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Adaptive identification of supply chain disruptions through reinforcement learning

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ABSTRACT

Proactive identification and the management of disruption risks play a crucial role in the achievement of a global supply chain's aims. Given the velocity and volume by which such disruption events occur, it is impractical to expect supply chain managers to determine the occurrence of such events manually. Given the pressures facing global supply chains due to the COVID-19 crisis, it is important for supply chain managers to proactively identify disruption risks to their supply chains and manage them to either achieve the outcomes or develop plans by which resilience against them can be built. In this paper, we demonstrate how the integration of natural language processing and reinforcement learning, which are fundamental artificial intelligence methods, can be used to assist supply chain risk managers in the timely identification of such disruption events. We explain in detail our proposed approach, namely RL-SCRI and show its superiority over the current models in achieving its aim.

1. Introduction

Global supply chains (SC) are a collaboration of different organisations spread across the world. Each organisation in the chain is responsible for certain tasks such as procurement, production, warehousing, transportation, distribution or retailing to ensure the product reaches the customers at the end of the chain (Stevenson & Spring, 2007). While these global organisations increase the efficiency of supply chains, they also make them vulnerable to various types of disruptions, such as geographical, social, etc. For an SC to perform competently and avoid failure, each organisation must manage disruptions to their operations. This explains the importance and the need for risk management (RM) to be an inherent part of any SC organisation. Risk management of disruption events identifies, assesses, evaluates, and manages the disruption events that may influence SC's performance (Purdy, 2010). This paper focuses on the risk identification stage, which commences with understanding the objectives of the SC organisation under investigation and identifying the related disruption risk events. We focus on the phase of risk identification only due to its importance in giving the inputs for the subsequent phases of risk management.

With the increasing complexity of SC, disruptions impacting an organisation are not uniform and can change over time. Furthermore, to ensure that the SC's objectives are not affected, each organisation should identify the disruption events impacting it proactively rather than reactively (Aboutorab, Hussain, Saberi, Hussain, & Chang, 2021). Proactive Supply Chain disruption Risk events Identification (SCRI) assists risk managers to prebuild plans by which they can either be managed or against which resilience can be developed. However, proactively identifying such risks manually is time-consuming. Thus, to assist risk managers, there is a need for an automated model that is adaptive and responsive in disruption risk event identification. This paves the way for using artificial intelligence (AI) models for SCRI. AI uses computer systems to deal with activities that are believed to require human intelligence, such as solving a math problem, understanding a language, or building applications that aim to attain intelligent behaviours (Nilsson, 2014). AI techniques have been applied in different domains, such as robotics, gaming, e-commerce, and healthcare to perform many tasks intelligently (Bawack, Wamba, Carillo, & Akter, 2022; Van Roy, Vertesy, & Damioli, 2020; Westera et al., 2020; Yu, Beam, & Kohane, 2018). For instance, in clinical practice and public health, natural language processing (NLP) has been used by computers to understand human language and achieve beneficial outcomes (Névéol, Dalianis, Velupillai, Savova, & Zweigenbaum, 2018). In

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agriculture, machine learning (ML) has been used to design computer programmes that develop automatedly by experience (Sharma, Jain, Gupta, & Chowdary, 2020). However, as demonstrated in our survey article (Aboutorab, Hussain, Saberi, Hussain, & Chang, 2021), AI methods have not been widely applied for proactive SCRI. In this paper, we focus on the application of AI techniques for SCRI. Specifically, the objective of this paper is to illustrate how the integration of reinforcement learning (RL) and NLP can be utilised to develop the RL-SCRI framework in an automated way that proactively and adaptively assists a supply chain organisation in identifying disruption risk events that may impact its operations. RL is a type of machine learning model in which an agent in a given environment learns to make smart decisions through a trial-and-error process. For instance, Zohora, Tania, Kaiser, and Mahmud (2020) utilised RL to predict type II diabetes. Wang, Sun, Duong, Nguyen, and Hanzo (2020) presented an adaptive model for the early identification of COVID-19. Zheng et al. (2018) introduced DRN, an RL-based news recommendation system. Specific to SCRI, the RL agent scans the different possible actions in a state of the environment from news articles and selects the action that recommends the related disruption events to the risk manager. In response, the RL agent receives feedback from the risk manager in the form of a reward or penalty. The goal of the RL agent is to maximise the cumulative reward in proactively recommending to the risk manager of an organisation the disruption events that may impact its operations (Sutton & Barto, 2018). To achieve this aim, RL-SCRI should address the following research questions:

- What are the different components required to achieve the aim of RL-SCRI in proactively identifying risks of interest and bringing them to the attention of the risk manager?
- Compared with other similar and manual approaches, does RL-SCRI perform better in proactively identifying risks?
- Is RL-SCRI capable of adapting to the changes in the risk manager's interest over time?

The remainder of this paper is structured as follows. In Section 2, related works in terms of how AI has been used in SCRI are presented. Section 3 illustrates the detailed framework and working of RL-SCRI. In Section 4, the performance of RL-SCRI in proactively recommending disruption risk events of interest is evaluated along with other models. Finally, Section 5 concludes the paper.

2. Related work

In our previous work (Aboutorab, Hussain, Saberi, Hussain, & Chang, 2021), we surveyed the different types of approaches used for SCRI. As this paper focuses on using the RL technique for RI, this literature review investigates how AI techniques have been applied to SCRI. To achieve this aim, we searched the phrases "supply chain risk identification" and "supply chains risk identification" in the article's title in Google Scholar and extracted 47 papers since 2019. From these papers, we only consider those articles that develop a model for SCRI. This resulted in only 19 papers, as shown in Table 1. These papers were analysed to determine if they utilised any AI technique for SCRI. This resulted in only five papers as follows. Deiva Ganesh and Kalpana (2022) developed an AI-based text-mining approach to analyse social media, specifically Twitter information, for real-time identification of potential risk factors in SC. Aboutorab, Hussain, Saberi, and Hussain (2021) proposed an AI-based news recommender model that identifies disruption risk events from news and presents them to the user. Salamai, El-kenawy, and Abdelhameed (2021) introduced a sine cosine dynamic group algorithm to detect the operational risks whereas Jung, Lee, Gim, Kim, and Lee (2022) improved the identification of global supply risky items by employing the random cut forest. Tang, Lu, Wang, and Li (2022) utilised a deep convolutional neural network model to identify the financial risks impacting a supply chain. From the analysed papers, it can be seen that only one focused on proactively identifying disruptions in supply chain operations. The rest of them focused on identifying other types of risks in supply chains. However, if supply chain disruptions are to be managed proactively, we need advanced methods in SCRI that assist the risk manager in getting a head start in identifying events of disruption that may later result in failure.

Such AI-driven risk identification methods have been applied widely in other domains. One of the practical AI applications is natural language processing (NLP), which is utilised in a wide range of risk identification techniques. Imanara, Nakajima, Samejima, Akiyoshi, and Morihisa (2012) used NLP to investigate project plan documents and collect risk expressions to identify project management risks. Daramola, Stålhane, Omoronyia, and Sindre (2013) introduced KROSA, which integrates NLP and case-based reasoning to detect hazards using the knowledge captured from past projects. The application of NLP was extended to detect heart disease risk in an automated manner (Yang & Garibaldi, 2015). Another application that has been implemented in risk identification models is data mining. Yu, Wang, and Lai (2010) proposed a customer relationship management model in which the risk of churn is detected by learning the patterns using a support vector machine (SVM)-based system. Kim, Lee, Park, Chung, and Hwang (2015) retrieved data from previous accidents and created a framework to identify hazards in construction. Subramanian et al. (2017) offered a risk identification technique for economic systems through past knowledge by employing text mining and ML. Lucas Luijckx, van de Brug, Leeman, van der Vossen, and Cnossen (2016) developed another approach to investigate the emerging chemical risks based on the semantic relationships of concepts, keywords, and rules in databases. Qu (2017) integrated the syntax-tree and part-of-speech tagging for text understanding to determine the risks in the public–private partnership life cycle. Wang, Huang, Luo, Pei, and Xu (2018) extracted information from historical data and recognised hazard information in the workplace through equivalent class information and change mining algorithms. Salamai, Saberi, Hussain, and Chang (2018) designed association rule mining (ARM) to detect variable relations of a database and the correlation between risks and their attributes in supply chains. Zhu and Cheng (2018) designed a deep learning-based geological disaster identification model by employing neural networks and intelligence reconnaissance. Lai, Zhang, Zhang, Su, and Heyat (2019) expanded the use of machine learning classifiers such as SVM, decision trees, and k-nearest neighbours to predict the risk of sudden cardiac death in an automated manner. Mangortey et al. (2020) also implemented machine learning to detect abnormal operations and anomalies and analyse their impact on flight safety. However, such advances are lacking in the area of SCRI.

This paper aims to apply an integration of NLP and RL to disruption risk identification in supply chains. As mentioned in Section 1 RL has the capability to best respond by sensing the environment. Due to this ability, it has been applied for risk identification and recommendation systems in different domains. However, none of the studies except our previous work (Aboutorab, Hussain, Saberi, & Hussain, 2021), which developed RL-PRI, employed RL for supply chain risk identification. However, a shortcoming of RL-PRI is that it works on a selected taxonomy and just identifies disruptions if the term exists in the taxonomy used. This limits the scope for the risk manager to proactively identify different disruption risk events and not just be limited to the taxonomy used. In this paper, we develop RL-SCRI and demonstrate how it addresses this shortcoming and gives better outputs compared to RL-PRI in assisting risk managers first identify the potential disruption risk events of interest to its SLAs and then determine if they are important to be brought to their attention before considering their feedback to automatedly learn and adapt its working intelligently.

Table 1
Supply chain risk identification models since 2019.

Paper	Method applied for SCRI	Do they apply AI in their workings?
Ulfah et al. (2023)	Fuzzy house of risk	✗
Deiva Ganesh and Kalpana (2022)	Data-mining	✓
Benedetti, Verderame, and Merlo (2022)	Breadth-first search algorithm	✗
Jung et al. (2022)	Random cut forest	✓
Tang et al. (2022)	Deep convolutional neural network	✓
Aboutorab, Hussain, Saberi, and Hussain (2021)	Integration of RL and NLP	✓
Salamai et al. (2021)	Dynamic voting classifier	✓
Hou and Zhao (2021)	System theory	✗
Li and Wang (2021)	Improved SCOR model	✗
Kusumaningtyas, Mustaniroh, Astuti, et al. (2021)	SCOR model	✗
Ray, Duraipandian, and Prabhakaran (2021)	Expert interview	✗
Chai, Liu, Zhang, and Li (2021)	Grounded theory	✗
Chen et al. (2021)	Factor analysis method	✗
Mahmud, Kamarulzaman, et al. (2020)	Fuzzy failure mode and effect analysis	✗
Duque, Ríos, and Gómez (2019)	Supply chain operation reference (SCOR) model	✗
Tama, Yuniarti, Eunike, Hamdala, and Azlia (2019)	SCOR model	✗
Zhu, Liu, and He (2019)	Integration of SCOR model and process modelling	✗
Tomé, Silva, and Leite (2019)	Semi-structured interview and questionnaires	✗
Handayani, Nadya, et al. (2019)	SCOR model	✗

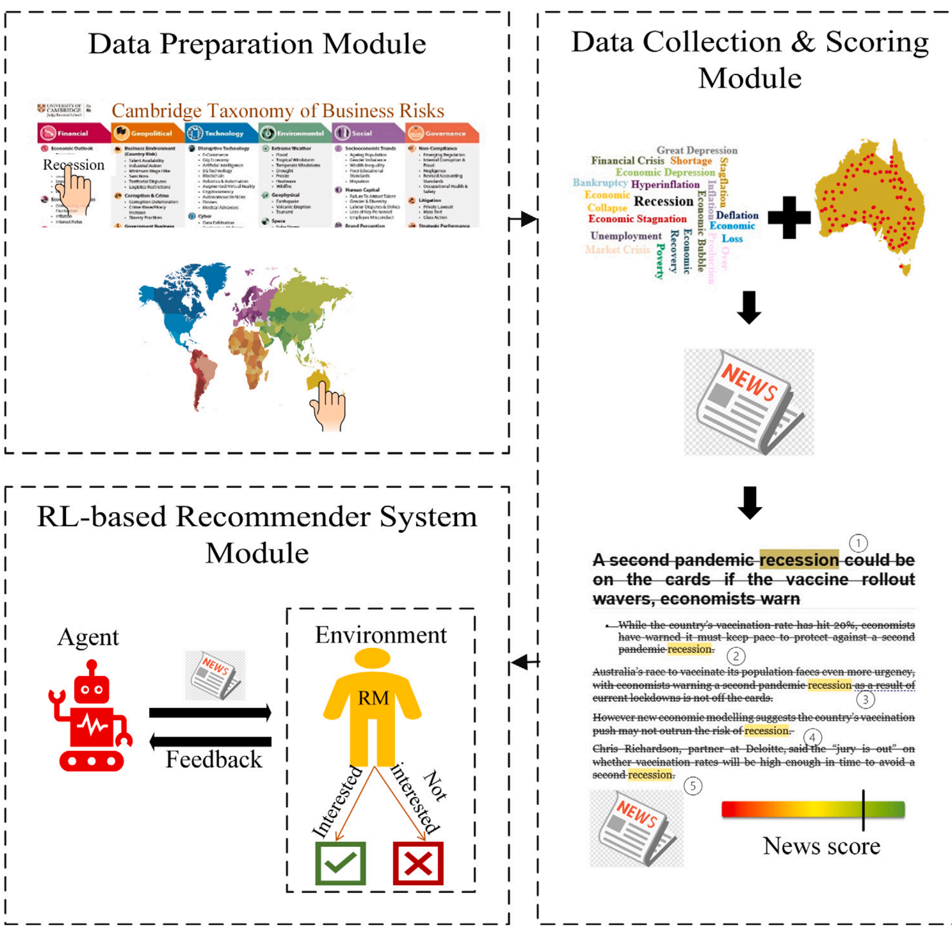

Fig. 1. Conceptual framework of the proposed RL-SCRI.

3. Reinforcement learning-based model for supply chain disruption risk identification (RL-SCRI)

Our proposed RL-SCRI framework consists of three modules, as shown in Fig. 1. Supply chain relationships between partners consist of formed agreements formalised in a service level agreement (SLA). Data Preparation is the first module in which the risk manager determines the risk events of interest from the SLA that is formed with other partners. The second module, namely Data Collection & Scoring, extracts relevant news of interest to the risk events of the SLA and calculates a score for each based on their relevance to the risk events. The last module is the RL-based recommender system in which an adaptive RL agent learns to select the most relevant news to the SLA and present it to the risk manager before considering their feedback to adapt its

Table 2
Terms rating database for *Recession*.

No.	Risk event	Rating
1	Recession	1
2	Market crisis	0.728
3	Economic collapse	0.719
4	Unemployment	0.707
⋮	⋮	⋮
2950	Combustible	0

Table 3
Locations rating database for *Australia*.

No.	Risk event	Rating
1	Australia	1
2	AUS	1
3	Victoria	1
4	Melbourne	1
⋮	⋮	⋮
24840	Zimbabwean	0

working for the next iteration. In the following subsections, the working of each module is explained in detail.

3.1. Data preparation module

This module is fundamental to the subsequent modules, in which the focus and orientation of the RL-SCRI are determined. This module generates two databases, namely *terms rating* and *locations rating*. Risk managers in this module use the Cambridge Taxonomy of Business Risks (CTBR) (Coburn, Ralph, Tuveson, Ruffle, & Bowman, 2013) to manually detect the disruption risk events that may negatively impact the SLA to which it has committed. CTBR is utilised to reduce the ambiguity that may arise when a disruption risk event is known by other variants by different risk managers. Furthermore, RL-SCRI improves from RL-PRI in this module by ensuring that it has an exhaustive list of disruption risk events for the risk manager to choose from. This is done by expanding CTBR with terms that are relevant to the chosen risk term by the risk manager and storing them in a database named terms rating. This is done by using the Wikipedia database and then scanning for the terms that are relevant to the chosen risk term. For example, if the supply chain organisation's risk manager identifies that the disruption risk event *Recession* will negatively impact its commitment to its SLA, then the created terms rating database is as shown in Table 2. This database has terms that are relevant to the disruption risk event *Recession* along with their similarity scores that are computed by comparing their vectors and lexical attributes by using the spaCy API (Honnibal, Montani, Van Landeghem, & Boyd, 2020). The other database that is created in this module is locations rating, as shown in Table 3. As global supply chains transcend boundaries, this database lists the different countries, cities, and nationalities. Based on the countries relevant to the risk managers in the SLA, this database is modified with a score of either 1 or 0. A score of 1 shows that the related locations are relevant to the SLA being considered whereas a score of 0 indicates otherwise. Once these two databases are created, RL-SCRI's work moves to the next module. Fig. 2 represents the high-level working of the Data Preparation Module in the form of a flowchart.

3.2. Data collection & scoring module

In this module, the risk managers select the risk events from the terms rating database that they are interested in being notified if they occur. Then, a natural language processing-based web crawler searches for the articles relevant to these terms from trustworthy news sources such as Google News and BBC. It also ensures that the searched news articles should be in locations with a score of 1 in the locations rating database. News articles that match these selection criteria are stored in the *news* database. Table 4 shows a sample of the news database for the aforementioned example.

In the next step, the relevance score (ns) for each news article in the news database is computed. This is done by determining the frequency of occurrence of each disruption risk event of interest in the terms rating database in each news article and multiplying it by the rating of that risk event, as shown in Eq. (1):

$$ns = \sum_{i=1}^{n} f_i tr_i \tag{1}$$

where n is the number of risk events of interest in the news article, f_i is the frequency of occurrence of the ith risk event and tr_i is the rating of the ith term in the terms rating database. The news database is updated by adding the calculated ns value for each news article as shown in Table 5. Fig. 2 shows the high-level working of the Data Collection & Scoring Module in the form of a flowchart.

3.3. RL-based recommender system module

This is the last module of RL-SCRI, in which an intelligent and automated news recommender using reinforcement learning is built. This is achieved by calculating the news articles' Q-values, making a decision on which news article is to be presented to the risk manager according to the values, and using the risk managers' feedback to update the values of the terms rating database. To calculate the Q-value of each news article, the information created in the previous modules is used and the environment is modelled as a Markov decision process (MDP) $M = (S, A, R, P)$ (Bertsekas & Tsitsiklis, 1996) as

$$Q_*(s_t, a_t) = ns_t + \gamma max_{a_{t+1}}(ns_{t+1}) \tag{2}$$

where $s_t \in S$ is the current state, $a_t \in A$ is the action taken by the agent in s_t, $ns_t \sim R(s_t, a_t)$ shows the probable reward based on the news score which is impacted by risk managers' feedback, $0 < \gamma < 1$ is the discount rate, and $s_{t+1} \sim P(s_t, a_t)$ is the probable future state.

A decision as to whether to show the news article to the risk manager or not is made by considering the calculated Q-values and obtaining the argument of the maximum (argmax). This helps determine the news article with the highest Q-value (a_{*t}), which represents the most interesting news article to be shown to the risk managers. a_{*t} is obtained by

$$a_{*t} = argmax_{a_t} Q_*(s_t, a_t) \tag{3}$$

Next, the news article with the highest Q-value is sent to the risk managers and their feedback is captured. The feedback can be in the form of either a ✓, which is considered a positive one and illustrates that the article is of interest to the risk managers, or a ✗as a negative one. So, if the risk manager considers a news article interesting and responds to it with a ✓click, then RL-SCRI updates the rating for the risk terms underlying the recommended news article in the terms rating database with the frequencies that were calculated for them using Eq. (4). In contrast, if the news article is not in the interest of the risk managers and they click on ✗, the frequency values for these terms are subtracted from the rating values in the terms rating database using Eq. (5).

$$tr_* = tr + f \tag{4}$$

$$tr_* = tr - f \tag{5}$$

It is important to mention here that while calculating the Q-value of each news article using Eq. (2), the possible future state, given this news article is recommended, needs to be determined. To obtain the future state, every determined news article on an interim basis is assumed to be of interest to the risk managers. On this basis, the frequencies of the risk terms are added to the terms rating database values, the steps of the previous modules are repeated for the interim terms rating database,

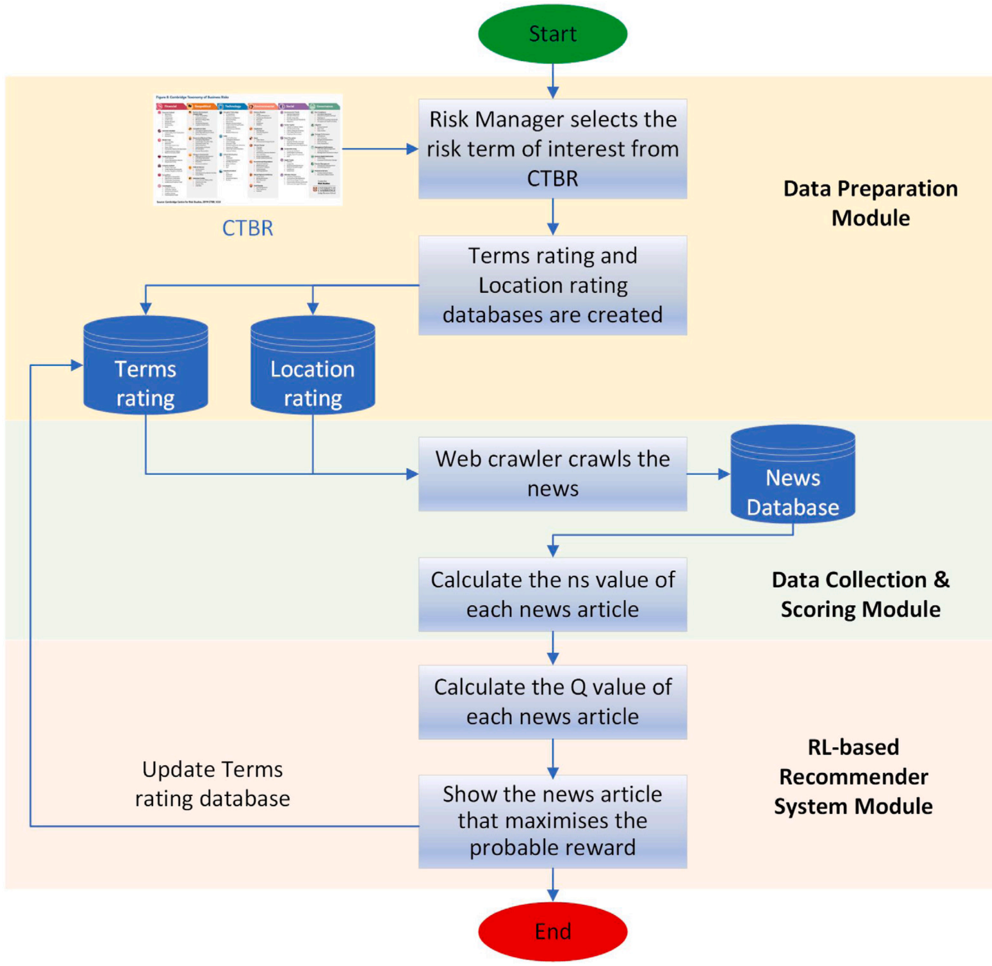

Fig. 2. Flowchart showing the working of the RL-SCRI framework.

Table 4
A sample of collected data in the Data Collection & Scoring Module for the risk term *Recession* and Location *Australia*.

Source	Title	Description	URL	PublishedAt
ABC News	Australia 'emerges from recession' after ...	The Reserve Bank governor is warning ...	https://www.abc.net ...	3/03/2021

Table 5
Expanding Table 4 with the computed ns value of each news article.

Risk event 1	Frequency 1	Risk event 2	Frequency 2	...	Risk event 18	Frequency 18	News score (ns)
Recession	0.007	Crisis	0.001	...	Coronavirus	0.002	0.017

and the score is calculated for each of the future state news articles (ns_{t+1}). However, in the end, the rating values of only those risk terms related to the news articles to whom the risk manager responded with a ✓click will be updated in the terms rating database. The workflow of this module is presented in Algorithm 1. Fig. 2 presents a high-level summary of the working of the RL-based Recommender System Module.

3.4. Exploration

RL-SCRI considers both exploitation (prior knowledge) and exploration (new options) concepts. Therefore, it continuously aligns itself with the risk manager's interest by exploring new risk events. In RL-SCRI, ϵ-greedy is used for the exploration strategy. where $0 \leq \epsilon \leq 1$ is considered as the exploration probability to decide which action to take (Tijsma, Drugan, & Wiering, 2016). In other words, with ϵ probability, a risk event is randomly selected from the terms rating database regardless of the ratings and moves through the steps to extract news articles, calculate their scores, send the one with the highest score to the risk managers, and update the terms rating database regarding the feedback as shown in Algorithm 2.

4. Performance analysis of RL-SCRI in identifying supply chain disruption risks proactively

In this section, we evaluate the performance of RL-SCRI in proactive supply chain disruption risk identification. We consider the hypothetical case scenario defined in Aboutorab, Hussain, Saberi, and Hussain (2021) as follows to assess the performance of RL-SCRI.

"ABC is a company based in Australia, and in addition to its national market, it exports goods to China. From Q1 of 2020, the trade relations between Australia and China deteriorated. Furthermore, due to the economic crisis during the COVID-19 situation, there is a probability of a recession in the Australian economy. In addition, as a result of La Nina developing

Algorithm 1 RL-based Recommender System

Input: news database, terms rating database
Output: updated terms rating database
Procedure :
for all news in news database **do**
  calculate the interim terms rating $tr_* = tr + f$
  calculate future state $ns_{t+1} = \sum_{i=1}^{n} f_i tr_{*i}$
  calculate $Q_*(s_t, a_t) = ns_t + \gamma max_{a_{t+1}}(ns_{t+1})$
end for
calculate $a_{*t} = argmax_{a_t} Q_*(s_t, a_t)$
send a_{*t} to the risk managers
if positive feedback **then**
  $tr_* = tr + f$
else
  $tr_* = tr - f$
end if
return updated terms rating database

Algorithm 2 Exploration

Input: ϵ, terms rating database
Output: updated terms rating database
initialisation :
define ϵ (in every n hours/days a term is selected randomly from the terms rating database)
Procedure :
for random term **do**
  proceed module 2
  proceed module 3
  calculate $a_* = argmaxns$
  send a_* to the risk managers
  if positive feedback **then**
    $tr_* = tr + f$
  else
    $tr_* = tr - f$
  end if
end for
return updated terms rating database

across the Pacific Ocean, there is a very high chance of floods occurring in Australia, resulting in climate change".

We assume that the ABC's risk manager considers *Tariff dispute*, *Recession*, *Sea level rise* and *Flood* as the disruption risk events that can potentially impact its SLA. RL-SCRI aims to proactively scan the environment for news articles, identify the ones related to the disruption risk events and highlight them to the risk manager so that it can proactively take actions to manage them before they occur. The best practice to assess the performance of RL-SCRI is to compare it to similar automated risk identification approaches. Therefore, we consider and apply RL-PRI (Aboutorab, Hussain, Saberi, & Hussain, 2021) on the same case study to assess the performance of RL-SCRI. Since one model for benchmarking RL-SCRI's performance may not be sufficient, we also compare its performance against Aylien[1] and the manual approach. Aylien is an advanced AI-based news intelligence platform with capabilities to proactively monitor and identify critical events, provide insights regarding emerging risks, and inform the stakeholders of this information. The manual approach is what risk managers would use to search for relevant news articles if they had done this process manually. To be consistent, location is not considered in any of the approaches due to Aylien not recommending any news articles relevant to the location of interest.

[1] https://aylien.com

Table 6
Number of news articles collected manually from Google, and automatedly by RL-PRI, Aylien, and RL-SCRI.

Method	Tariff dispute	Recession	Sea level rise	Flood	Total
Manual	13	162	189	175	539
RL-PRI	7	71	17	77	172
Aylien	0	19	0	192	211
RL-SCRI	7	69	12	77	165

4.1. Comparing RL-SCRI's performance with other approaches in determining which news articles are of interest to the disruption risk events

In this subsection, we demonstrate the superiority of RL-SCRI's Data Collection & Scoring Module compared to other methods in determining which news articles from the shortlisted ones are linked to the disruption risk events. In doing so, we also answer the second research question (compared with other similar and manual approaches, does RL-SCRI perform better in proactively identifying risks?) and demonstrate RL-SCRI's performance improvement against other baseline approaches. To determine the results that would have been achieved if this process had been done manually, Google was used to search for news articles related to the disruption risk events (*Tariff dispute*, *Recession*, *Sea level rise* and *Flood*) with no boundaries set for the location of interest to cater for results from Aylien. A total number of 539 articles, as shown in Table 6 were returned. Similarly, RL-PRI, Aylien, and RL-SCRI returned a total number of 172, 211, and 165 news articles, respectively in less than five minutes for the four risk terms of interest, as shown in Table 6 . Two experts ranked the news articles recommended by each method to determine if they truly were related to the disruption events of interest and were relevant to be presented to the risk manager. A score of 1 or 0 was used by each expert in the ranking process, where a value of 1 suggested that the expert considers the news article to be of interest to the disruption risk event and a score of 0 represents otherwise. Only those articles that both experts ranked as 1 were considered relevant to the disruption risk event of interest. Table 7 shows the ranking analysis of the experts. For instance, it can be seen that for the risk term *flood*, only 79 of the 175 articles recommended by the manual method were found to be relevant, whereas from the ones recommended by RL-SCRI, 73 of the 77 articles recommended were found to be relevant compared to 68 of the 77 articles recommended by RL-PRI, and 62 of the 192 articles recommended Aylien. The Cohen Kappa coefficient (Landis & Koch, 1977) was utilised to assess the agreement between the experts on the analysis of the articles collected by these four models by

$$k = \frac{p_o - p_e}{1 - p_e} \tag{6}$$

where p_0 is the observational agreement between two experts and p_e is the hypothetical expected agreement probability. Then, k was calculated as 1, which confirms an almost perfect agreement on the experts' analysis.

To determine the accuracy of the outputs recommended by RL-SCRI against the manual approach and existing approaches such as RL-PRI and Aylien, we compute the accuracy (a), precision (p), recall(r), and $F1$ score metrics by

$$a = \frac{TP + TN}{TP + FP + FN + TN} \tag{7}$$

$$p = \frac{TP}{TP + FP} \tag{8}$$

$$r = \frac{TP}{TP + FN} \tag{9}$$

$$F1 = \frac{2pr}{p + r} \tag{10}$$

where TP, FP, FN, and TN are defined as

Table 7
Experts' analysis of the news articles collected manually from Google, and automatedly by RL-PRI, Aylien, and RL-SCRI.

Scoring metric	Manual				RL-PRI				Aylien				RL-SCRI			
	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood
Both experts score 1	6	70	9	79	6	58	9	68	0	9	0	62	6	64	9	73
Both experts score 0	7	90	179	92	1	13	8	9	0	10	0	123	1	5	3	4
only expert 1 scores 1	0	2	1	3	0	0	0	0	0	0	0	5	0	0	0	0
only expert 2 scores 1	0	0	0	1	0	0	0	0	0	0	0	2	0	0	0	0

Table 8
Number of TP, FP, FN, and TN of the news articles collected manually from Google, and automatedly by RL-PRI, Aylien, and RL-SCRI.

Category	Manual				RL-PRI				Aylien				RL-SCRI			
	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood
TP	6	70	9	79	6	58	9	68	0	9	0	62	6	64	9	73
FP	7	92	180	96	1	7	13	9	0	10	0	130	1	5	3	4
FN	0	9	0	72	0	21	0	73	6	70	9	79	0	15	0	68
TN	0	10	0	126	6	89	172	213	7	92	180	92	6	97	173	218

Table 9
a, p, r, and $F1$ scores of the news articles collected manually from Google, and automatedly by RL-PRI, Aylien, and RL-SCRI.

Metric	Manual				RL-PRI				Aylien				RL-SCRI			
	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood	Tariff dispute	Recession	Sea level rise	Flood
a	0.462	0.409	0.048	0.320	0.923	0.812	0.958	0.774	0.538	0.558	0.952	0.424	0.923	0.89	0.984	0.802
p	0.462	0.432	0.048	0.451	0.857	0.817	0.529	0.883	–	0.474	–	0.323	0.857	0.928	0.75	0.948
r	1	0.886	1	0.523	1	0.734	1	0.482	0	0.114	0	0.440	1	0.81	1	0.518
$F1$	0.632	0.581	0.091	0.485	0.923	0.773	0.692	0.624	–	0.184	–	0.372	0.923	0.865	0.857	0.67

True Positive (TP): Number of news articles that are relevant to the SLA and recommended by the model (relevant and presented)

False Positive (FP): Number of news articles that are not relevant to the SLA but recommended by the model (irrelevant and presented)

False Negative (FN): Number of news articles that are relevant to the SLA but not recommended by the model (relevant and not presented)

True Negative (TN): Number of news articles that are not relevant to the SLA and not recommended by the model (irrelevant and not presented)

Continuing with the case study, TPs are the news articles that are scored 1 by the two experts. FPs are the news articles that are scored 0 by either of the experts. FNs are the news articles that are scored 1 by both the experts and are recommended by one of these four models but not by the one being investigated. Finally, TNs are the news articles that are scored 0 by either one or two experts and presented by one of these four models but not by the one being investigated. The summary of this analysis for the news articles collected manually from Google and automatedly by RL-PRI, Aylien, and RL-SCRI is shown in Table 8. Based on this information, we calculate the a, p, r, and $F1$ scores of these four models as shown in Table 9.

Furthermore, the average scores for a, p, r, and $F1$ in the risk terms being considered are shown in Table 10. From Table 10, it can be seen that RL-SCRI outperforms the manual process except in the recall metric and RL-PRI and Aylien in all the metrics. The recall value of the manual process is higher because it shows all news articles collected from Google regardless of their relevancy. This in fact is a drawback of the manual process as the risk manager needs to decide manually first if it is relevant to its SLA before considering it further. RL-SCRI does this step automatedly for the risk manager and only recommends those news articles that are of interest to it based on the disruption risk events being considered. The performance of RL-SCRI is better than that of RL-PRI because of the improvements it makes in the way it analyses if a given news article is of interest to the risk events or not.

Table 10
Average a, p, r, and $F1$ scores of the news articles collected manually from Google, and automatedly by RL-PRI, Aylien, and RL-SCRI.

Metric	Manual	RL-PRI	Aylien	RL-SCRI
a	0.310	0.867	0.618	0.9
p	0.348	0.772	–	0.871
r	0.852	0.804	0.138	0.832
$F1$	0.447	0.753	–	0.829

4.2. Evaluating the taxonomy enhancement of RL-SCRI through a comparison with other approaches by identifying which news articles are of interest to the disruption risk events

In this subsection, we demonstrate the superiority of RL-SCRI's Data Preparation Module compared to other methods in identifying which news articles are of interest to the disruption risk events. In doing so, we also answer the second research question defined in Section 1. In Section 3, we explain how RL-SCRI enhances the taxonomy in the Data Preparation Module. This means that it does not just focus on the disruption risk event mentioned in the SLAs, it also focuses on the risk events that are related to it. Continuing with the case study, RL-SCRI, in addition to *Recession* as the risk event of interest mentioned in the SLA, considered the top three similar risk events, namely *Market crisis*, *Economic collapse*, and *Unemployment* as shown in Table 2 and extracted

Table 11
Experts' analysis of the news articles collected automatedly by RL-SCRI for *Market crisis*, *Economic collapse*, and *Unemployment*.

Scoring metric	Market crisis	Economic collapse	Unemployment
Both experts score 1	55	57	9
Both experts score 0	12	5	3
only expert 1 scores 0	0	0	0
only expert 2 scores 0	0	0	0

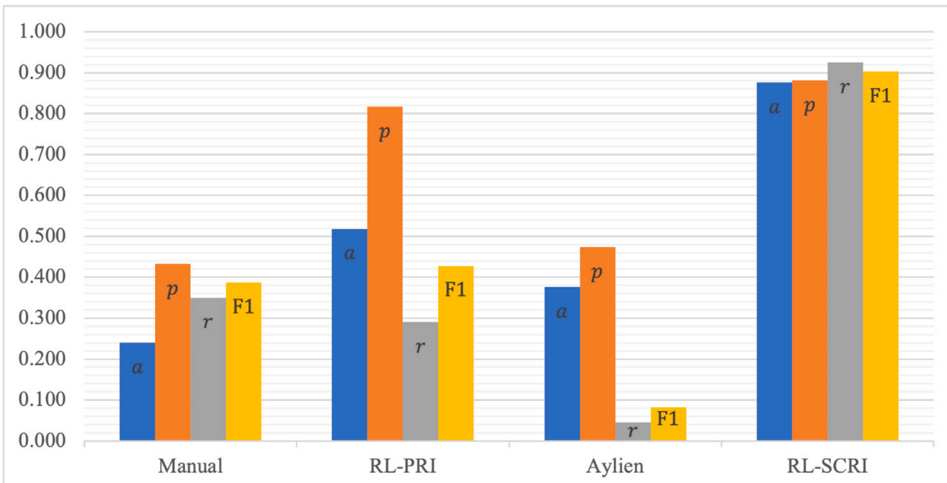

Fig. 3. a, p, r, and $F1$ scores for manually collecting news articles from Google, and automatedly by RL-PRI, Aylien, and RL-SCRI by considering added risk events for *Recession*.

Table 12
Updated analysis for the risk term *Recession*.

Category	Manual	RL-PRI	Aylien	RL-SCRI
TP	70	58	9	64 + 121
FP	92	13	10	5 + 20
FN	9 + 121	21 + 121	70 + 121	15
TN	10 + 20	89 + 20	92 + 20	97

Table 13
Updated a, p, r, and $F1$ scores for the risk term *Recession*.

Metric	Manual	RL-PRI	Aylien	RL-SCRI
a	0.240	0.519	0.376	0.876
p	0.432	0.817	0.474	0.881
r	0.350	0.290	0.045	0.925
$F1$	0.387	0.428	0.082	0.902

news articles related to them. Then, two experts determined if these news articles are truly related to *Recession* as shown in Table 11.

Based on the experts' analysis, as shown in Table 12, we update the number of TP, FP, FN, and TN for the collected news articles related to *Recession*. As a result, the a, p, r, and $F1$ scores for risk identification are updated as presented in Table 13. Fig. 3 illustrates a comparison of the a, p, r, and $F1$ scores for the risk event *Recession* for these four models. It can be seen that, with the comprehensive application of RL-SCRI, the scores for the metrics increase significantly compared to the other approaches.

4.3. Assessing the learning rate of RL-SCRI in adapting to the feedback from the risk manager

Furthermore, to assess the learning rate of our RL-based recommender system, an expert set up the RL-SCRI for *Recession* and *Australia* as the risk event and location, respectively. In doing so, we also answer the third research question 'Is RL-SCRI capable of adapting to the changes in the risk manager's interest over time?'. RL-SCRI began by extracting 8 news articles related to the SLA, calculating their scores and sorting them. The expert also ranked these news articles manually by their relevance to his objectives. Then, the Spearman's rank correlation coefficient (Zar, 1972) for those two rankings was calculated as −0.0238 by

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{11}$$

where d_i is the difference between the ith ranks of the two observations.

RL-SCRI continued its process for 90 iterations and updated the terms rating database at each iteration based on the expert's feedback. At this point, we used RL-SCRI to calculate the score for the 8 news articles that were initially extracted with the new terms ratings and sorted them. Then, Spearman's rank correlation coefficient was calculated for the new ranking and the expert's as 0.714. By comparing these two rank correlation coefficients, it can be seen that there is a significant improvement in the performance of the RL-based recommender system in presenting the most relevant news article to the expert. Fig. 4 illustrates the correlation between the rankings of the 8 news articles by the expert, initially by RL-SCRI (state S_0), and by RL-SCRI after 90 iterations (state S_{90}). It can be seen that RL-SCRI learnt through the feedback that it received from the expert and moved forward to adapt itself to his interest.

5. Conclusion

In this paper, we propose and explain how RL-SCRI, which is an AI-based approach for disruption risk identification, can assist risk managers in their aim to achieve proactive supply chain risk identification. RL-SCRI intelligently helps risk managers detect disruptions worldwide that may affect their operations through the integration of NLP and RL techniques. In addition, to answer the research questions we compared RL-SCRI with automated and manual approaches that assist the risk manager in achieving the same aim. The results demonstrate that RL-SCRI significantly increases the accuracy, precision, and recall in identifying and capturing disruptions through news articles, allowing the risk managers to get a headstart in developing plans to manage the identified disruptions. We also assessed the improvement of RL-SCRI in

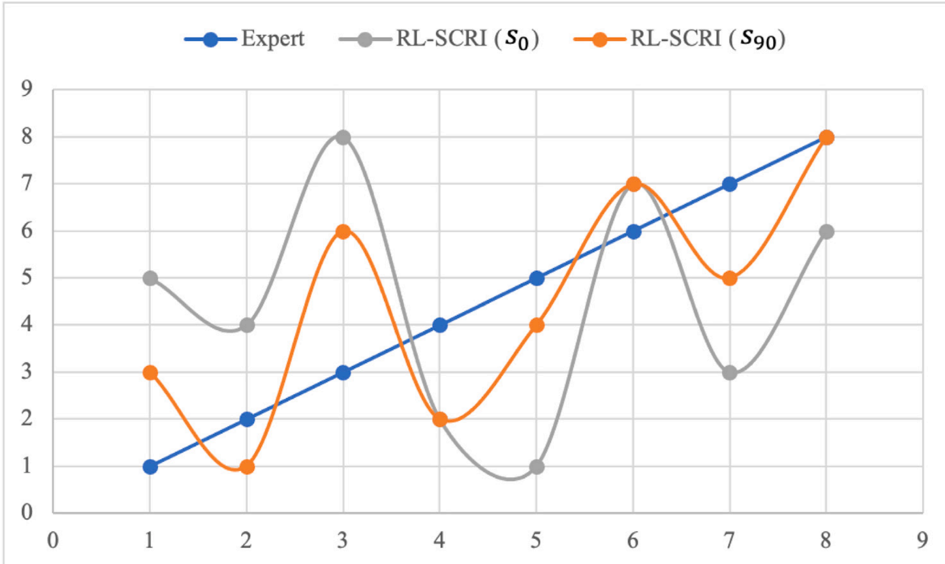

Fig. 4. Correlation between news articles' rankings by experts, RL-SCRI (S_0), and RL-SCRI(S_{90}).

identifying disruption risk events thoroughly and its ability to better capture new risk events as a result of using an enriched taxonomy. Finally, we investigated our RL-based recommender system's performance in terms of its adaptation to the user's interest, which illustrates a significant improvement in a short time. While we demonstrate the application of our model in SC, it can be applied in various other fields such as the stock market or medical diagnosis to identify different types of risks by analysing the reports. Therefore, this paper opens a new door to AI-based risk identification techniques.

CRediT authorship contribution statement

Hamed Aboutorab: Conceptualization of the idea, Formal analysis, Investigation, Data curation, Development, Completion of all the technical parts of the paper, Initial draft version and Finalisation of the manuscript. **Omar K. Hussain:** Conceptualization of the idea, Led the project in setting its scope, Assisted in supervision completing the experiments part and in the overall writeup of the manuscript. **Morteza Saberi:** Assisted in the RL-based aspects of the paper along with the experiment setup stage, Review of the paper write-up and feedback towards finalization. **Farookh Khadeer Hussain:** Overall project guidance, Final draft review and feedback, Writing – review & editing. **Daniel Prior:** Overall project guidance, Final draft review and feedback, Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Omar K. Hussain reports financial support was provided by Australian Research Council.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eswa.2024.123477.

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