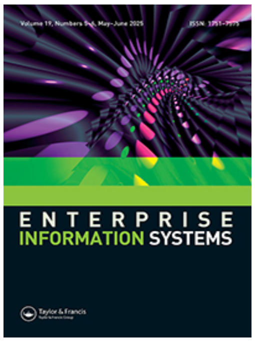

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Modelling supply chain risk events by considering their contributing events: a systematic literature review

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ABSTRACT
Proactive Supply Chain Risk Management (SCRM) helps organisations anticipate and mitigate risks, ensuring business continuity and resilience in a violet market. Existing research proposes various techniques to quantify risk occurrence, but none account for the causal relationships between contributing events and risk events. This paper addresses this gap through a systematic literature review of SCRM techniques and outlines future research directions to enhance proactive SCRM by incorporating causal dependencies in risk quantification.

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Supply chain risk management; artificial intelligence (AI); machine learning (ML); contributing event; risk identification; risk assessment

1. Motivation of the paper

Supply Chains transcend geographic boundaries. Therefore, Supply Chain Risk Management (SCRM) is important in managing their supply chain operations (Fan and Stevenson 2018; Kassa et al. 2023). SCRM involves strategies for identifying, assessing, treating, and monitoring vulnerabilities (Peck 2005; Zsidisin, Melnyk, and Ragatz 2005). Vulnerabilities are weaknesses in the supply chain that, if exploited, will adversely impact the chain and the organisations that are a part of that chain. Vulnerabilities may be internal (e.g. organisational procedures) or external (e.g. supplier unreliability) (Spieske et al. 2023). Risk assessment should be undertaken to identify any vulnerabilities in the different areas of a supply chain, such as operational (Ye, Zarat´e, and Kamissoko 2022; Chen et al. 2013; Cigolini and Rossi 2010), security (B. Liu and Qu 2016; Speier et al. 2011), reputational (Lemke and Petersen 2013, 2018; Petersen and Lemke 2015) etc.

This paper focuses on supply chain risks, which lead to supply chain disruptions, impacting the company's commitment to its service level agreements (SLA). As defined by Rangel et al. (Rangel, Oliveira, and Leite 2014), this includes anything that impacts supply chain activities, such as planning, sourcing, operating, and the return process and covers the operational and disruption aspects of the supply chain. Effective SCRM involves the sequential and iterative implementation of risk identification, assessment, treatment,

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and monitoring steps to identify vulnerabilities and ascertain their impact. This will assist the risk manager in developing strategies to manage risk. To be effective in the SCRM process, researchers (Jerome et al. 2024; Kırılmaz and Erol 2016; Mohammed et al. 2023; J. Wang et al. 2018; Yang et al. 2023) have emphasised the need to be *proactive* rather than *reactive*. In proactive SCRM, the risk manager identifies risk events that can negatively impact a supply chain's operation before they occur. This assists risk managers in developing and applying strategies to mitigate the occurrence and impact of threats before they occur. A key difference between proactive and reactive strategies in SCRM lies in the requirement for proactive techniques to incorporate intelligence and foresight. These elements enable anticipating and managing potential risk events before they occur. Recent studies have shown significant advancements in applying Artificial Intelligence (AI) technologies, blockchain, cloud chain and so on in supply chain sustainability and (Kangning Zheng, Zhang, and Wu 2021; Tasnim et al. 2023). Specifically, with the recent development of big data and data analytics, researchers have demonstrated how SCRM techniques in the literature are evolving from reactive to proactive in their working nature (Aboutorab et al. 2021). However, a key shortcoming of these proactive techniques is that they only ascertain the occurrence of a known risk event.

To explain with an example, during the COVID-19 pandemic, *staff shortage* was one of the most common risk events impacting supply chain companies. Existing techniques in the literature utilise different algorithms and models to proactively ascertain the chance of this risk event occurring. However, as shown in Figure 1, many contributing events lead to a staff shortage. For example, an increase in COVID cases will result in border closure. It will also result in more staff becoming sick, so they must quarantine. When these two factors occur simultaneously, they lead to staff shortages. In this example, the red node is the *risk event* of interest, and the other nodes are the *contributing events*. If only the risk

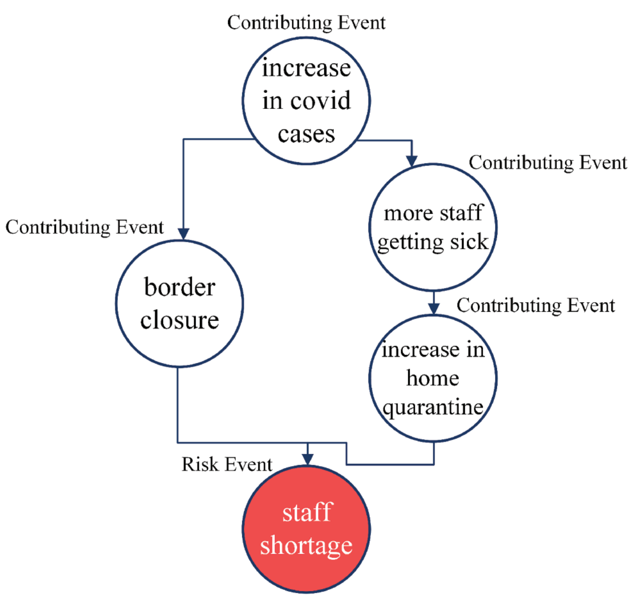

Figure 1. Contributing events leading to the occurrence of a risk event (reproduced from (Shahsavari et al. 2023)).

event of interest is considered for the proactive identification of risks, it is limited to identifying the risk events only in their known form. This ignores that the risk event/s being studied will occur due to their contributing events. However, this is an unrealistic consideration, as agreed by the experts who stress the need to consider these contributing events. For example, Christopher et al. (Christopher et al. 2002) state that to assess its supply chain risk exposure, a company must also identify the potential causes and contributing events leading to the risk event of interest. This view is supported by Cohen et al. (M. Cohen and Kunreuther 2007), who state that constructing contributing events that may lead to the occurrence of specific risks is a very important first step. When contributing events are complemented by their chance of occurrence as ascertained from current scenario information (such as news and social media), it significantly assists the process of risk identification. It proactively assists the risk manager in managing supply chain risks. However, a key point to note is that not all contributing events will lead to the occurrence of the risk event. As shown in Figure 1, there will be some risk events for all contributing events to eventuate simultaneously for the risk to occur. On the other hand, some risk events will occur even if one contributing event eventuates. So, the risk manager should ascertain the causal relationship among the contributing events resulting in the risk event of interest. This is important for the early identification and detection of the risk event and for proactively preparing the organisation to take preventive action.

While existing SCRM techniques in the literature are evolving from reactive to proactive in their working nature (Aboutorab et al. 2021), our research objective in this paper is to conduct a systematic analysis of those approaches from the perspective of their working style to ascertain if they also consider the contributing events along with their impact in their analysis. As previously discussed, such approaches need to be proactive in their working nature. The structure of the paper is as follows. Section 1 details the process we utilise to shortlist the papers to analyse in this systematic literature review. This section also presents the classification we use to categorise the shortlisted papers. Section 3 discusses papers focusing on risk identification and analyses them to ascertain if they identify risk occurrence by capturing the contributing events leading to them. Section 3 does the same by focusing on papers that assess risks. Section 4 discusses the gaps in the existing approaches and the agenda for future research. Section 5 concludes the paper.

Process to shortlist papers for the systematic literature review

To answer the paper's research objective, a systematic literature review (SLR) was conducted by adopting the paradigm proposed by Durach et al. (Durach, Kembro, and Wieland 2017) for SLRs in the supply chain domain. This method follows a six-step paradigm, as shown in Figure 2 and outlined and detailed below:

(1) **Defining the research questions**: This step involves specifying the research questions to guide the review process. These questions were formulated to address the scope and ensure that the SLR remains focused and relevant to the intended research objective of the study.
(2) **Determining the required characteristics of the primary studies**: This step established the inclusion and exclusion criteria for selecting high-quality and relevant studies. In establishing the criteria, the aim was to focus on recent, credible, and well-documented research from appropriate disciplines, ensuring alignment with the scope of the review. Studies with insufficient methodological details, irrelevant

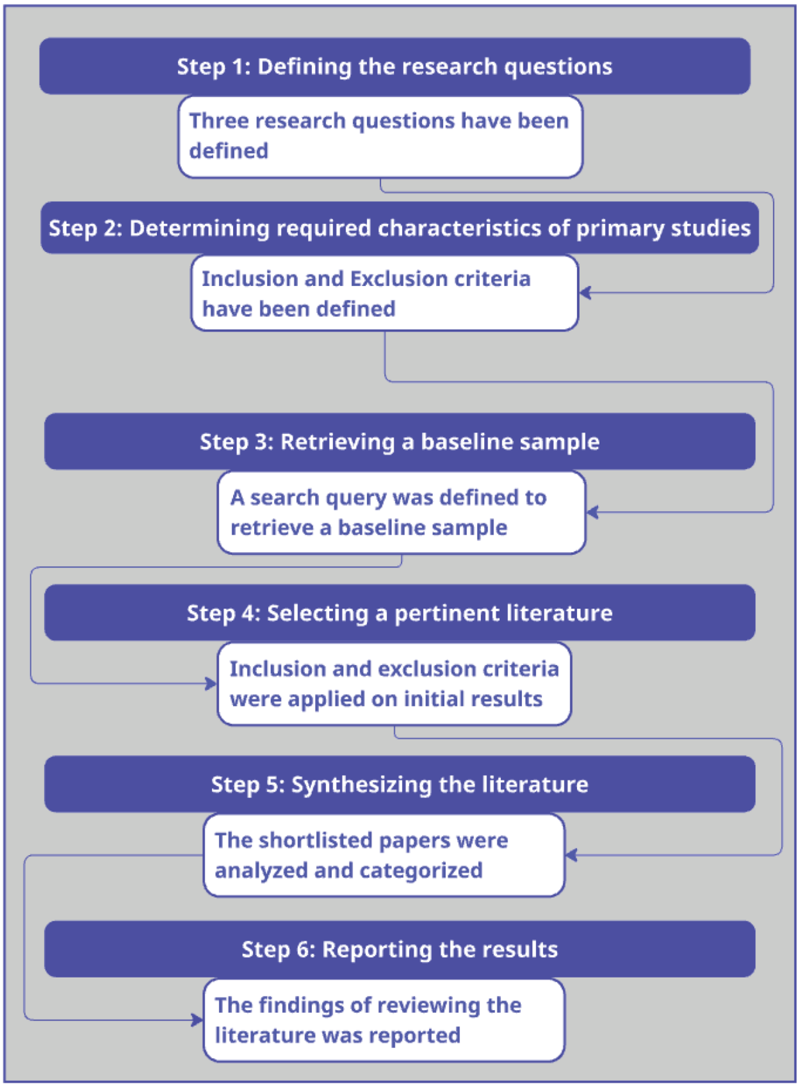

Figure 2. The flow diagram showing the process of shortlisting the articles used in this SLR.

findings, or limited conceptual accuracy were excluded. This approach ensured that the shortlisted literature effectively addressed the research questions.

(3) **Retrieving a baseline sample**: In the third step, a comprehensive search query was designed and applied to retrieve a broad set of potentially relevant studies. Scopus was the primary database used, and the search strings were applied to the title, abstract, and keywords to ensure precision.

(4) **Selecting pertinent literature**: The retrieved studies were screened in this step to identify the most pertinent papers for further analysis. The inclusion and exclusion criteria were applied to ensure that only high-quality, relevant studies were shortlisted for further synthesis.

(5) **Synthesising the literature**: This step involved systematically analysing and coding the shortlisted studies. Key information, such as research contexts, methods, findings, and theoretical contributions, was extracted. This process enabled the identification of themes, patterns, and relationships across the studies, leading to a deeper understanding of the literature and categorising the papers.
(6) **Reporting the results**: The final step focused on presenting the results of the SLR. It reports the findings from the analysis of the shortlisted studies, including key insights, thematic outcomes, and identified trends. This step also highlights gaps in the literature and provides suggestions for future research to address these gaps and advance the current body of knowledge in the supply chain domain.

This structured six-step approach ensured a transparent and comprehensive reporting of the literature. In the following sections, we explain each step in detail and the corresponding outcomes.

1.1. Step 1: defining the research question

The research question this paper answers is:

Do the existing proactive supply chain identification and assessment techniques determine risks by considering their contributing events and their impact?

For risk managers to have such an approach, techniques should have the ability to meet the following three requirements, which are the criteria we use to analyse the literature:

Requirement 1 (R1): Ascertain the different contributing events to a risk event of interest:
To proactively identify risks, techniques should be used to determine the events that contribute to the occurrence of the risk events of interest. Furthermore, they should model the interrelationship/s between the different contributing events as a causal effect between them.
Requirement 2 (R2): Identify and quantify the occurrence of contributing events in the real world:
Once the contributing events have been identified, they should be identified and quantified. This can be done using different methods, such as monitoring news articles, using AI techniques to ascertain their likelihood of occurrence, etc.
Requirement 3 (R3): Propagate the occurrence of each contributing event to quantify the chance of occurrence of the risk event of interest:
After quantifying the chance of occurrence of each contributing event, the next requirement is to quantify the chance of occurrence of the main risk event by propagating the causal relationship/s between them.

To answer the research question, we use R1-R3 to critique the existing papers in the literature on the proactive identification of risks to ascertain if they identify risks by considering their contributing events and their impact. Based on the analysis, we then identify the open gaps that need to be addressed in the domain of supply chains to make the risk identification and assessment techniques more proactive.

1.2. Step 2: determining the required characteristics of the primary studies

To ensure that the review focuses on the right studies, it is essential to define clear inclusion and exclusion criteria for selecting studies. These rules help us review the studies that are directly related to the research question and are reliable and useful. By doing this, we ensure the review is focused, high-quality, and provides meaningful insights. The inclusion and exclusion criteria are explained below and shown in Table 1.

(1) Inclusion Criterion 1 (I1): This criterion applies the search strings only in the title, abstract, and keywords of the Scopus database results. It ensures that selected studies explicitly focus on the topics of interest, minimising irrelevant results and improving the efficiency of the search process.
(2) Inclusion Criterion 2 (I2): This criterion includes papers published after 2018 to ensure that the review captures recent developments and reflects advancements in proactive supply chain risk management (SCRM), particularly to emerging technologies.
(3) Inclusion Criterion 3 (I3): This criterion ensures that we include journal articles, conference papers, reviews, and book chapters. These publication types are peer-reviewed and widely recognised for their academic rigour, ensuring the credibility and quality of the selected studies.
(4) Inclusion Criterion 4 (I4): This criterion ensures that only papers written in English are considered to ensure consistency in the interpretation and analysis of the results.
(5) Inclusion Criterion 5 (I5): This criterion includes papers from Computer Science, Decision Systems, Business, Management and Accounting, Decision Sciences, Economics, and Econometrics and Finance. These fields are directly relevant to the theoretical and applied aspects of SCRM, ensuring the selected studies align with the research objectives.

The exclusion criteria were chosen to filter out studies that do not meet this review's quality and relevance requirements.

Table 1. Inclusion and exclusion criteria applied to the initial results from the database search.

Ref.	Description
Inclusion Criteria	
I1	Search strings should only be in the title, abstract and keywords in the Scopus search results
I2	Published after 2018
I3	Journal articles and conference papers, reviews, book chapter
I4	Written in the English language
I5	Papers in 'Computer Science', 'Decision Systems', 'Business, Management and Accounting', 'Decision Sciences', 'Economics', 'Econometrics and Finance'
Exclusion criteria	
E1	Papers that do not have relevant outcomes
E2	Papers that do not have a well-organized methodology
E3	Papers in which the results do not reflect any facts in the real world
E4	Papers that are not conceptually correct
E5	Papers that are not accessible

(1) Exclusion Criterion 1 (E1): This criterion excludes papers that do not present relevant outcomes, ensuring that the reviewed studies contribute meaningfully to answering the research question. Specifically, papers that do not employ AI-based techniques, such as those relying on Multi-Criteria Decision-Making (MCDM) approaches like DEMATEL for causal analysis, are excluded, as they do not align with this review's focus on AI-driven SCRM methods.
(2) Exclusion Criterion 2 (E2): This criterion excluded studies that lack a well-organised methodology. This ensures that only methodologically sound papers are included, enhancing the reliability of the review.
(3) Exclusion Criterion 3 (E3): This criterion excluded papers with results that do not reflect real-world phenomena. This is important to ensure that the review's findings have practical and actionable implications.
(4) Exclusion Criterion 4 (E4): This criterion excludes conceptually flawed papers and ensures that the studies included in the review provide accurate and meaningful insights.
(5) Exclusion Criterion 5 (E5): This criterion excluded papers that are not accessible as having full access to the content is essential for thorough review and analysis.

1.3. Step 3: retrieving a baseline sample

The PRISMA methodology applied a search query to the Scopus database, targeting titles, abstracts, and keywords. This query, shown in Figure 3, ensured comprehensive coverage across supply chain risk identification, risk assessment, and AI applications in SCRM. As previously discussed, the paper's objective is to perform a systematic analysis of approaches from the perspective of their working style to see if they also consider the contributing events along with their impact in their analysis. This is only possible if knowledge synthesis and data analytics techniques are used for SCRM. These techniques come under the broad domain of Artificial Intelligence methods that leverage computers and machines to mimic the problem-solving and decision-making capabilities of the human mind.

Furthermore, as the main focus of this study is to emphasise the need to identify the contributing events along with their impact, this should be applied to identify any risks in the supply chains. Thus, to ensure that we are not limiting the scope while finding the

```
(( "supply chain"  OR  "supply network"  OR "value chain" OR "channels of supply")

AND

     ("Risk identification" OR "hazard identification" OR "vulnerability
     identification" OR "risk assessment" OR "hazard assessment" OR "vulnerability
     assessment" OR "identifying risk" OR "identifying hazard" OR "identifying
     vulnerability"
     OR "assessing risk" OR "assessing hazard" OR "assessing vulnerability")
AND
   ("nlp"  OR "natural language processing" OR "AI" OR "text mining "  OR "machine
   learning" OR "natural language processing " OR "causal relationship" OR "cause and
   effect" OR "natural language inference" OR "causal inference" ))
```

Figure 3. Query for database search.

existing works, the search query we formed is general to the areas of risk identification and assessment in supply chains without specifically focusing on operational or disruption risks. Thus, the search query covers the areas of:

(1) Supply chain risk identification or risk assessment to include papers in areas where the contributing events leading to a risk event are considered.
(2) Applying AI methods that include data mining techniques such as text-mining, natural language processing or machine learning used in these steps of SCRM. By doing so, we include any articles that analyse data in risk identification and assessment steps.

The search query, shown in Figure 3, initially retrieved 170 papers.

1.4. Step 4: selecting pertinent literature

We applied the search query to the paper's title, abstract and keywords in the Scopus database. We chose Scopus for its comprehensive range of articles, as its collection represents almost all of the publishers where the academic literature is indexed. The search query returned 170 papers in total. We limited the search to papers that were published from 2018 onwards. This is because Baryannis et al. (George Baryannis, Validi, and Antoniou 2019) performed a literature survey covering papers from 1978 to 2018 and concluded that data patterns related to a specific risk could be used to identify risks using data mining and machine learning techniques. This paper proposes that a proactive approach to SCRM requires risks to be determined by considering their contributing events and impact. Achieving this aim requires an extension of analysing the underlying data to identify the events contributing to the risk event of interest. As this is an extension of the open gaps mentioned by (George Baryannis, Validi, and Antoniou 2019), we focus on the literature published since 2018 to investigate if any existing research considers this line of work. As a result of this filter, the number of papers was reduced to 147. Only journal articles, conference papers, reviews, and book chapters written in English were included, which left 132 papers across domains ranging from computer science to business, social science to environmental science, engineering, medical science, and humanities. However, as the scope of this paper is to analyse if the existing risk identification and assessment techniques in supply chains are proactive in their analysis by taking into consideration events that contribute to the risk event of interest, only papers that are relevant to the following fields were considered:

- Computer science
- Engineering
- Decision Systems
- Business, Management and Accounting
- Decision Sciences
- Economics, Econometrics and Finance

After this filtration step, 116 papers remained. The exclusion criteria listed in Table 1 were then applied to the remaining articles.

It is important to note that MCDM techniques, such as DEMATEL (Shafiee et al. 2022), are commonly used for causal modelling of risk events in SCRM. These methods provide structured decision-making frameworks for analysing relationships between risk factors. However, this study focuses specifically on AI-based techniques, which Sarker (Sarker 2022) defines as models trained on data to generate predictive intelligence. Since MCDM techniques do not align with this definition, they were excluded under Exclusion Criterion 1 (E1). After applying all exclusion criteria, 90 papers were selected for the SLR. A summary of the selection process and the number of papers at each stage is presented in Figure 4.

1.5. Step 5: synthesizing the literature

To answer the research question defined in Section 1, we first categorised the shortlisted papers according to their focus areas of *risk identification* or *risk assessment*, as shown in Figure 5. We further categorised the papers in each area according to their working style. This is done in the risk identification category according to their approaches. The first approach is to identify risks by synthesising knowledge from existing underlying information, and the second approach is to identify risks by integrating external information with the existing underlying information. In both approaches, the aim is to ascertain if the risks are identified by considering their contributing events or not. In the risk assessment category, the existing approaches are also categorised according to their approach to risk assessment. The first category consists of approaches that quantify a specific risk as an independent event, not as one influenced by other variables. The second category consists of approaches that consider features that contribute to or cause risk occurrences while being assessed. This classification facilitated a detailed critique of existing techniques against R1, R2, and R3 research requirements.

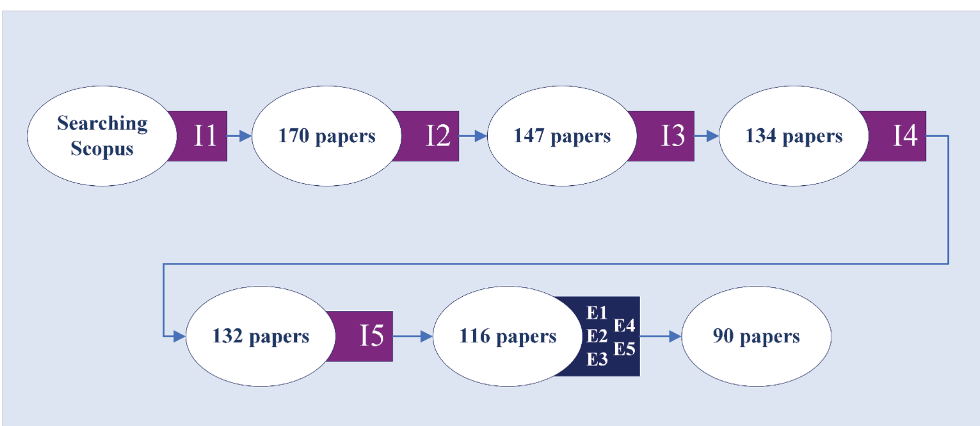

Figure 4. Inclusion and exclusion criteria applied to the initial results from the database search.

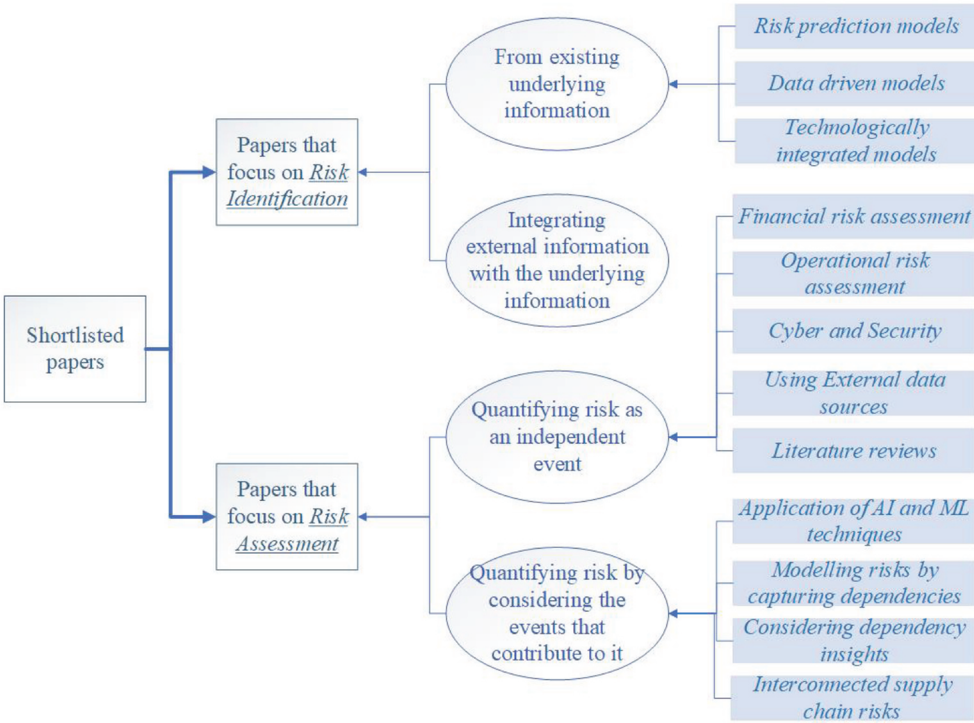

Figure 5. Categorisation of shortlisted papers.

1.6. Step 6: reporting the results

The sixth step of the applied paradigm for systematic literature reviews in supply chain management (Durach, Kembro, and Wieland 2017) is reporting the results. We report the results of analysing the shortlisted papers in Sections 2 and 3.

In the following sections, we analyse the selected studies, present the key findings, and identify the existing gaps in the literature. Based on these insights, we also provide suggestions for future research directions to address the identified gaps and advance the current body of knowledge.

2. Analysis of shortlisted risk identification techniques in SCRM

Supply chain risk identification is a critical step of the SCRM process. It analyzes the supply chain's information, data, and phenomena for identifying the risks (C. Han and Zhang 2021; Wu, Blackhurst, and Chidambaram 2006). In this section, we analyse the relevant works from the shortlisted papers that identify risks and evaluate them based on their alignment with requirements R1 to R3.

2.1. Risk identification by knowledge synthesis of existing information

This section focuses on papers that identify risks using supply chain information system data such as product features, transaction data, material price fluctuation and other day-to-day occurrences in the supply chain environment. In these studies, expert knowledge and historical data define the scope of risks that must be monitored. AI and data analysis techniques have brought about a transformative shift in identifying risks. The increasing complexity and interconnectedness of global supply chains necessitate sophisticated approaches for effective risk identification. Recent research in this domain has leveraged cutting-edge AI methodologies, including Machine Learning (ML) algorithms, Natural Language Processing (NLP), and integrating Internet of Things (IoT) technologies, to identify risks ranging from operational disruptions to cybersecurity threats. To analyse the papers in this domain, we divide them into one of the following three categories:

(1) Prediction models
(2) Data-driven models for risk identification
(3) Technological integration models for enhanced risk identification

2.1.1. Prediction models

Prediction models use AI and ML algorithms to predict potential risks in supply chains. They include studies that develop predictive models based on historical data, expert knowledge, and ML techniques to identify risks such as product fraud, delivery delays, and other operational vulnerabilities before they impact the supply chain. For example, Zhou et al. (Zhou, Song, and Zhou 2021) proposed a risk identification model that uses historical data and expert knowledge to ascertain whether a product is fraudulent. Baryannis et al. (Baryannis, Dani, and Antoniou 2019) developed a framework for predicting delivery delays in supply chains using historical data and expert knowledge. Kumar and Sharma (Kumar and Sharma 2023) integrated the SCOR model with machine learning algorithms, including SVM, k-NN, Random Forest, Decision Tree, and Linear Regression, for risk prediction using supply chain data. Sarbas et al. (Sarbas et al. 2023) implemented a machine learning-based method and used historical data to predict late order deliveries in supply chains. Dong et al. (Dong et al. 2021) utilised a similar approach to detect product fraud in supply chains. However, as shown in Table 2, while techniques in this category utilise AI and ML algorithms for analysing historical data and expert insights, they only focus on the studied risk event, thus failing to meet R1 to R3. Furthermore, techniques in this category focus primarily on internal data, thus missing out on the rich

Table 2. Critical analysis of the literature on identifying risks using knowledge synthesis of existing information against R1-R3.

Research work	R1	R2	R3
Zhou et al. (Zhou, Song, and Zhou 2021)	No	No	No
Baryannis et al. (Baryannis, Dani, and Antoniou 2019)	No	No	No
Kumar (Kumar and Sharma 2023)	No	No	No
Sarbas et al. (Sarbas et al. 2023)	No	No	No
Dong et al. (Dong et al. 2021)	No	No	No
Sheikhattar et al. (Sheikhattar and Mansouri 2023)	No	No	No
Lu and Systems (S. Lu et al. 2021)	No	No	No
Hongjin (Hongjin, Ramachandran, and Ramachandran 2021)	No	No	No
Ye et al. (Ye, Zarat´e, and Kamissoko 2022)	No	No	No
Hatzivasilis et al. (Hatzivasilis et al. 2023)	No	No	No
Xu et al. (Z. Xu et al. 2023)	No	No	No
Ramachandran et al. (K et al. 2023)	No	No	No
Aljabhan (Aljabhan 2023)	No	No	No

Table 3. Analysis of the literature on risk identification by knowledge synthesis of external information based on the three research requirements.

Research work	R1	R2	R3
Aboutorab et al. (Aboutorab et al. 2023)	No	No	No
Chu et al. (Chu, Park, and Kremer 2020)	No	No	No
Hassan (Hassan 2019)	No	No	No
Ganesh et al. (Deiva Ganesh and Kalpana 2022b)	No	No	No
Yao et al. (Yao et al. 2023)	No	No	No
Chu et al. (Chu, Park, and Kremer 2019)	No	No	No
Sadeek et al. (Sadeek and Hanaoka 2023)	No	No	No

insights that external factors such as geopolitical dynamics, environmental shifts, and social trends could offer in understanding the root causes of supply chain disruptions (R1). These gaps highlight a need for future research to integrate external data sources into predictive models to identify the causal links between external events (contributing events) and supply chain risks. This will then assist them in meeting R2 and R3.

2.1.2. Data-driven models for risk identification

Data-driven models encompass structured and unstructured data analysis for risk identification. Such models use NLP, ML, and Data Mining techniques to extract and analyse information from diverse data sources to identify hidden or non-obvious risks by analysing trends, patterns, and anomalies in supply chain data. An example of this type of model is the one proposed by Lu et al. (S. Lu et al. 2021). This approach used the backpropagation neural network method to identify and assess business risks using historical sales data. Sheikhattar et al. (Sheikhattar and Mansouri 2023) applied AI techniques such as word embedding and non-negative matrix factorisation to analyse unstructured risk data to improve decision support systems by finding hidden risks by examining trends, patterns, and anomalies in data. However, as shown in Table 2, despite these advancements, a significant gap remains in these models' ability to identify the causal relationships between contributing events and supply chain risks, so they don't meet R1. This gap points to the need for these models to extend their analysis beyond historical sales and unstructured risk data and incorporate external data sources that could offer insights into the causes of these risks. Furthermore, while models in this category are proficient in analysing historical and static data, they cannot often integrate and interpret live data streams that identify risk-causing events, thus they do not meet R2 or R3.

2.1.3. Technological integration models for enhanced risk identification

Models in this category integrate advanced technologies like IoT and AI with supply chain operations to improve their risk identification capabilities. These models also provide risk managers with real-time monitoring and analysis, thereby facilitating the early detection of risks associated with supply chains' financial, operational, and security aspects. For example, Ye et al. (Ye, Zarat´e, and Kamissoko 2022) developed a decision support system by utilising expert knowledge and data monitoring using sensors. The integrated data is then analysed to identify risks, recommend decisions, and prioritise management strategies. Hongjin (Hongjin, Ramachandran, and Ramachandran 2021) and Xu et al. (Z. Xu et al. 2023) conducted similar work to identify and manage risks in the financial supply chain. Hatzivasilis et al. (Hatzivasilis et al. 2023) proposed an approach to monitor security in supply-chain ecosystems continuously. They focus on detecting and mitigating vulnerabilities through real-time data analysis and monitoring. Ramachandran et al. (K et al. 2023) explored using AI, including predictive analytics and machine learning, for risk management and enhancing business resilience. Their research focuses on the application of AI in SCRM, highlighting its role in risk identification and management without delving into the analysis of specific events affecting the supply chain. Aljabhan (Aljabhan 2023) used an adaptive logistic regression classifier for risk identification and classification in supply chain risk management, focusing on how five major organisations implement SCRM strategies to improve their operations. Integrating advanced technologies such as IoT and AI into supply chain operations is a significant leap forward in improving risk identification capabilities. However, while these models excel at monitoring and detecting risks in real-time, they often lack the depth to specifically understand the contributing events that lead to these risks (R1). As shown in Table 2, these models can provide information on what is wrong but cannot always provide information as to why or what led to the problem in the first place. This shortcoming means that, although such techniques can alert an organisation to potential risks, they fall short in identifying the occurrence of these risks (R2). As a result, techniques in this category do not use information about contributing events to predict how likely a major risk event will occur (R3).

2.2. Risk identification by integrating external information with the existing underlying information

This section reviews papers that use external information like news articles or social media to identify risks. Approaches in these categories use a combination of prediction, data-driven, and technological integration approaches to quantify the occurrence of risks. For example, Aboutorab et al. (Aboutorab et al. 2023) utilised reinforcement learning to scan news articles for known risk events. The proposed approach uses the Cambridge Taxonomy of Business Risks to identify risk events of interest and then proactively determine which news articles are important and should be shown to the risk manager. Chu et al. (Chu, Park, and Kremer 2020) proposed a text-mining-based approach to analyse and categorise global supply chain risk literature. The authors then utilise sentiment analysis to identify the patterns related to risks. Hassan (Hassan 2019) utilised machine learning to identify risks from news articles. After processing the textual documents, the author trained a classification model that classified them as relevant. Ganesh et al. (Deiva Ganesh and Kalpana 2022b) leveraged text mining to extract information from social media (such as tweets) and identify potential supply chain risks. Yao et al. (Yao et al. 2023) utilised natural language processing to create a predictive framework that combines social media sentiment analysis with traditional risk assessment methods to predict the credit risk of listed companies in supply chains. Chu et al. (Chu, Park, and Kremer 2019) developed a text mining method to identify the risks impacting supplier selection. Sadeek et al. (Sadeek and Hanaoka 2023) applied a Latent Dirichlet allocation algorithm and sentiment analysis on news media and Twitter data to identify supply chain risks during disruptive events like the COVID-19 Omicron phase and the Ukraine-Russia war. While techniques in this category collectively advance the field of risk management by incorporating various computational techniques, as shown in Table 3 , they do not consider the contributing events impacting the occurrence of a risk event. Although some

Table 4. Analysing the literature in quantifying risks as a standalone factor based on the three research requirements.

Research work	R1	R2	R3
Han et al. (C. Han and Zhang 2021)	No	No	No
Wei (Y. Wei and Karuppanan 2022)	No	No	No
Podile et al. (Podile et al. 2023)	No	No	No
Liu (Y. Liu 2023)	No	No	No
Li (L. Li and Chen 2022)	No	No	No
Ni et al. (Ni et al. 2023)	No	No	No
Xu et al. (S. Xu and Chen 2022)	No	No	No
Li et al. (Y. Li, Stasinakis, and Yeo 2022)	No	No	No
Liu et al. (T. Liu and Yu 2022)	No	No	No
Rajesh et al. (Rajesh 2020)	No	No	No
Xuan (Xuan and Ramachandran 2021)	No	No	No
Rajagopal et al. (Rajagopal et al. 2023)	No	No	No
Wang (Y. Wang and Chen 2021)	No	No	No
Salamai et al. (Salamai, El-Kenawy, and Ibrahim 2021)	No	No	No
Sun et al. (Sun et al. 2020)	No	No	No
Lau et al. (Lau et al. 2021)	No	No	No
Malmstedt et al. (Malmstedt and Backstrand 2022)	No	No	No
Tiwari (Tiwari 2022)	No	No	No
Zhu et al. (T. Zhu and Liu 2023)	No	No	No
Sedamaki et al. (Sedamaki and Kattepur 2022)	No	No	No
Nguyen et al. (Nguyen Thi Thu, Nghiem, and Nguyen Duy Chi 2023)	No	No	No
Ma et al. (Ma, Yang, and Miao 2023)	No	No	No
Ghabak et al. (Ghabak and Seetharaman 2023)	No	No	No
Burstein et al. (Burstein and Zuckerman 2023)	No	No	No
Wong et al. (Wong et al. 2021)	No	No	No
Cohen (M. A. Cohen 2022)	No	No	No
Lin et al. (Lin, Chang, and Hsu 2023)	No	No	No
Prathyusha et al. (Prathyusha et al. 2023)	No	No	No
Radanliev et al. (Radanliev and De Roure 2023)	No	No	No
Radanliev et al. (Radanliev et al. 2020)	No	No	No
Rezki et al. (Rezki and Mansouri 2023)	No	No	No
Janjua et al. (Naeem Khalid Janjua and Prior 2023)	No	No	No
Handfield et al. (Handfield, Sun, and Rothenberg 2020)	No	No	No
Ganesh et al. (Deiva Ganesh and Kalpana 2022a)	No	No	No
Sarkar et al. (Sarkar and Das 2023)	No	No	No
Wei et al (Z. Wei et al. 2023)	No	No	No
Baryannis et al. (George Baryannis, Validi, and Antoniou 2019)	No	No	No
Zhang et al. (Zhang, Ling, and Lin 2023)	No	No	No

methods, such as (Aboutorab et al. 2023), show promise in detecting the presence of risk events, they often overlook the detailed analysis required to pinpoint and monitor the specific events leading to these risks. This oversight limits the ability to fully identify and assess the early indicators or precursors that could inform more proactive risk management strategies. Due to this limitation, the methods fail to accurately forecast the likelihood of contributing events and the associated risks through analysis of these events.

3. Analysis of shortlisted risk assessment techniques in SCRM

After the risk identification process in SCRM, it is important to assess and prioritise risks to choose management actions appropriate to the situation (Christopher et al. 2002) in the risk assessment step. Risk assessment is expressed in terms of the probability of the risk occurring and having an adverse impact on the supply chain (Aseem Kinra et al. 2020). This section reviews the shortlisted papers focusing on risk assessment to determine if they quantify the risk as an independent or a dependent event.

3.1. Quantifying risk as an independent event

This section reviews the work done in supply chain risk assessment that quantifies it as an independent or a standalone factor. Due to the number of works in this category, we categorise them according to their focus areas:

(1) Quantifying financial risks,
(2) Quantifying risks that impact the operations of a company,
(3) Quantifying cyber and security risks, and
(4) Literature review and theoretical contributions that conceptualise risks.

3.1.1. Quantifying financial risks

This category encompasses research efforts to evaluate financial vulnerabilities in supply chains, such as credit risk, investment risk, and supplier financial stability. Financial risks are one of the important areas of risk in businesses (Gurtu and Johny 2021). In response to its importance, different researchers have utilised various techniques to quantify financial risks of different types. For example, Han et al. (C. Han and Zhang 2021) developed an SCRM model using machine learning and neural networks based on statistical data from questionnaires to assess risks across supply chains at various levels of severity. Wei (Y. Wei and Karuppanan 2022) developed a linear regression algorithm based on machine learning to enhance supplier selection and risk prediction. Podile et al. (Podile et al. 2023) proposed an enhanced ensemble machine learning model for credit risk assessment in supply chain finance. Liu (Y. Liu 2023) focused on a financial risk network assessment model using AI and ML for analysing historical data and assessing risks. Li (L. Li and Chen 2022) utilised a backpropagation neural network and logistic regression for investment risk prediction in supply chains. Ni et al. (Ni et al. 2023) used machine learning, especially support vector machine algorithms, to improve corporate credit risk prediction by analysing extensive supply chain and network data. Xu et al. (S. Xu and Chen 2022) developed a financial credit risk assessment model using deep learning and the AdaBoost algorithm for the pharmaceutical supply chain, targeting enhanced risk management during public health emergencies. Li et al. (Y. Li, Stasinakis, and Yeo 2022) combined extreme gradient boosting and multi-layer perceptron for credit risk assessment in digital supply chain finance. Liu et al. (T. Liu and Yu 2022) integrated machine learning with particle swarm optimisation and blockchain technology for financial risk evaluation. Rajesh et al. (Rajesh 2020) combined multi-criteria decision aid with AI to analyse financial risks and their interrelations within supply chains. Xuan (Xuan and Ramachandran 2021) integrated machine learning, regression analysis, and fuzzy logic for financial risk management in supply chains, developing a risk evaluation index system. Rajagopal et al. (Rajagopal et al. 2023) proposed an AI model for evaluating monetary risks in supply chain financing, using principal component analysis, support vector machine algorithms, and ensemble learning methods. Wang (Y. Wang and Chen 2021) explored financial risk assessment in supply chains using blockchain technology and fuzzy neural networks, highlighting a tech-driven approach.

While approaches in this category have utilised many technological advancements to quantify financial risk, as shown in Table 4, they fall short in quantifying it from the perspective of the impact that contributing events have on the risk event. For example, while researchers such as Han et al. (C. Han and Zhang 2021), Wei (Y. Wei and Karuppanan 2022), and Podile et al. (Podile et al. 2023) primarily leverage historical data, machine learning, and neural networks to evaluate financial risks, they lack a comprehensive approach to ascertain and model the interrelationships between different contributing events and the risk event (R1). They also fail to monitor and quantify real-world occurrences of contributing events, representing another significant shortfall (R2). While some models utilise AI to analyse historical data, a notable lack of real-time data analysis and monitoring (e.g. news articles and market trends) could provide early warnings of emerging financial risks (R3). This limitation undermines supply chain risk managers' ability to respond to risks promptly and effectively.

3.1.2. Quantifying risks that impact the operations of a company

This category quantifies the risks associated with the day-to-day and strategic operations within supply chains. Operational and disruption risks impact supply chain processes' efficiency, reliability and agility. Thus, these risks represent a crucial area and need effective management (Gurtu and Johny 2021; Nimmy et al. 2022). As in the financial category, researchers have proposed different models to quantify risks in this category. For example, Salamai et al. (Salamai, El-Kenawy, and Ibrahim 2021) proposed a method to quantify operational risks in Supply Chain 4.0 using a voting classifier and a sine cosine dynamic group algorithm, relying on product features and service level agreements. Sun et al. (Sun et al. 2020) conducted a quantitative risk analysis using SVM and fuzzy sets, informed by expert opinions and focusing on agile supply chain processes. Lau et al. (Lau et al. 2021) aimed to identify and assess cold chain risks using federated learning and multi-criteria evaluation, integrating expert knowledge for risk categorisation. Malmstedt et al. (Malmstedt and Backstrand 2022) focused on predictive modelling and AI-driven tools for enhancing the resilience of inbound supply chains, especially in volatile environments. Tiwari (Tiwari 2022) implemented neural networks for risk assessment in food supply chains to improve safety and management effectiveness. Zhu et al. (T. Zhu and Liu 2023) created a risk management framework for prefabricated building supply chains, integrating a work breakdown structure and neural network models. Sedamaki et al. (Sedamaki and Kattepur 2022) introduced an innovative method for managing supply chain delays by evaluating supplier risk with machine learning and optimising order allocation using reinforcement learning. Using machine learning techniques, Nguyen et al. (Nguyen Thi Thu, Nghiem, and Nguyen Duy Chi 2023) presented a comprehensive approach to risk assessment in supply chain networks. Complementing this, Ma et al. (Ma, Yang, and Miao 2023) applied ensemble learning and ML to big data for risk assessment in airport supply chains, showcasing the use of big data analytics. Ghabak et al. (Ghabak and Seetharaman 2023) studied the integration of ML in agile supply chain management to boost efficiency and responsiveness. In contrast, Burstein et al. (Burstein and Zuckerman 2023) created an objective supply chain risk assessment method using machine learning to minimise human bias. Wong et al. (Wong et al. 2021) enhanced maritime supply chain management by integrating blockchain technology, cloud computing, and machine learning. Cohen (M. A. Cohen 2022) used analytics and machine learning to boost supply chain resilience, focusing on global strategies and tool development for risk mitigation. Lin et al. (Lin, Chang, and Hsu 2023) offered a method combining slack-based measure network data envelopment analysis with AI to analyse supply chain risks, focusing on the semiconductor industry's performance and risk management.

Despite such technological advancements and the development of sophisticated models for operational risk management, there are evident gaps in the existing approaches to meeting R1 to R3. As shown in Table 4, the current models demonstrate a limited capacity to fully identify and model the complex network of contributing events that lead to operational risks. This is crucial for pre-emptively recognising and addressing risks before they occur (R1). This leads to the next gap in the existing research, namely methods that actively monitor and quantify the occurrence of these contributing events in a real-time context. Many models rely heavily on historical data and expert opinions, missing out on the dynamic analysis of current events and trends that could signal impending risks (R2). Furthermore, the existing methodologies often do not extend to quantifying the likelihood of the main risk event (R3) by effectively analysing the causal relationships between contributing events and risk events. This analytical depth is necessary for formulating more accurate and proactive risk management strategies.

3.1.3. Quantifying cyber and security risks

Cyber and security risk management is crucial in supply chains due to the increasing digitalisation and interconnectedness of supply chain operations. This integration enhances efficiency but also exposes supply chains to cyber threats and vulnerabilities, impacting the continuity of operations and potentially causing significant financial and reputational damage (Pandey et al. 2020). Addressing risks in these areas can enhance supply chain resilience against cyber threats, ensuring operational continuity, protecting sensitive data, and maintaining trust among supply chain partners (Ghadge et al. 2019). Researchers have proposed different methods to quantify security risks in supply chains. For example, Prathyusha et al. (Prathyusha et al. 2023) applied various ML algorithms for cyber threat assessment in supply chains. Radanliev et al. (Radanliev and De Roure 2023) introduced algorithmic solutions for vaccine production, supply chain bottlenecks, and risk forecasting in healthcare systems. Radanliev et al. (Radanliev et al. 2020) developed an AI/ML-based dynamic system for managing cyber risks in Industry 4.0 and IoT supply chains, enhancing network resilience. Rezki et al. (Rezki and Mansouri 2023) used artificial neural networks to improve risk assessment in automotive supply chains, aiming for a data-driven, objective approach to reduce human subjectivity. Efforts by researchers such as Prathyusha et al. (Prathyusha et al. 2023), Radanliev et al. (Radanliev and De Roure 2023), and Rezki et al. (Rezki and Mansouri 2023) demonstrate the application of ML algorithms and AI to bolster cybersecurity in supply chain contexts. These initiatives aim to safeguard the digital integrity of supply chains, from healthcare systems to automotive and Industry 4.0 environments, enhancing overall network resilience against cyber threats.

Despite these advancements, the current approaches exhibit limitations when evaluated against proactive risk identification and assessment requirements. For example, as shown in Table 4, none of the existing works fully address the need to identify and map out the complex network of events contributing to cyber risks (failing to meet R1). Understanding these events and their causal relationships is fundamental for pre-emptive risk identification and assessment. There is a noticeable gap in actively monitoring and quantifying real-world occurrences of events contributing to cyber risks. Relying predominantly on historical data, such models lack the capacity for real-time analysis, which is crucial for the early detection and response to emerging cyber threats (R2). Moreover, none of the existing methods propagate the occurrence of contributing events to accurately quantify the main cyber risk event's likelihood (R3). This step is critical for developing targeted and effective risk management strategies.

3.1.4. Risk assessment using external data sources

This category discusses techniques that leverage diverse and real-time data for comprehensive risk assessment. As supply chains operate within a dynamic global environment, where external factors such as social, political, and economic events can have immediate impacts, this area has attracted considerable interest from researchers for use in risk assessment. For example, Janjua et al. (Naeem Khalid Janjua and Prior 2023) created a framework to analyse social media for disruption events using a Bi-LSTM CRF model and fuzzy theory, focusing on the probability and impact of these disruptions on supply chains. Handfield et al. (Handfield, Sun, and Rothenberg 2020) used machine learning to predict factory risks through the analysis of newsfeeds, employing an alternative hypothesis approach for risk visualisation. Ganesh et al. (Deiva Ganesh and Kalpana 2022a) conducted a literature review on AI and ML in SCRM, emphasising the need for proactive risk management and using real-time data from social media and online news. However, from the perspective of considering the contributing events for the assessment of risks, as shown in Table 4, there are still gaps in these techniques about identifying what causes risks, identifying if these contributing events will occur, and determining how likely it is for the risk to happen. Even though these studies are a good start, they often fall short of systematically identifying and modelling the causal relationships between external events and specific supply chain risks (R1).

Furthermore, the current methodologies tend to lack the capacity to identify and quantify real-world occurrences of contributing events accurately. While they use social media and newsfeeds, the full potential of these data sources has not yet been realised, particularly in providing preventive and actionable, real-time intelligence for risk management (R2). Lastly, there is a notable gap in the ability of these approaches to effectively propagate and relate the occurrences of contributing events to the risk event to quantify the likelihood of the main risk event occurring accurately. This is crucial for transitioning from reactive to proactive risk management, enabling supply chains to anticipate and mitigate potential disruptions before they occur (R3).

3.1.5. Literature review and theoretical contributions that conceptualize risks

This section discusses reviews and theoretical explorations from the literature that critically assess the current state of knowledge, identify gaps and propose frameworks or models that contribute to the conceptual foundations of SCRM. For example, Sarkar et al. (Sarkar and Das 2023) analysed deep and machine learning in supply chain risk assessment, highlighting the lack of application for SMEs and the untapped potential of natural language processing and large language models for early risk event identification. Wei et al. (Z. Wei et al. 2023) performed a bibliometric analysis on the application of ML in industrial risk assessment, focusing on evolution, hotspots, and the importance of fault detection and real-time monitoring without specifically addressing the proactive identification of risk-contributing events. Baryannis et al. (George Baryannis, Validi, and

Antoniou 2019) examined the literature to understand how AI technologies are applied in SCRM, covering various aspects from risk identification to mitigation. They concentrated on the transformative impact of AI in supply chain risk management, including machine learning and big data analytics. Zhang et al. (Zhang, Ling, and Lin 2023) provided an overview of risk management research, suggesting a focus on deep learning and high-performance models for future research without specifically targeting the identification of contributing events before risks occur. While such reviews offer a thorough overview of the contributions made in the literature to the SCRM field, as shown in Table 4, there is a notable shortfall in addressing the requirements of R1 to R3. In other words, most risk assessment literature focuses on general risk management strategies without delving into the details of pinpointing the contributing events that could potentially trigger risk events within supply chains (R1). Additionally, the literature reviews reveal a lack of emphasis on methodologies for identifying and quantifying the occurrence of these contributing events (R2). This is a missed opportunity to harness real-time data and advanced analytics to measure the frequency and impact of these risk early indicators, which is crucial for dynamic risk management. Lastly, the reviewed literature does not sufficiently explore how to leverage the identification and quantification of contributing events to accurately assess the likelihood of a risk event occurring (R3). This indicates a need for more sophisticated predictive models integrating various data points to offer a comprehensive risk assessment.

3.2. Quantifying risk as a dependent event

In the field of SCRM, various studies have explored the interrelationships between the different risk factors, highlighting the importance of understanding these dependencies to quantify and mitigate risks effectively. This section discusses approaches that quantify risks as a dependent factor in the following categories:

(1) Application of AI and ML for risk quantification,
(2) Risk quantification by modelling its dependencies,
(3) Enhancing supply chain resilience by considering dependency insights, and
(4) Quantifying interconnected supply chain risks.

3.2.1. Application of AI and ML for risk quantification

This category focuses on studies that leverage AI and ML techniques to quantify risk by analysing the dependencies among risk factors, suppliers, and other elements in the supply chain. These approaches enable the modelling of complex, non-linear relationships that traditional methods might not capture effectively. For instance, Liu et al. (M. Liu et al. 2021) investigated supplier selection and disruption risk using a Bayesian network (BN) to minimise disruption probability and cost, highlighting the ripple effect of supply chain disruptions. Mukherjee et al. (Mukherjee et al. 2022) also used BNs to study the ripple effect of supplier disruptions, demonstrating how the dependency between suppliers and manufacturers can affect manufacturing outcomes. Hosseini et al. (Hosseini and Ivanov 2020) surveyed the literature on using BNs in SCRM, especially for modelling risk propagation and the ripple effect. Song et al. (Song et al. 2024) proposed the multi-structure cascaded graph neural network for analysing enterprise credit risk. The proposed model integrates knowledge graphs and hypergraphs for detailed risk analysis. This innovative approach is particularly effective in understanding enterprise interrelations in supply chain contexts. Fayyaz et al. (Rishehchi Fayyaz, Rasouli, and Amiri 2021) proposed a data-driven model to predict credit risks within a supply chain finance network using machine learning and social network analysis. Belhadi et al. (Belhadi et al. 2021) used ensemble machine learning to forecast credit risk in SMEs in agriculture. In this process, they identify the significant factors which influence credit risk. Yang et al. (Y. Liu et al. 2023) applied decision tree analysis to evaluate the risk of water pipe accidents, focusing on significant contributing factors like building density. Punyamurthula et al. (Punyamurthula and Badurdeen 2018) utilised Bayesian belief networks and system dynamics to analyse the dynamic nature of risk events and their impact on production lines over time. Using machine learning, Zhu et al. (Q. Zhu, Li, and Chai 2018) developed new weather indices in China to manage risks in international supply chains. Liu et al. (Y. Liu et al. 2023) highlighted challenges like supply chain transparency and data disconnectedness in supply chains by creating a knowledge graph for improving decision-making and risk management.

To summarise, while various innovative methodologies to assess and mitigate risks across different aspects of the supply chain have been proposed, as shown in Table 5, there are areas where these approaches do not fully meet R1 to R3. The primary shortfall is in the detailed identification of contributing events leading to a risk event (R1). While many studies adeptly quantify the impact of known risk factors and their

Table 5. Critical literature analysis in quantifying risk as a dependent event against R1-R3.

Research work	R1	R2	R3
Liu et al. (M. Liu et al. 2021)	No	No	No
Mukherjee et al. (Mukherjee et al. 2022)	No	No	No
Hosseini et al. (Hosseini and Ivanov 2020)	No	No	No
Song et al. (Song et al. 2024)	No	No	No
Fayyaz et al. (Rishehchi Fayyaz, Rasouli, and Amiri 2021)	No	No	No
Belhadi et al. (Belhadi et al. 2021)	No	No	No
Yang et al. (Y. Liu et al. 2023)	No	No	No
Punyamurthula et al. (Punyamurthula and Badurdeen 2018)	No	No	No
Zhu et al. (Q. Zhu, Li, and Chai 2018)	No	No	No
Liu et al. (Y. Liu et al. 2023)	No	No	No
Bhattacharyya et al. (Bhattacharyya et al. 2024)	No	No	No
Mostafa et al. (Mostafa et al. 2021)	No	No	No
Kara et al. (Merve Er Kara and Bititci 2021)	No	No	No
Wang et al. (Y. I. Wang et al. 2021)	No	No	No
Ying et al. (Ying, Chen, and Zhao 2021)	No	No	No
Wang et. al (Y. Wang et al. 2022)	No	No	No
Nazari et al. (Nazeri et al. 2023)	No	No	No
Lam et al. (Lam and Cruz 2019)	No	No	No
Kumar et al. (Kumar and Kumar Barua 2022)	No	No	No
Liu et al. (J. Liu, Gu, and Chen 2023)	No	No	No
Teng et al. (Teng, Wang, and You 0000)	No	No	No
Jayasinghe et al. (Jayasinghe, Rameezdeen, and Chileshe 2022)	No	No	No
Büyüközkan et al. (Büyüközkan, Havle, and Feyziog˘lu 2021)	No	No	No
Hossain et al. (Hossain et al. 2019)	No	No	No
Vafadarnikjoo et al. (Vafadarnikjoo et al. 2022)	No	No	No
Zhai et al. (Zhai 2023)	No	No	No
Surange et al. (Surange and Bokade 2023)	No	No	No
Pandey et al. (Shipra Pandey, Singh, and Gunasekaran 2023)	No	No	No
Mital et al. (Mital, Del Giudice, and Papa 2018)	No	No	No
Panova et al. (Panova and Hilletofth 2018)	No	No	No

interdependencies, they often overlook the initial signs or events that lead to these risks. This gap indicates a need for models that can detect and analyse the precursors to supply chain disruptions or credit risks, offering a more comprehensive approach to risk management. Moreover, there is a notable deficiency in the models' capability to pinpoint the actual occurrence of contributing events that lead to risk. While the reviewed studies are proficient at mapping out the complex interrelations among risk factors, they often do not track or identify when these critical contributing events occur in real-time (R2). Lastly, these models do not adequately estimate the likelihood of risk events based on the contributing factors. While they provide insights into the ripple effects and dependencies within supply chains, there is a significant opportunity to enhance predictive accuracy by integrating the analyses of contributing events. Doing so would allow for a more dynamic risk assessment, capable of anticipating disruptions before they unfold (R3).

3.2.2. Risk quantification by modelling its dependencies

This section focuses on the methods that quantify risk by modelling their dependencies rather than using AI or ML. These methods emphasise the strength of statistical models and network analysis in mapping out the complex network of supply chain connections and their vulnerability to different risk elements. For example, Bhattacharyya et al. (Bhattacharyya et al. 2024) have studied the interrelationship between risk events for developing a risk simulation framework to analyse market risk in a closed-loop supply chain, particularly for acquiring end-of-life vehicles. Mostafa et al. (Mostafa et al. 2021) explored the use of fuzzy sets for assessing supplier risks, focusing on risk factors across different supply periods to enhance decision-making in supplier selection. Using system dynamics modelling, Kara et al. (Merve Er Kara and Bititci 2021) identified climate change factors affecting supply chain performance and their causal relationships. Wang et al. (Y. I. Wang et al. 2021) analysed financial risk propagation in supply networks, focusing on sub-tier suppliers and employing an empirical approach with global data. Ying et al. (Ying, Chen, and Zhao 2021) identified risks in supply chains through a special-purpose dictionary based on bank reports, identifying key risk management factors. This paper also discusses the differing impacts of these factors in various financing contexts to help supply chain finance service providers evaluate and avoid risks by monitoring these factors. Wang et al. (Y. Wang et al. 2022) examined risk factors in fresh product supply chains, utilising the N-K model and social network analysis to identify and analyse direct and indirect risks. Nazari et al. (Nazeri et al. 2023) developed a risk assessment model for Iran Khodro's sustainable supply chain. The main objective is to identify the main dimensions of risk assessment in the automotive industry's sustainable supply chain and to understand the cause-and-effect relationships among these risks. Lam et al. (Lam and Cruz 2019) used probabilistic network modelling to assess and manage the risks associated with gas usage in Japan, identifying interdependencies. Kumar et al. (Kumar and Kumar Barua 2022) explored risk interconnections in the sustainable petroleum supply chain using an integrated approach of decision-making techniques. This approach helps categorise and evaluate risk factors, leading to a more robust understanding of their dynamics and interdependencies. The research results offer insights into the primary risk factors within the sustainable petroleum supply chain and their causal relationships.

While these studies consider the importance of understanding hierarchical and causal relationships between different factors within supply chains, there is still a limited depth of analysis on the cause-effect relationships between various contributing events and risks. In other words, as shown in Table 5, these studies focus on the interrelationships among risk factors within supply chains but overlook the initial identification of specific contributing events that lead to risk scenarios (R1). This oversight limits the ability of risk managers to understand the root causes of potential disruptions. They also lack the mechanisms to actively monitor and identify the real-time events leading to risks (R2). Additionally, while these quantitative methods map out dependencies and relationships among risk factors, they often do not extend to estimating the likelihood of risk events based on the analysis of contributing events (R3).

3.2.3. Enhancing supply chain resilience by considering dependency insights

This category focuses on approaches that understand how dependencies between risks impact the resilience of supply chains. This category underscores the importance of understanding the complex interdependencies within supply chains, recognising that resilience is not merely about recovery but also about proactively identifying and mitigating potential vulnerabilities before they develop into crises (Singh, Soni, and Badhotiya 2019). For example, Liu et al. (J. Liu, Gu, and Chen 2023) developed a technique to examine the hierarchical and causal connections between factors that enable Maritime Supply Chain Resilience (MSCR) and categorised them based on their roles in driving or depending on resilience within the maritime supply chain amidst the COVID-19 pandemic. Teng et al. (Teng, Wang, and You 0000) focused on relationships within sports service bases, using fuzzy comprehensive appraisal and AI for risk evaluation and optimisation of the sports service system. Jayasinghe et al. (Jayasinghe, Rameezdeen, and Chileshe 2022) looked at risks in reverse logistics for demolition waste, aiming to improve operational performance through risk identification and assessment. Büyüközkan et al. (Büyüközkan, Havle, and Feyziog˘lu 2021) explored the cause-effect relationships between different risk factors in supply chains using the cognitive map approach in an intuitionistic fuzzy environment. Hossain et al. (Hossain et al. 2019) developed a Bayesian framework to assess the resilience of the oil and gas supply chain, evaluating how various capacities impact overall resilience.

These studies have contributed significantly to understanding how supply chains can better withstand and recover from adverse events using various methodologies, such as hierarchical and causal analysis, fuzzy comprehensive appraisal, and cognitive mapping. However, despite these advancements, as shown in Table 5, a gap remains in identifying the root events that cause disruptions in the first place (R1). While understanding the relationships and impacts of various risk factors is crucial, pinpointing the initial triggers of these disruptions could offer even more strategic value for proactive risk management. Consequently, there is a noticeable gap in actively identifying the occurrence of contributing events that lead to disruptions (R2). Furthermore, these studies do not sufficiently address the estimation of the likelihood of risk events based on the analysis of contributing events (R3). While they contribute to a broader understanding of risk interdependencies and the factors that influence supply chain resilience, they fall short in leveraging this information to predict the probability of disruptions.

3.2.4. Quantifying interconnected supply chain risks

This category explores methods that recognise supply chain operations as a network of interlinked processes and entities where dependencies play a pivotal role in the propagation and impact of risks. The studies within this category focus on identifying, analysing, and managing the complex dependencies within supply chains, from supplier interrelations to logistical coordination and beyond. By acknowledging that risks are not isolated events but are often interconnected through various layers of supply chain activities, these frameworks aim to provide a holistic view of potential vulnerabilities and strategies for mitigation. For example, Vafadarnikjoo et al. (Vafadarnikjoo et al. 2022) assessed risk in the electric power supply chain by examining causal relationships with the neutrosophic revised decision-making trial and evaluation laboratory method. Zhai et al. (Zhai 2023) modelled the interconnection between risks to construct a system dynamics model for evaluating and managing risks in the cross-border supply chain of fresh agricultural products. Surange et al. (Surange and Bokade 2023) modelled the interrelationships among critical risk factors in the Indian manufacturing industry, particularly in the automotive sector. This study provides an in-depth analysis of the interactions among risk factors, offering a structured approach to risk management. Pandey et al. (Shipra Pandey, Singh, and Gunasekaran 2023) identified multiple supply chain risks to prioritise them and analyse their cause-and-effect relationships, aiding in strategic decision-making. Mital et al. (Mital, Del Giudice, and Papa 2018) identified and assessed supply chain risks across different product categories using cognitive maps and the analytic hierarchy process methodology. Their study focuses on understanding risk indicators, their impacts, and the cause-and-effect relationships along the supply chain to prioritise supply chain objectives and select the best suppliers. Panova et al. (Panova and Hilletofth 2018) addressed cause-and-effect relationships between construction delays and their impact on supply chain disruptions.

While these approaches model risks as a network, as shown in Table 5, they do not focus on pinpointing how these risks start (R1). Understanding the root causes of supply chain disruptions is key to preventing them in the first place rather than just responding after they occur. In addition, there is also a notable shortfall in these studies regarding R2 in identifying the occurrence of contributing events as they happen. While these frameworks map out the network of dependencies and potential vulnerabilities within supply chains, they often lack the dynamic capability to monitor and identify these contributing events in real-time (R2). Additionally, they frequently fall short in predicting the likelihood of risk events based on quantifying the probability of contributing events.

4. Research gaps, challenges and future research agenda

From the analysis in Sections 2 and 3, it is clear that researchers have made significant progress in identifying and assessing supply chain risks. However, achieving a comprehensive, proactive approach to SCRM remains challenging, particularly in integrating causal relationship modelling with real-time risk prediction methods. While advanced techniques leveraging AI, ML, and NLP offer promising potential, their adoption in real-world scenarios faces significant obstacles. This section explores these critical gaps, providing insights into key limitations and directions for future research. It also provides insights into key challenges that should be addressed in future research.

4.1. Visualizing and assessing risk as a causal chain

While existing approaches model risk as a dependent variable (Section 3.2), this dependency is often limited to understanding how other risks impact it or how various factors/ indices influence it. However, current methods fail to consider the non-risk events that affect the risk and their causal relationship, thus falling short of meeting R1. This represents a significant gap in SCRM, where the absence of interconnected modelling limits the ability to predict risks proactively and effectively.

For example, Gao et al. (Luo et al. 2016) explore the relationships between risk factors in SCRM using IoT technologies, such as RFID and wireless networks, to monitor and assess risks in real-time. While their work considers the interactions between risks and contributing factors, it does not explicitly represent these relationships as a causal chain. Instead, the focus remains on risk tracking, case-based reasoning, and simulation-based analysis. To address this gap, a given risk event should be represented as a causal chain that allows risk managers to understand the contributing events leading to a risk event. Such a representation is critical for improving predictive capabilities in SCRM and transitioning from reactive strategies to proactive risk management. By visualising risks as causal chains, risk managers can anticipate potential vulnerabilities and prepare mitigation strategies before risks materialise. Significant advancements in the field of NLP have been made in cause-effect detection (Ali et al. 2023; Law et al. 2017; Z. Li et al. 2021; Xie and Mu 2019; Xie and Mu2019), enabling computational systems to parse, interpret, and generate causal relationships from text documents. These tools are particularly promising for supply chain applications, where identifying the chain of events leading to risk can dramatically enhance management strategies. For example, causal chains can be modelled using Bayesian Networks (BNs), which logically represent interrelated components contributing to a risk event. These models hold great potential to enable risk managers to assess and manage risks proactively.

Despite all these advancements in AI, NLP, and LLMs, the application of these technologies for building causal chains within SCRM remains under-explored. To address this, future research should focus on:

(1) Developing comprehensive frameworks for causal modelling of risk events: Future efforts should integrate NLP advancements and BNs to create frameworks capable of mapping causal relationships in supply chains. These frameworks should focus on logical representation and capturing the full network of contributing events leading to a risk event of interest.
(2) Enhancing predictive accuracy of contributing events: Incorporating real-time data sources, such as news and social media, to improve the robustness of causal chains, making them better suited for proactive risk prediction. Capturing this information also assists in determining the occurrence of contributing events, leading to the occurrence of the risk event.
(3) Bridging Implementation Challenges: Practical challenges, such as computational complexity and the lack of standardised tools for causal modelling in SCRM, should be addressed to facilitate adoption in real-world scenarios.

By focusing on these areas, researchers can bridge the current gap and enable more effective, proactive risk management strategies in supply chains.

4.2. Having a logical and complete causal chain of events

A causal chain will benefit proactive SCRM only if it is both *logical* and *complete*. Logical refers to the BN's objective representation of the contributing events and their relationships to the risk event of interest. For instance, as shown in Figure 1, the causal chain linking an increase in COVID cases, more staff getting sick, an increase in home quarantine, and resulting staff shortages is an example of an objective and logical representation. Any variation or misrepresentation of the chain would make it illogical, reducing its utility for risk managers. Despite the potential of causal chains, existing approaches lack mechanisms to validate and ensure their logical consistency. Future research must focus on developing approaches to support risk managers in validating causal relationships. Digital transformation initiatives, such as crowdsourcing (J. Lu et al. 2019) and expert consultation, can gather diverse insights to build consensus on causal relationships. These methods can ensure that the BN reflects a comprehensive and agreed-upon understanding of causal dynamics, enhancing its reliability and practical value for SCRM.

The completeness of a BN is equally important. Completeness ensures the causal chain captures all contributing events leading to a risk event. For example, Figure 1 identifies two contributing events between an increase in COVID cases and a staff shortage. An incomplete BN, failing to include significant contributing events, would limit a risk manager's ability to fully understand the risk landscape and prepare effective mitigation strategies. Current approaches in the literature (Hosseini and Ivanov 2020; M. Liu et al. 2021; Mukherjee et al. 2022) use BNs to represent dependencies among risk events but do not evaluate these networks for their logical consistency or completeness. This represents a significant gap, as incomplete or inconsistent models undermine the effectiveness of proactive risk management. To address these limitations, future research should focus on the following:

(1) Automated validation of a BN's logical consistency: Tools that integrate AI and Large Language Models need to be developed to identify and validate causal relationships in SCRM. These tools should assist risk managers in ensuring the logical accuracy of causal chains, especially in complex and dynamic scenarios.
(2) Ensuring completeness with semi-automation: There is a need to identify and incorporate missing contributing events in causal chains semi-automatically. AI-based techniques and external data sources such as real-time news or industry reports should be used to achieve this goal.
(3) Interactive validation frameworks: Interactive systems that allow risk managers to refine causal chains collaboratively must be developed. By combining semi-automated suggestions with expert insights, these systems can balance computational efficiency and domain knowledge.
(4) Benchmarking logical and complete models: Benchmarks and best practices for assessing the logical and complete representation of causal chains must be developed. These benchmarks can provide a standardised way to evaluate and improve BNs for SCRM applications.

By addressing these gaps, future research can ensure that causal chains are both logically consistent and complete, enabling risk managers to transition from reactive to proactive decision-making.

4.3. Representing a dynamic BN with a feedback loop to assess whether it is logical and complete

Due to the dynamic nature of supply chains, which are influenced by global market fluctuations, geopolitical tensions, technological advancements, and environmental changes, there is a need to identify and map causal chains to be inherently adaptive. The external and internal factors impacting supply chains evolve, as do the causal events that lead to a risk event. Consequently, a static causal model is insufficient for proactive SCRM. Instead, SCRM systems must incorporate continuous learning and adaptation mechanisms such as concept drift (Aboutorab et al. 2024; Žliobaitė, Pechenizkiy, and Gama 2016), enabling them to update and revise causal chains in real-time as new data becomes available. To complement the dynamic nature of BN, it is essential to integrate a feedback loop into the causal structure analysis. This feedback mechanism can be applied using techniques such as reinforcement learning within the framework of dynamic BN (Zheng and Zhang 2020). Future work should be done to allow the BN to continuously refine and adjust its structure and parameters by incorporating real-time data and outcomes into the system. This adaptive model ensures that the causal chains remain relevant and accurate, reflecting the ever-changing external events affecting supply chains and effectively accounting for concept drift in causal relationships.

4.4. Semi-automated representation of the causal BN with a rich underlying dataset to make the causal chain

Existing approaches in the literature, such as (M. Liu et al. 2021; Mukherjee et al. 2022; Punyamurthula and Badurdeen 2018Nawaz et al. 2019) utilise a BN to represent the factors that are related to the risk event or the relationship between different risk events. However, most develop it manually using expert knowledge. This works when a limited number of nodes must be represented in a causal chain. However, in the context of SCRM, there may be (a) a significant number of nodes that need to be represented in a causal chain, (b) many nodes for which such a causal chain needs to be built, and (c) the emergence of new and rapidly propagating risk events (like COVID) need to be mapped as quickly as possible. This cannot be done manually. Thus, future research should focus on developing the causal BN in a semi-automated manner. The proposed approach should also assist the risk manager in constantly evaluating the BN in terms of its *logical* representation and *completeness* metrics at each addition of a causal event. Future research should also address the limited scope of data sources used in SCRM research as they directly impact the ascertaining of causal events to risk events of interest. Most studies depend heavily on internal supply chain data, which, while crucial, only provides a limited view and can only help in a post hoc analysis, making the approach reactive rather than proactive. Expanding data sources to include external data, such as news articles and social media, could offer a wealth of real-time insights. These sources reflect current market sentiments, emerging trends, and early indicators of potential risks, often not captured by traditional supply chain data.

4.5. Addressing the lack of supply chain operations knowledge represented as graph structures to build a logical causal chain

One of the key requirements in building a logical causal chain is to capture the interrelationships between the different contributing events and their impact on the risk event. For example, Figure 1 represents border closure and an increase in home quarantine as the two contributing events impacting the risk event of interest. However, it does not represent the relationship that should be present between these two contributing events for the main risk event to happen. In other words, it does not represent if both these contributing events should occur simultaneously for the risk event to occur or if only one contributing event is sufficient. While approaches in the literature utilise the concept of *All*, *One or More* and *Exactly One* compositors to address this issue (Long et al. 2020), it is done manually. Future research should focus on determining the relationship between the contributing events semi-automatedly. To do this, the underlying knowledge from which the events contributing to a risk event of interest are determined should be visualised as a graph structure. Knowledge graphs have been used widely in the literature to achieve this aim in the different domains of finance (W. Liu et al. 2020; Tran et al. 2022), social networks (Leban et al. 2014; X. Wang et al. 2019; Zou 2020), etc. However, this has not yet been applied to the supply chain domain to find the events contributing to a risk event, which is an open gap to address.

4.6. Developing a lightweight approach to ascertain the chance of the occurrence of a contributing event during risk assessment

After identifying an event that contributes to a risk event of interest, the next task in the SCRM process is to ascertain its chance of occurrence. Researchers in the literature have addressed this problem under the domain of event identification (Aboutorab et al. 2022; Y. Chen et al. 2015; S. Han, Huang, and Liu 2021), using different machine learning models. However, these models must have the underlying data they can train before being applied to unseen data. This is not an issue for known events for which such models are repeatedly used. However, having underlying data is a challenge for contributing events as they may be significant in number and may have to be used occasionally. To address this, there is a need to develop a lightweight approach that can ascertain the chance of occurrence of a contributing event during risk assessment without sacrificing accuracy. While researchers have proposed the use of techniques such as reinforcement learning (Zheng and Zhang 2020) 142] to shortlist news articles that relate to a search term of interest, they do not ensure that the shortlisted news article refers to the search term of interest as occurring in the future. In other words, it may relate to an event that has already occurred. However, articles that relate to the search term as occurring in the future are also of interest during risk assessment. This is an open gap in the literature.

4.7. Using interdisciplinary approaches for scenario analysis integrated with AI

To build a logical and complete BN, insights from experts from different areas need to be incorporated to understand how various external events worldwide impact supply chains. For example, this needs to include experts from various areas, such as environmental scientists, technologists, IT experts, economists, financial analysts, political scientists, and legal experts. By collaborating with experts in these fields, supply chain managers can gather diverse datasets essential for a comprehensive causal analysis. This multidisciplinary approach helps identify potential risk events from a broader perspective but also aids in selecting the most relevant datasets for effective risk management strategies.

Challenges in developing and adopting a causal representation of a risk event of interest in real-world scenarios

While the identified techniques for proactive SCRM offer significant advancements, their adoption in real-world scenarios faces several challenges:

(1) Data Availability and Quality: Many techniques rely heavily on high-quality, real-time data to identify and quantify contributing events. However, obtaining such data across global supply chains is often difficult due to proprietary restrictions, incomplete data sharing, and inconsistent reporting. This leads to an over-reliance on synthetic data, which may not accurately represent real-world complexities and variations in supply chain risk management. To bridge this gap, a future research agenda should focus on developing mechanisms and frameworks for accessing real datasets. This includes building collaborations between academic institutions and industry to facilitate data sharing and ensuring that sensitive information remains protected through confidentiality agreements and privacy-preserving technologies.
(2) Integration Complexity: Integrating advanced AI, ML or NLP methods into existing supply chain systems requires significant infrastructure upgrades. Due to limited resources and technological maturity, this may present challenges for companies, especially small to medium enterprises.
(3) Computational costs and Scalability: Techniques such as BN or NLP-based event detection are computationally intensive, particularly when applied to large and complex supply chains. Ensuring scalability while maintaining accuracy remains a significant challenge. This is especially important when existing techniques, particularly those that model causal relationships (e.g. Bayesian Networks), rely on manual input from expert knowledge. This time-consuming approach may not scale effectively when dealing with numerous interconnected risk events. To address this, a semi-automated approach that takes insights from diverse domains, such as finance, environmental science, and logistics. Coordinating such expertise should be considered, as it is both challenging and resource-intensive.
(4) External Data Integration: While external sources like news articles or social media provide valuable insights, filtering accurate and relevant data from these noisy sources remains challenging. NLP and AI systems must be enhanced to process and extract relevant data effectively.
(5) Resistance to change and Challenges of using LLMs by companies: Organisational resistance and resistance to adopting new technologies can delay the implementation of proactive SCRM approaches. Training personnel and overcoming cultural barriers are necessary for successful adoption. Organisations often face difficulties providing high-quality, domain-specific data to fine-tune LLMs, ensuring data privacy and security, and obtaining consistent, accurate results tailored to their unique business needs. Additionally, understanding LLM outputs and managing the high costs of running and maintaining them can be challenging.

5. Conclusion

In an era where supply chain vulnerabilities have profound implications on global operations and global markets are volatile and interconnected, there is a critical need for a forward-thinking approach to managing these risks to maintain business continuity, competitiveness, and resilience. This paper highlights the significant gap in current SCRM practices: the lack of consideration for the causal relationships between contributing events and the resultant risk events. Using a comprehensive systematic literature review, we analysed the existing SCRM techniques that use AI and highlighted a persistent reliance on techniques that merely identify risk events in isolation. This isolated approach overlooks the network of contributing events that precede to the occurrence of these risks. Our analysis clearly shows a big gap in the research: scant work is being done to measure risk events in advance by looking at what causes them. This missing piece weakens SCRM strategies and their use in the timely prediction of risks. To respond to this gap, we propose a paradigm shift to an integrated approach that involves identifying and assessing risks by deeply analysing their contributing events. By leveraging advancements in big data and large language models, this paper advocates for developing SCRM techniques that are predictive and grounded in understanding causal relationships.

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Data sharing does not apply to this article as no new data were created or analysed in this study.

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