No	No	No	Yes	No	No	Multiple machine learning models
Baryannis *et al.* (2019 a)	2019	Yes	No	No	No	Yes	No	Yes	DT/ and SVM
Fu and Chien (2019)	2019	Yes	No	No	No	No	Yes	No	Time series
Zhou *et al.* (2020)	2020	Yes	No	No	No	Yes	No	No	CNN
Brintrup *et al.* (2020)	2020	Yes	No	No	No	No	Yes	No	RF, SVM, logistic regression and linear regression

Source(s): Authors' own creation

Table 6. Comparison of papers focused on identification stage (2021–2022)

Source	Year	Which SCRM stages are the area of focus? S1	S2	S3	S4	Which requirements are addressed? R1	R2	R3	Methods
Hongjin (2021)	2021	Yes	No	No	Yes	Yes	Yes	No	Machine learning and IoT
Zhou *et al.* (2021)	2021	Yes	No	No	No	Yes	No	No	XGBoost
Melançon *et al.* (2021)	2021	Yes	Yes	Yes	No	Yes	No	Yes	GBDT, XGBoost, RF, LR and NN
Salamai *et al.* (2021)	2021	Yes	No	No	No	Yes	Yes	No	Voting classifier
Luo *et al.* (2022)	2022	Yes	No	No	No	Yes	No	No	PCA, SVM and AdaBoost
Aboutorab *et al.* (2022)	2022	Yes	No	No	No	No	Yes	No	Reinforcement Learning-based approach from text data
Heydarbakian and Spehri (2022)	2022	Yes	No	No	No	Yes	No	Yes	DT and Naïve Bays
Liu *et al.* (2022)	2022	Yes	No	No	No	Yes	Yes	No	ANN, GA, PSA
Ganesh and Kalpana (2022b)	2022	Yes	No	No	No	Yes	No	No	Text mining
Shahidzadeh *et al.* (2022)	2022	Yes	No	No	No	Yes	Yes	No	CNN
Kosasih *et al.* (2022)	2022	Yes	No	No	No	Yes	No	Yes	Graph neural network
Makridis *et al.* (2022)	2022	Yes	Yes	No	Yes	No	Yes	No	RL, NLP and Time series
Abouloifa and Bahaj (2022)	2022	Yes	No	No	No	Yes	Yes	No	KNN, LR and RF
Lolla *et al.* (2022)	2022	Yes	No	No	No	Yes	No	No	LR, XGBoost, Light GBM, RF

Source(s): Authors' own creation

Table 7. Comparison of papers focused on identification stage (2023–2024)

Source	Year	Which SCRM stages are the area of focus? S1	S2	S3	S4	Which requirements are addressed? R1	R2	R3	Methods
Li and Donta (2023)	2023	Yes	No	No	No	No	No	No	Machine learning
Gabellini *et al.* (2023)	2023	Yes	No	No	No	Yes	No	No	Machine learning
Gabellini *et al.* (2023)	2023	Yes	No	No	No	Yes	No	No	Machine learning
Xiao *et al.* (2023)	2023	Yes	No	No	No	No	Yes	No	Machine learning
Yacoubi *et al.* (2023)	2023	Yes	No	No	No	Yes	No	No	Rule-based model
Zaoui *et al.* (2023)	2023	Yes	No	No	Yes	No	Yes	Yes	Machine learning
Atek *et al.* (2023)	2023	Yes	No	No	Yes	No	Yes	No	Machine learning
Zheng *et al.* (2023)	2023	Yes	No	No	Yes	Yes	No	No	Federated learning
Li and Zhou (2024)	2024	Yes	No	No	No	No	Yes	Yes	Time series
Yang *et al.* (2024)	2024	Yes	No	No	No	Yes	Yes	Yes	Graph neural network
Aboutorab *et al.* (2024)	2024	Yes	No	No	No	No	Yes	No	RL and NLP
Bassiouni *et al.* (2024)	2024	Yes	No	No	No	Yes	No	No	DP and machine learning
Kong *et al.* (2024)	2024	Yes	No	No	Yes	Yes	No	No	Federated learning and neural network

Source(s): Authors' own creation

correlation of logistic variables with increasing supply chain costs. They concluded that ANNs, in combination with other developed models, are more practical and flexible. Later, in the early 2010s, Boonyanusith and Jittamai (2012) considered an SCN for blood donation, in which the main entity is different groups of blood units, and the main supplier of blood units is the donator. They compared decision trees (DT) and ANN to predict whether individuals are blood donors or not to identify the supply fluctuation; the results are necessary for the blood SCN as the blood is the essential raw material for their SCN; finally, the results revealed that the ANN performed better than a DT. The behavioural features of the individuals are considered for the prediction process.

As the capability of the AI methods improved, different variants were applied for risk identification. For example, Slimani *et al.* (2015) employed ANN to forecast the demand in a two-echelon SCN with one product to reduce the risk of fluctuations. Meanwhile, more analysis for sharing information between the players of the SCN is conducted using game theory to improve the accuracy of the identification system. Machine learning models have demonstrated effectiveness. In the early stages, researchers focused on comparing different ML models to identify the most suitable one. For instance, Zhu *et al.* (2017) compared three types of machine learning models, namely individual, ensemble and integrated ensemble machine learning models, for identifying the credit risks of small and medium enterprises (SMEs). Finally, they concluded that RS-boosting, an integrated ensemble machine-learning model, had the best performance. More recently, the interpretability of the identification tools is an important factor, which Baryannis *et al.* (2019a) claimed that scholars only partially attend; their research focused on improving the interpretability of the tools in the identification of supply chain risks, two machine learning methods, namely Support Vector Machine (SVM) and DT, were compared. The DT is known as a white-box method, which is more interpretable. The demonstrated case study showed that the SVM model performs better in case of accuracy. So, they concluded that increasing the interpretability may decrease the accuracy of the results. Fu and Chien (2019) identified the risk of demand fluctuation in a case study of electronics distribution; the demand fluctuation may cause disruptions in other echelons of the SCN or cause financial loss or social dissatisfaction for the service providers and users. Several time horizons were considered, and then three forecast models were used at each level. The weighted combination of these three models was the final solution. The external impact was considered by considering different time horizons. ML models [e.g. Convolutional Neural Networks (CNN), SVM and DT] also have applications in financial fraud detection; the results showed that the CNN method had better results, with a 90% F1 score. The Apache Spark and Hadoop software was used to manage the supply chain finance (SCF) (Zhou *et al.*, 2020). Another study focused on predicting suppliers' delays in an Original Equipment Manufacturer (OEM) company. Researchers used feature engineering and different machine learning classifications such as random forest (RF), logistic regression, SVM and linear regression, in which RF had the best performance at 83% precision (Brintrup *et al.*, 2020). Table 5 presents a comparative analysis of the techniques discussed in this section.

Discussion and implications: As stated in the summary of the papers published in 2020 or before, there are some general implications and answers to the RQs. As the observation of the literature in this period, the neural network models were almost the first generation of AI models used for risk identification, and later, researchers utilised more advanced methods such as SVM and RF to reduce the shortcomings of the neural networks in complex problems. An increasing number of AI-based models is needed compared to AI-based models, which are different for each case. More specifically, an investigation to find answers for the RQs shows that most risk identification models can connect the players (i.e. RQ1) according to their capabilities to connect data of different features and use their correlations. Moreover, the issue of interpretability was considered for clarifying the used methods (Baryannis *et al.*, 2019a).

3.1.2 Stage 1 – identification of risks (2021–2022). Between 2021 and 2022, machine learning models were widely applied for risk identification. For example, (Hongjin (2021) used machine learning to identify financial credit risks in SCM. It could effectively identify and analyse SCN's financial risks. Moreover, an IoT structure with three layers was developed to monitor risks. Comparing ML models across various scenarios helps researchers to find the best one for their problems. Zhou *et al.* (2021) applied different machine learning prediction models for fraud detection in a transaction in a financial case study. The XGBoost showed better results than other used prediction models, with an F1 score of 99.31%. Melançon *et al.* (2021) compared methods like GBDT, XGBoost, RF, LR and NN to identify service-level failure risks in a manufacturing company. The GBDT model as an ensemble model showed the best results. It was essential to increase the explainability of the results since it increased users' trust. Fortunately, the explainability of the method was sufficient because it used a tree for decision-making. Moreover, a user interface is designed to assist the planner. Since interoperability of the ML models is challenging, Shapley values are estimated using the TreeSHAP method to increase the explainability of the results. The results showed that prediction models were helpful, and the explainability of the method helped users accept it. As a meter, they calculated the precision and recall of the models and claimed acceptable results. Finally, they also generated assessment and mitigation for the predicted risks.

Salamai *et al.* (2021) studied identifying internal and external operational risks in SCM 4.0, combining SCM and Information technology (IT). They used a voting classifier based on the Sine-Cosine Dynamic Group (SCDG), a combination of the Sine-Cosine Algorithm (CSA) and two dynamic groups of agents that could be changed with each other. The proposed method had 98.9% accuracy, which had privileges compared to other optimisation-based and ensemble classifiers. Luo *et al.* (2022) identified credit financial risk in the energy electric vehicle industry by classifying trustable and untrustable companies. Firstly, they applied principal component analysis (PCA) to reduce the dimensions of the features. Then, the SVM model was used, which was empowered by particle swarm optimisation to avoid local optimum and combined with the AdaBoost model. They used various criteria to compare methods, including accuracy, recall, precision, specificity, G-means, F1-score and AUC. Compared with SVM, AdaBoost, PSO-SVM, DPSO-SVM and BP-AdaBoost, the proposed method had a higher accuracy of 96.13%. In another research, it is considered that users' feedback is crucial to enhance the accuracy of the AI models; Aboutorab *et al.* (2022) used a reinforcement learning-based approach for textual data to identify all risks in a global supply chain. Firstly, the risk manager must manually extract the term database from the Cambridge Taxonomy of Business Risks. Then, the web crawler automatically searched the news agencies to prepare the augmented news database using an Application Programming Interface (API) coded in Python. The augmented database included information like the person, nationality, physical facilities and geographic location of the news, which helped to analyse the news. Then, the augmented news database was used for the reinforcement learning machine to predict the risks and disruptions; finally, the proposed model was implemented in a hypothetical supply chain scenario, and the results were compared with the manual approach. The proposed method could proactively identify risks with 92% accuracy compared with the 33% accuracy of the manual approach.

Heydarbakian and Spehri (2022) applied clustering models (i.e. DBSCAN algorithm) to label the dataset's record. Then, they applied DT and Naïve Bays to classify the automotive supply chain's resilient supplier capacity (absorptive, adaptive, restorative). Results showed that DT had better interpretability capability while Naive Bayesian had better flexibility and insights. Liu *et al.* (2022) used ANN, Genetic Algorithm (GA) and Particle Swarm Algorithm (PSA) to identify financial service risk in energy global SCN for SMEs. The results of the early-warning mechanism showed reduced bank risks, improved accuracy of forecasting external environmental risks and helped in information collection and credit assessment, which showed that SMEs could enter the energy trading business. Ganesh and Kalpana (2022 b) used sentiment analysis for the real-time identification of supply chain risks through text data from Twitter. The proposed method showed promising results. For future research, the authors recommended a digital twin for identifying, assessing and mitigating risk from social media. Shahidzadeh *et al.* (2022) used deep learning (DL) based on Convolutional Neural

Networks (CNN) and long and short-term memory. They also used sentiment analyses in social media for waste management to reduce disruptions and risks in the manufacturing process. The method could predict customer behaviour to reduce returned products. The paper was based on Logistics 4.0, and the proposed method was not biased based on specific languages or geographical locations. Kosasih *et al.* (2022) focused on the issue of complex interdependencies in the SCN and the lack of transparency caused by manual collection of data or unwillingness to share data. They proposed a method that combined a graph neural network and knowledge graph reasoning to forecast the hindered risks in the SCN. They applied their proposed method to two case studies of the automotive and energy industries. Makridis *et al.* (2022) employed Reinforcement Learning (RL), NLP and time series for forecasting the hazards related to food safety. RL was used to predict future food recalls based on the food recall history, possibly because of allergens or contamination. NLP and time series were used to monitor and analyse risks. The results showed 95% precision for different scenarios. On another case of financial risks, Abouloifa and Bahaj (2022) compared e K-Nearest Neighbor (KNN), Logistics regression and RF to identify the fraud in SCN finance for different types of fraud such as financial frauds (e.g. Billing fraud), misrepresentations (e.g. quality assurance fraud), sanctions violations (e.g. turning off a ship's tracking system) and bribery (e.g. gifts). They concluded that cross-validation of the ML models is equally important to the type of chosen ML model since it can reduce errors in ML models. The KNN could predict the target value better than other models for this case. Lolla *et al.* (2022) used Logistic Regression (LR), XGBoost, Light GBM and RF for late delivery risk. The results showed an F1 score of more than 0.99 for different combinations of used methods. The proposed method increased the SCN's explainability and improved the system's trustability. Table 6 presents a comparative analysis of the techniques discussed in this section.

Discussion and Implications: In this section, as summarised, the ML's efficiency is still under compression. As per the observation of the current SLR paper, the main difference is the appearance of Ensemble-based models, such as XGBoost and GBDT and voting classifiers, which combine the results of multiple ML models and conclude the results by aggregating them. Moreover, reinforcement learning has been validated as a good model for improving the performance of AI models. Finally, regarding theRQ, the explainability and transparency of the methods (i.e. RQ3) are considered in more detail using XAI methods like Shapely values or simply showing the results by DT for better understanding. ML models consider the connection among different features (i.e. RQ1) to consider their correlations. Finally, some papers focused on external risks, such as the COVID-19 pandemic, which reflects the risks and disruptive events related to the specific periods.

3.1.3 Stage 1 – identification of risks (2023–2024). Since 2023, ML models have been integrated with other advanced techniques and have been increasingly applied for risk identification. Li and Donta (2023) proposed a new ML model, which first filters the noise of the dataset and then predicts the effectiveness of the green supply chain practices to contribute to the sustainability of the organisations. They confronted a challenge with high computational complexity; therefore, they also compared the computational complexity of different models by increasing the size of the problem, providing insight into the scalability of the SCRM problems. Gabellini *et al.* (2023) employed different ML models to predict the operational risks in the automotive industry. They claimed that using and developing ML models is necessary for SCRM to identify the risks. The COVID-19 pandemic was one of the most influential external events, significantly impacting the SCN. Xiao *et al.* (2023) considered it as a very influential external event. They proposed a new method for prediction, including decomposition of the problem, predicting and ensampling the results, which showed better performance than the other seven baseline models. They applied their propounded method to case studies of four Asian maritime ports for container throughput forecasting. Yacoubi *et al.* (2023) provided a rule-based for improving the logistics planning and handling risks for a decision support system for SCNs. They applied their methodology to a global SCN and proposed some association rules. Zaoui *et al.* (2023) considered France's COVID-19 vaccine supply chain to predict vaccine delivery and vaccination rate and identify related risks; they considered the interpretability of the learning systems and proved that the proposed method is applicable in case of crisis. Atek *et al.* (2023) considered the impact of the COVID-19 pandemic as an intense influential external events in the healthcare industry, and the results show that the machine learning model could perfectly predict regional colour codes of COVID-19 risks, demands of the hospitalisation and supply level. They concluded that using effective predictive models is essential in crisis circumstances.

Zheng *et al.* (2023) addressed the interconnection of the players in a SCN. They claimed that most of the proposed ML models try to predict the risks in SCN for a single company. However, most of the companies do not have enough datasets to predict their risks; meanwhile, sharing their incomplete data with other players of the SCN has privacy issues; therefore, they proposed a federated learning (FL) algorithm, which combines datasets of different players while securing their privacy and security of the information. The proposed method was implemented in a maritime case study, and the results show the comparable performance of the proposed model with other ML models with the privilege of data sharing and privacy protection. Li and Zhou (2024) focused on supply chain finance by developing a time series model (i.e. Wavelet Long Short-Term Memory (LSTM)) to predict the financial capital inflows and outflows. The proposed method was applied to a competition's dataset with a 427-day time horizon. The proposed model outperformed existing ones (e.g. ARIMA and Prophet models) by lower RMSE and higher R^2 scores, which first decomposed the financial data by wavelet transforms, then calculated the coefficients by LSTM and reconstructed the coefficients for forecasting capital flows.

Yang *et al.* (2024) developed a comprehensive risk identification framework to predict the annual sales change rates considering the flood data in Japan as an external factor; they also employed a graph neural network and considered the interconnection of tiers of the SCN. Moreover, they were concerned about the explainability of their results. Therefore, they used XAI methods to clarify their output for the DMs. The proposed framework outperformed other models. Aboutorab *et al.* (2024) developed a text mining framework for proactive risk identification using NLP and reinforcement learning (RL). The RL ensures that the system continually improves using feedback from the DMs and feeding it into the model. The proposed model outperformed the baseline models in all criteria with a 90% F1 score. Bassiouni *et al.* (2024) employed a DL model to extract the features and several machine learning models to predict the risk delay in a global SCN. The proposed accuracy for different machine learning models ranged from 74% to 95%. They also used five-fold cross-validation, which ensured underfir or overfit on the dataset. Two of the DL models combined by SVM achieved an accuracy of 100%. Kong *et al.* (2024) employed the FL framework to predict the order level risk, and the supplier late payment risk was predicted accurately in an aerospace case study. The FL could improve the protection of the stakeholders' privacy since it trains the machine for each entity separately, and different variations of neural networks were used for each local and federated model. Therefore, the risk of a data breach would be reduced, and the organisations would be more willing to implement the method. Table 7 presents a comparative analysis of the techniques discussed in this section.

Discussion and implications: Developing risk identification methods based on AI has been extensively worked on in the papers in this section. The increase in the number of papers in the last two years reflects the increasing interest and necessity of using AI in risk identification; as the observation of this paper, the COVID-19 pandemic had such a severe impact on the SCM that it needs to develop proactive methods to avoid similar risks in the future, which enhances considering the impact of the external events (i.e. RQ2). Moreover, using cross-validation proved to be a practical approach to increasing the accuracy of the ML model and reducing the errors they caused. The issue of privacy violation is considered, and FL models were suggested (Zheng *et al.*, 2023; Kong *et al.*, 2024).

3.2 Stage 2 – assessment of risks

Risk assessment is the second stage of SCRM, where the identified risks are prioritised based on their severity, frequency and probability. Scholars employed AI-based techniques to quantify the importance of risks. In this section, articles focusing on risk assessment are analysed. Table 8 summarises the reviewed articles and compares the techniques and analysed SCRM's stages apart from the assessment stage (i.e. S1, S3 and S4). Furthermore, it also presents the techniques used and whether their analysis assists in meeting RQ1, RQ2 and RQ3.

Risk assessment involves multiple criteria, making decision-making complex. As a result, scholars widely apply Multi-Criteria Decision-Making (MCDM) methods (e.g. Analytic Hierarchy Process (AHP) and Analytic network process (ANP)). However, scholars utilised AI-driven methods like clustering to enhance the intelligence of the risk assessment methods. For instance, El Khayyam and Herrou (2018) combined clustering with AHP to cluster supply, production and demand risks in a case study of a footwear company. In another research, Rajesh (2020) proposed a Grey-layered ANP decision support system to prioritise strategies to overcome risks. An electronic supply chain case study considered twelve risks (e.g. lead time, sourcing, flexibility and integration) and 21 resilient strategies. Yazdani *et al.* (2020) prioritised aspects of sustainability in an agricultural production system, which may cause risk in the supply chain. The impact of financial, environmental and social aspects was assessed by combining fuzzy logic and DEMATEL as inputs to a Quality Function Deployment (QFD) mechanism. Kara *et al.* (2020) assessed fifteen risks in the global supply chain through interviews, focus groups and discussions, and they used a Data Mining (DM) method to show its application in SCRM. Mostafa *et al.* (2021) used fuzzy logic to assess the suppliers' risk by considering the quantity, quality and month of ordering using a trapezoidal membership; finally, the proposed method enabled managers to evaluate supply risks and negotiate contracts more effectively. Kayouh and Dkhissi (2022) used the Best-Worst Method (BWM), Risk

Table 8. Comparison of papers focused on assessment stage

Source	Year	Which SCRM stages are the area of focus? S1	S2	S3	S4	Which requirements are addressed? R1	R2	R3	Methods
El Khayyam and Herrou (2018)	2018	No	Yes	No	No	No	No	No	Clustering and AHP
Rajesh (2020)	2020	No	Yes	Yes	No	Yes	No	Yes	AI and Grey-layered ANP
Yazdani *et al.* (2020)	2020	No	Yes	No	No	No	No	No	Fuzzy logic, DEMATEL and QFD
Kara *et al.* (2020)	2020	Yes	Yes	No	Yes	No	Yes	No	Data mining
Mostafa *et al.* (2021)	2021	No	Yes	No	No	No	No	No	Fuzzy logic
Kayouh and Dkhissi (2022)	2022	No	Yes	No	No	No	No	No	BWM and RPN
Dong (2022)	2022	Yes	Yes	No	No	Yes	No	No	Delphi method, trend-adjusted exponential smoothing method
Shiralkar *et al.* (2023)	2023	Yes	Yes	Yes	No	Yes	No	No	Clustering and optimisation
Liu (2023)	2023	Yes	Yes	No	No	Yes	Yes	Yes	Machine learning
Mittal and Panchal (2023)	2023	Yes	Yes	No	No	No	No	No	fuzzy C-Means clustering
Sharma *et al.* (2024)	2024	Yes	Yes	No	No	No	No	No	fuzzy method
Teng *et al.* (2024)	2024	Yes	Yes	No	No	No	No	No	AI and Fuzzy method
Chiu *et al.* (2024)	2024	Yes	Yes	No	No	Yes	No	Yes	NLP and AHP

Source(s): Authors' own creation

Priority Number (RPN), combined with other MCDM models to assess logistical risks in the automotive industry. The three factors of RPN (i.e. severity, occurrence and detection) were considered. Then, by using BWM, the weight of these factors was specified. Then, using experts' opinions, the weights and the Fuzzy-TOPSIS method, the ranking of the risks were calculated and sorted according to their importance. Finally, 14 logistic risks were prioritised based on the experts' opinions. For future studies, implementing this method for mitigation and monitoring was recommended. Dong (2022) used the Delphi and a trend-adjusted exponential smoothing method to assess raw material value in SCN. Important factors influencing raw materials were found, such as economic and technological factors, price stability and quality assurance. The result showed that its prediction could be made with a 9% error.

In more recent research, Shiralkar *et al.* (2023) assessed the financial risks of the suppliers using Python to implement supplier segmentation based on risk factors and categorised customers into four categories by considering return and risk percentages; they also employed a stochastic optimisation model to minimise the financial risks of the suppliers. Liu (2023) used a machine learning algorithm, a DT, to assess and evaluate the financial risks in an SCF in a bank. The employed method showed an acceptable accuracy of more than 88%. Using a DT can improve the interpretability of the methods. Mittal and Panchal (2023) proposed a risk assessment and management tool including different machine learning and AI models to categorise the risks by fuzzy C-Means clustering model and risk prediction by DL, for various risks such as supply, process and demand risks. They used multiple ML models for prediction, in which the voting classifier performed best. Sharma *et al.* (2024) employed the fuzzy method to evaluate and assess different risks and sub-risks in the pharmaceutical industry in India. The main recognised risks are demand, financial and logistics risks. The main sub-risks are drug counterfeiting, demand fluctuation and customer loss. Some technologies, such as AI and blockchain, are recommended for mitigating counterfeit risk. Teng *et al.* (2024) considered the sport SCN and proposed a combined AI and Fuzzy method to evaluate the risks for the stakeholders. They suggested that public attention should be paid more to sports operations and that the SCN should be managed more strongly. Chiu *et al.* (2024) developed a framework for green SCN to integrate an NLP model and Life Cycle Assessment (LCA) models into one Analytic Hierarchy Process (AHP). The advantage of their research is that it extracts insight from unstructured data by NLP with 81.7% accuracy. The LCA captures suppliers' environmental-related risks to support sustainable risk management. Table 8 presents a comparative analysis of the techniques discussed in this section.

Discussion and implications: The proposed AI-based models in the risk assessment stage focus significantly on prioritising the risk factors. As the observation of the current SLR, the traditional MCDM methods are enhanced by combining with the ML models to classify the risks better. Moreover, clustering models can efficiently categorise events based on their severity and frequency. To increase the transparency and explainability (i.e. RQ3), providing DTs is utilised (Liu, 2023). Comprehensive risk assessment requires considering external events as well (RQ2). The risk assessment stage mainly focuses on the risks themselves; that is why some attempts to connect different players (i.e. RQ1) are made only when other stages are considered as well.

3.3 Stage 3 – mitigation of risks

Risk mitigation, the third stage of SCRM, focuses on reducing the adverse impact of identified risks. In this section, articles focusing on risk mitigation are analysed. Table 9 summarises the reviewed articles and compares the techniques and analysed SCRM's stages apart from the mitigation stage (i.e. S1, S2 and S4). Furthermore, it also presents the techniques used and whether their analysis assists in meeting RQ1, RQ2 and RQ3.

Mitigating risks is the most practical stage of the SCRM since it aims to reduce the impact of risk factors. Kumar *et al.* (2010) tried to minimise the costs and operational risk factors

Table 9. Comparison of papers focused on mitigation stage

Source	Year	Which SCRM stages are the area of focus? S1	S2	S3	S4	Which requirements are addressed? R1	R2	R3	Methods
Kumar *et al.* (2010)	2010	Yes	No	Yes	No	Yes	No	No	Optimisation model and metaheuristic algorithms
Pimentel *et al.* (2011)	2011	No	No	Yes	No	Yes	No	No	Multi-objective stochastic programming
Matta and Miller (2018)	2018	No	No	Yes	No	Yes	No	No	Optimisation model
Hombach *et al.* (2018)	2018	No	No	Yes	No	Yes	No	No	Optimisation model
Singh *et al.* (2019)	2019	No	No	Yes	No	Yes	No	Yes	Optimisation model
Bottani *et al.* (2019)	2019	No	No	Yes	No	Yes	No	No	Optimisation model
Kellner *et al.* (2019)	2019	No	No	Yes	No	Yes	No	No	Optimisation model
Oger *et al.* (2019)	2019	No	No	Yes	No	Yes	No	Yes	BI
Jacyna and Semenov (2020)	2020	No	No	Yes	No	Yes	No	No	Genetic algorithm
Hassouna *et al.* (2022)	2022	No	No	Yes	No	Yes	No	No	Optimisation model
Ordibazar *et al.* (2022a)	2022	Yes	No	Yes	No	Yes	No	Yes	Optimisation model
Zhang *et al.* (2022)	2022	No	No	Yes	No	Yes	No	No	Blockchain technology
Vedat (2023)	2023	No	No	Yes	Yes	No	Yes	No	AI and machine learning
Lee *et al.* (2023)	2023	Yes	No	Yes	Yes	Yes	Yes	No	Federated learning-based model and blockchain technology
Hatzivasilis *et al.* (2024)	2024	Yes	Yes	Yes	No	Yes	No	No	Swarm-intelligence algorithms

Source(s): Authors' own creation

impact on the multi-echelon global SCN. They first identified the risk factors and then tried to minimise them in the SCN. To minimise the risks, first, the cost of each risk is calculated, and an optimisation model minimises the cost, which consequently mitigates the risks. Because of the problem's computational complexity, AI-based methods like GAs, bee colonies and particle swarm intelligence are applied. The interconnection of the SCN players is considered in the optimisation model. Pimentel *et al.* (2011) used a multi-objective stochastic programming approach to plan for capacity management problems in a Global mining SCN for using the existing facilities or establishing new ones and related decisions to reduce the capacity violation risks. Matta and Miller (2018) designed an optimisation model to maximise profit and control all aspects of a global SCN. A Lagrangian relaxation-based heuristic procedure solves the optimisation model and demand that exceeds the forecast is the significant risk of the considered network. Robust optimisation may contribute to capturing and reducing the uncertainty on the parameters, which leads to the adverse impact of risks on the system. Hombach *et al.* (2018) designed a robust multi-objective optimisation model to capture uncertainty in different parameters, such as price, capacity, emission, area availability and demand in the German biodiesel supply chain. Firstly, risk attitude is specified by the decision maker and then the Pareto front, the trade-off of the objective functions, was shown to assist decision-making. A robust approach is ideal when uncertainty distribution is unknown and planning flexibility is limited.

Singh *et al.* (2019) proposed a rule-based ontology-based decision-making support system for SCN resiliency. They considered four risk categories, including (1) Fire, machine failure and natural hazards, (2) fluctuating raw materials, (3) Increasing demand and (4) link disruption caused by flood. The proposed method comprises three sections: (1) an optimisation model by optimising the resiliency (satisfying the demand), (2) Particle swarm optimisation (PSO) is the Meta-heuristic to solve the model and (3) semantic web rule language (SWRL) for designing rules for players and threats. Finally, the proposed model could properly recommend SC prescriptive mitigation strategies for disruptions. Bottani *et al.* (2019) proposed a bi-objective optimisation model to maximise the profit and minimise the lead time, considering the demand fluctuations and raw material supply disruption, to solve the model in a case study of the Food Supply Chain (FSC) for ready-made UHT tomato sauce, they used Ant Colony Optimisation (ACO) Meta-heuristic algorithm. The proposed algorithm could solve the FSC to a near-optimal solution and the sensitivity analysis showed that the model could optimise both objectives effectively. So, it helped plan a resilient SCN. Kellner *et al.* (2019) designed a multi-objective optimisation model with four objectives: reducing cost, increasing sustainability, increasing logistic service and reducing supply risk. The paper aims to reduce supplier selection risk in Germany's automotive OEM. The Pareto solution of the optimisation model helps the decision maker to choose one. Oger *et al.* (2019) used BI software and experts' opinion system in a pharmaceutical company for supplier selection. The research was conducted at the company's request because of a previous supplier disruption. The supply chain risks were identified, and the mitigation recommendations were generated.

Jacyna and Semenov (2020) used a GA to consider the risk of incomplete information in the spare parts supply for vehicle service in Poland. There are three segments, and each segment demonstrates different decisions. Hassouna *et al.* (2022) used ant colony and PSO in a multi-objective optimisation problem to mitigate cost and time risks in transporting goods. They recommended considering other objectives for future studies, such as reducing resource consumption and speeding up processes. Ordibazar *et al.* (2022a) used optimisation models combined with an LR prediction model and counterfactual explanation models to mitigate delay risk in distribution centres. They used counterfactuals to increase the explainability of the results of the AI methods. The results showed that the proposed method could prevent risks while increasing the financial cost by less than 1%. Considering more echelons, risks, ripple effects and more ML models were recommended for future studies. Zhang *et al.* (2022) used blockchain technology, ant colony and GAs to mitigate supply, credit and operational risks in smart contract supply chain logistics. The risk of the supply chain was reduced by 50%. Vedat (2023) considered the SCRM on offshore sector logistics operations; they proposed a transparent tracking system based on AI and using machine learning to optimise the operations. Finally, their recommender system caused a significant reduction in delivery time and CO_2 emissions. Lee *et al.* (2023) used a FL-based model combined with Blockchain technology smart contracts to predict the fruit ripeness in fresh SCN; the monitoring data helped to train the identification of SCN features, which finally assists DMs for data-driven decision making, which resulted in reduction in costs and fruit loss. Hatzivasilis *et al.* (2024) applied a risk assessment and handling system based on swarm-intelligence algorithms on the European healthcare supply chain for cyber-security-related risks. The proposed system identified, assessed and mitigated the related risks, which complies with the EU regulations for cyber security. Finally, they suggest implementing the proposed system in fields other than healthcare to evaluate the results for future studies.

Discussion and Implications: As the literature reflects, optimisation models are highly employed in the mitigation stage yet have a high capacity for connecting different parameters of an SCN in all echelons (i.e. RQ1). In addition, adverse and unpleasant objectives, such as financial costs, environmental impacts and social dissatisfaction, can be calculated and minimised altogether while maximising the profit and resiliency of the system as the objective functions, and the output of the model can be the mitigation strategies. The most helpful factor of optimisation models is considering inter-dependencies of all aspects of an SCN holistically and optimising multi-objective problems. Furthermore, stochastic and robust optimisation models can significantly consider uncertainty in parameters of an SCN such as demand, transportation time and costs and price of products. The optimisation models can generate prescriptive recommendations to mitigate risks. Therefore, the risks of the SCN are effectively considered and managed, and the outputs of the optimisation models give holistic mitigation strategies. Moreover, some XAI methods, like counterfactual explanations, have an optimisation nature, which makes them capable of integrating with SCN models for more explainability (i.e. RQ3). The negative aspect of optimisation models is that their complexity increases with an increase in the players of the problem, thereby increasing the time and effort to reach the optimal solution. Therefore, meta-heuristic algorithms are implemented to reduce the impact of risks on the SCN.

3.4 Stage 4 – monitoring of risks

Risk monitoring, the fourth stage of SCRM, observes the risk occurrence and effectiveness of the risk management strategies. The analysis of this stage helps feed inputs to the other stages of SCRM. Among the shortlisted papers, most techniques focus on combining emerging technologies with AI-driven methods to enhance risk monitoring. The reviewed articles in the literature are explained in detail, and the overall results are summarised and compared in Table 10. The comparison tables consider whether the reviewed papers have focused on any other stages (i.e. S1, S2 and S3) of SCRM and if they addressed the questions of this research (i.e. RQ1, RQ2 and RQ3). Finally, the proposed method is also mentioned, which is helpful for researchers and practitioners looking for a specific method.

The risk monitoring stage is mainly affected by emerging technologies such as the Internet of Things (IoTs) and their ability to combine with AI tools to assist DMs in monitoring SCN activities. Similar to other stages, risk monitoring in SCN has been improved during this time.

Emerging technologies, especially the IoTs, have improved the AI-based risk monitoring of SCNs. In the 2000s, Chan *et al.* (2006) proposed a framework with four components for simulating the SCN: pattern recognition, prediction by time-series models and providing recommendations. The proposed knowledge-based simulation and analysis of supply chain performance can help monitor the new entries and analyse the risks. In the early 2010s, Liu *et al.* (2011) generally introduced emerging technologies such as IoT to design a platform for monitoring chemical SCNs, which shows the increasing interest in emerging technologies in risk monitoring. Later, more intelligent monitoring systems were proposed for risk monitoring. Hiromoto *et al.* (2017) combined an IoT-based architecture with machine learning models to observe the system and identify the cyber risks. Tsang *et al.* (2018) designed a monitoring dashboard for the risks related to the quality of cold products through automatic data collecting by IoT service management, which includes the wireless sensor and

Table 10. Comparison of papers focused on monitoring stage

Source	Year	Which SCRM stages are the area of focus? S1	S2	S3	S4	Which requirements are addressed? R1	R2	R3	Methods
Chan *et al.* (2006)	2006	Yes	No	Yes	Yes	Yes	No	No	Time-series
Liu *et al.* (2011)	2011	No	No	No	Yes	Yes	No	No	IoT
Hiromoto *et al.* (2017)	2017	Yes	No	No	Yes	Yes	No	No	IoT and machine learning
Tsang *et al.* (2018)	2018	No	No	No	Yes	No	Yes	No	IoT
Gao *et al.* (2020)	2020	No	No	No	Yes	No	Yes	No	Iot and simulation
Zhang (2021)	2021	No	No	No	Yes	No	Yes	No	Blockchain
Wittmann *et al.* (2023)	2023	Yes	No	No	Yes	Yes	Yes	No	CPS and machine learninig
Mitra *et al.* (2024)	2024	Yes	Yes	No	Yes	Yes	No	No	Blockchain and MLP
Trautmann *et al.* (2024)	2024	Yes	No	No	Yes	Yes	No	No	Blockchain

Source(s): Authors' own creation

cloud database services; their proposed monitoring system could capture the adverse impact on cold products, especially from external environmental changes (e.g. temperature, humidity and lighting intensity), to prevent the risk of quality degradation. Gao *et al.* (2020) combined simulation analysis and an IoT platform to monitor the identified internal and external risks. The framework helped e-business organisations to observe different risks, such as demand fluctuations, manufacturing and inventory.

In 2021, researchers proposed Blockchain technologies for risk monitoring. Zhang (2021) used a qualitative approach to consider the effectiveness of blockchain technology in monitoring risks and improving the resiliency in the steel manufacturing supply chain in China during the COVID-19 pandemic. The results showed promising applications for blockchain technology in risk monitoring. For future studies, developing AI and blockchain technology frameworks in the digital transformation of SCM was recommended. Wittmann *et al.* (2023) proposed a monitoring system for SCN by using Cyber-physical systems (CPS) to observe the operations; then, they used machine learning models to identify nine movement classes, which have accuracy ranges from 0.95% to 100%. Mitra *et al.* (2024) combined blockchain technology with AI for chemical SCN. They employed a Multi-Layer Perceptron (MLP) model to evaluate the safety risks; all the purchase and sales information are stored in a smart contract. Trautmann *et al.* (2024) proposed a blockchain-based system for monitoring the pharmaceutical SCN to reduce related risks. The proposed framework can combine with IoT and AI to improve its applicability. Table 10 presents a comparative analysis of the techniques discussed in this section (Hiromoto *et al.*, 2017).

Discussion and implications: In the monitoring stage, technology plays an important role, and the progress of the employed AI-based models for monitoring the risks is presented in this section. In the 2000s, due to a lack of technology, researchers tried to provide some monitoring using time series and simulation models (Chan *et al.*, 2006); however, later, by developing the technologies, the IoT and Blockchain were used for tracking the disruptions. Later, the technologies were combined with other models (e.g. ML) to enhance efficiency and add risk identification. In this stage, different types of risks are considered; in cases where the risks are unknown, the monitoring assists the DMs in being prepared for any upcoming event with probable risks. More specifically, investigation of the read papers revealed that the monitoring stages have a significant role in capturing the impact of the external events (i.e. RQ2); combining them with other models can enhance their ability to connect the components of the SCN (i.e. RQ1). Since the combined models are a part of the proposed methods in this stage, only some attempts were observed to enhance the explainability of the proposed models.

4. Open issues

This section presents the open issues found in the literature, specifically regarding RQ1–RQ3. Section 4.1 lists identified research gaps. Section 4.2 provides detailed explanations for the research gaps.

4.1 Summary

This section identifies four research gaps (RGs) based on a comprehensive literature review and scholars' suggested future directions.

(1) *RG1:* Lack of existing approaches in considering SCRM as a holistic process and across the whole SCN

(2) *RG2:* Not considering the external exposure aspect of an SCN

(3) *RG3:* Lack of interpretability in the analysis of SCRM

(4) *RG4:* Challenges of applying AI methods for SCRM

4.2 Main findings and managerial insights

In this section, the RGs listed above are explained in detail. It is suggested that scholars pay attention to the following open issues and try to address them. Most of the RGs concern the RQs mentioned in Section 1.

(1) *RG1:* Although various SCRM approaches exist, this SLR found that most methods conduct limited cause-effect analyses rather than adopting a holistic, multi-echelon approach that accounts for both internal and external factors (Ivanov *et al.*, 2019); the need and importance of addressing this gap are applicable in all four stages of SCRM to make the whole SCN resilient, as without that, an SCN is as strong as its weakest link. Moreover, most of the methods focus on one of the SCRM stages (i.e. S1–S4), as it is shown in Tables (5-10). While this improvises on the analysis obtained for that stage, it needs to carry this analysis forward in making an informed judgement and comprehensively managing risks across the SCN. The absence of such an integrated system for SCRM negatively impacts the efficiency of the SCRM, and a systems thinking-based approach towards SCRM regarding RQ1 is needed.

(2) *RG2:* Considering the impact of external events on the SCN is crucial to modelling it according to the dynamics of its environment regarding the RQ2. However, efforts have been made to consider the knowledge of an external event while risk analysis (Aboutorab *et al.*, 2023), but it is limited to the risk identification stage. Moreover, commercial tools have been proposed to ascertain the impact of external events; however, their analysis is limited to only one stage of SCRM, or they are propriety and have limited open access that researchers and practitioners can use (Analytics, 2024). Enhancing the SCRM methods' ability to capture the global exposure of an SCN (RQ2) can be beneficial for SCRM. Especially in the identification, assessment and mitigation stages, as shown in Tables (5-10), little attention to considering the external events is paid.

(3) *RG3:* This open issue highlights the research gaps of existing SCRM approaches in all stages to explain the reasons for their analysis. In the identification stage (i.e. S1), researchers have used different AI models to improve the accuracy of the outputs. Techniques such as machine learning or DL methods have been proposed to predict the probable risks and evaluate the accuracy of the results. However, little attention has been paid to improving the output's explainability regarding the RQ3. When a whole SCN is considered, and the analysis of upstream partners is included, the risk manager would need explainability to trust the analysis presented before taking action. The need for this also applies in the assessment stage (i.e. S2) as shown in Table 8, where the reasons for the risk scoring and clustering must be explained. Similarly, in the mitigation stage, strategies need to be explained to build trustworthiness. While researchers have recommended designing user-friendly dashboards (Zhang and Gong, 2021) and digital twins (Tsang *et al.*, 2018) in the monitoring stage to improve explainability, further research is needed to implement these solutions effectively. In other domains, such as finance (Ni *et al.*, 2022), global SCN (Ordibazar *et al.*, 2022 a) and medical analysis (Mehrotra *et al.*, 2020), researchers in the literature have highlighted addressing this gap to improve trust among human users, especially those users without expertise in AI.

(4) *RG4:* In the reviewed papers, all researchers used AI for SCRM and illustrated the benefits of using that. However, the challenges of applying AI methods in SCRM should also be studied. The most crucial obstacle to applying AI methods in all systems is more available and complete datasets. Different enterprises should also be willing to share information. The literature highlights a few available qualified open datasets that researchers can use to validate their proposed methods and models (Wang *et al.*, 2019;

Hassan, 2019; Bui *et al.*, 2023). In practical cases, gathering datasets and preparing them for use in AI methods is an obstacle, too. Researchers need to interpret how the datasets link to each other, which facilitates data-driven SCRM in a much better fashion.

5. Future research directions

This section discusses future directions and recommendations to address the open issues for SCRM from the perspective of an SCN. It is categorised into areas essential to improving SCRM based on the knowledge gained by reviewing the papers. Each recommendation has three parts: First is *Issues and evidence* which reflects clearly the issue. The second part, *Related RQ(s) and RG(s)*, indicates the RQ or Research Gap (RG) related to the recommendation. The last part, *Future research direction(s) for the researchers*, specifies the recommendation for researchers and practitioners for future research regarding the mentioned issues. The recommendations are as follows:

5.1 Modelling ripple effects across the SCN to better answer RQ1

Issues and evidence: Existing AI-based SCRM methods primarily focus within mainly two echelons or, in some cases, in three echelons and, in rare cases, in deeper tiers. However, SCRM is effective only when disruptions are modelled across the entire SCN. For instance, a delay in the first echelon might seem minor. Still, propagating through SCN can lead to significant long-term delays, lack of resources or unsatisfied demands. Disregarding such an impact, which is also called a ripple effect, leads to incorrectly capturing the SCN's exposure to uncertainties. Many researchers have highlighted this ripple effect as a gap (Kravchenko *et al.*, 2024; Hosseini and Ivanov, 2022; Pavlov *et al.*, 2022). *Related RQ(s) and RG(s):* Future research should expand the scope of SCN modelling to account for deeper interconnections and explicitly incorporate the ripple effect. Addressing these aspects will directly contribute to answering RQ1 and closing RG1. *Future research direction(s) for the researchers:* Reviewing the literature showed that advancements in two areas could solve the issue. First is the ability to model the SCN as a graph network consisting of nodes and relationships between them; each node may represent a supply chain partner consisting of different sub-nodes, showing the dependence of the supply chain partner on other entities and processes. The relationship between the sub-nodes across each node captures the dependence across the different partners of the SCN. To achieve this aim, researchers can investigate using knowledge modelling techniques such as knowledge graphs that attempt to organise relevant knowledge from different scattered databases before presenting a unified model of their relationship (Yun *et al.*, 2021). Developing such a unified model across the SCN requires efforts towards knowledge acquisition, conceptualisation, integration and implementation. Future research should shift from data analysis to knowledge acquisition and synthesis to better capture SCN interdependencies (Kosasih *et al.*, 2022). Second, Researchers should explore more System Dynamics (e.g. causal loop diagrams or stock-and-flow models) or similar approaches to model the flow of the ripple effect through the SCN. Once these models are analysed, the supply chain and the impacts of SCRM across the SCN can be managed using a system thinking-based approach. Ascertaining the impact's polarity and strength across the interdependent sub-nodes and nodes determines the effects of an event over different others in a complex and dynamic system.

5.2 Incorporating the notion of explainability in each stage of SCRM

Issues and evidence: Users' main obstacle to trusting AI-based SCRM methods is the need for more explainability (Baryannis *et al.*, 2019a). Risk managers unfamiliar with AI may struggle to trust AI methods since they are unsure how the AI's results are generated. This issue can cause a gap between researchers and practitioners, and the proposed methods may not apply to real-case scenarios. **Related RQ(s) and RG(s):** Future research should focus more on the Explainability of the proposed AI-based models. Addressing these aspects will directly contribute to answering RQ3 and closing RG3. *Future research direction(s) for the researchers:* Researchers should focus more on the Explainability of the AI-based SCRM methods, mainly when there is conflict among supply chain partners. As a promising advancement, many XAI methods have been used, such as SHAP (Melançon *et al.*, 2021), LIME (Visani *et al.*, 2022), counterfactual explanations (Kanamori *et al.*, 2020; Mothilal *et al.*, 2020; Ordibazar *et al.*, 2022b) and LINDA-BN (Nimmy *et al.*, 2023b). However, XAI methods must be tailored to the requirements of an SCN according to interdependencies among different partners. Another consideration is that enhancing the transparency of the methods should not conflict with the accuracy (Baryannis *et al.*, 2019a).

5.3 Using text mining and NLP methods to process the exposure of an SCN to external events

Issues and evidence: Textual data (e.g. news and social media) are among the unstructured data, which are challenging to use in the AI models (Ganesh and Kalpana, 2022b). However, they are crucial for risk management. First, they reflect the external events on a real-time basis. Second, the collection of textual data from online sources is accessible. Third, there are numerous different online sources for cross-validation. Therefore, text mining methods can assist in the identification and monitoring stage of SCRM to improve the determination of external events impacting an SCN. However, analysing this kind of data is complicated because of its unstructured nature. *Related RQ(s) and RG(s):* Addressing these aspects will directly contribute to answering RQ2 and closing RG2. *Future research direction(s) for the researchers:* Scholars should explore developing text mining, NLP and Large Language Models (LLMs) to help risk managers improve their knowledge of external events and to identify and monitor risks from textual sources. Secondly, integrating knowledge graphs and LLMs may increase decision-making accuracy (Pan *et al.*, 2024). However, developing the knowledge graphs for the SCN is complex and challenging due to the need for more relevant information (Nimmy *et al.*, 2023 a), and researchers hardly get access to SCN-related data due to the privacy and sensitivity of this information. This constraint makes developing LLM-based models challenging for monitoring operational risks. Still, these methods can be used for the risks that can be inferred without access to the company's in-house dataset but from external datasets related to geographical, social, political and natural risks (e.g. road closure, earthquake, storm, pandemic and war).

5.4 Considering all stages of SCRM together to reinforce their benefits

Issues and evidence: As specified in this paper, AI-based methods primarily focus on one stage of SCRM (i.e. identification, assessment, mitigation and monitoring). In contrast, a few articles focus on two, three or all four stages. Designing a comprehensive SCRM system that identifies, assesses and monitors potential risks while proposing mitigation strategies to avoid them proactively can contribute to industrial applicability. The issue makes the gap between theoretical and real-world investigations. *Related RG(s):* Addressing these aspects will directly contribute to closing RG1. *Future research direction(s) for the researchers:* As a suggestion for researchers for further SCRM research development, considering all stages of risk management has significant benefits for industrial applications. Integrating AI models with advanced digitisation technologies can enhance the application of the methods.

5.5 Designing user-friendly interfaces/dashboards to answer RQ3

Issues and evidence: In the reviewed literature, a few articles provided visual dashboards to help users understand the AI models' output. Designing dashboards and user interfaces that efficiently and comprehensively illustrate understandable indicators and indexes significantly improves the interpretability and trustworthiness of the SCN status regarding risks and their possibilities. *Related RQ(s) and RG(s):* Dashboards are helpful for all stages of SCRM to show the status of the identified risks, their probabilities, their impact and the reason for AI decisions. Addressing these aspects will mainly contribute to answering RQ3 and closing RG3. *Future research direction(s) for the researchers:* Researchers are suggested to design dashboards (e.g. real-time analysis, diagrams and explanations) to facilitate industrial or academic benchmarking of the proposed methods, allowing DMs and researchers to test and validate them.

6. Conclusion

The current SLR paper analysed the convergence of AI in SCRM across the SCN, identifying research gaps and open issues. Scopus and (WoS) are two well-known research databases that were used to find, shortlist and read relevant articles. Each selected article was discussed concerning the employed methods, risks and application areas before comparing them against the defined RQs for addressing SCRM from the SCN's perspective, which led to the identification of open gaps, followed by future research directions to address these shortcomings. Future studies should focus on how SCRM models can model risks from the perspective of the SCN. The current SLR paper covered research papers in the field of SCRM that used AI methods. However, like any research, there were also some limitations. Only two well-known research databases were searched; researchers commonly use these two datasets and include almost all research articles; however, other databases may be searched to ensure broader coverage.

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