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ARTICLE

Event Identification for Supply Chain Risk Management Through News Analysis by Using Large Language Models

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Abstract

Event identification is important in many areas of the business world. In the supply chain risk management domain, the timely identification of risk events is vital to ensure the success of supply chain operations. One of the important sources of real-time information from across the world is news sources. However, the analysis of large amounts of daily news cannot be done manually by humans. On the other hand, extracting related news depends on the query or the keyword used in the search engine and the news content. Recent advancements in artificial intelligence have opened up opportunities to leverage intelligent techniques to automate this analysis. This paper introduces the LUEI framework, a lightweight framework that, with only the event's name as input, can autonomously learn all the related phrases associated with that event. It then employs these phrases to search for relevant news and presents the search engine results with a label indicating their relevance. Hence, by conducting this analysis, the LUEI framework is able to identify the occurrence of the event in the real world. The framework's novel contribution lies in its ability to identify those events (termed as the Contributing Events (CEs)) that contribute to the occurrence of a risk event, offering a proactive approach to risk management in supply chains. Pinpointing CEs from vast news data gives supply chain managers actionable insights to mitigate risks before they escalate.

Keywords Supply chain risk management · Event identification · Risk identification · Large language models · Bayesian network · Natural language processing · Information retrieval

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1 Introduction

Supply chain risk management (SCRM) is a systematic and iterative approach involving risk identification, assessment, treatment, and monitoring to manage supply chain business operations [1–3]. This research focuses on the step of risk identification, which involves identifying disruptive events before their potential impact on operations is quantified. The successful completion of the risk identification phase is important as it allows the risk manager to develop appropriate strategies to address these vulnerabilities during the risk management process. By using quantitative or qualitative approaches, existing works on proactive risk identification aim to determine the risk event/s that have the potential to impact the outcome to be achieved [4–9]. While this is beneficial, it does not consider the contributing events (CEs) leading to the risk event, thereby limiting their ability to proactively determine the occurrence of the risks. This is supported by Cohen et al. [10] and Chapman et al. [11] who state that a company assessing its supply chain risk exposure, apart from merely identifying the risk event/s, must also identify the potential causes and CEs leading to such risk event/s. To explain with an example, during the COVID-19 pandemic, *staff shortage* was one of the risk events impacting supply chain companies. However, this risk event occurs for many reasons. For example, an increased number of COVID cases will result in border closures (see Fig 1). It will also result in the likelihood of more staff becoming sick, so they must quarantine. When these factors occur simultaneously, they lead to the risk event of *staff shortage*. As shown in Fig 1, in this scenario, the red node is the risk event, and all the other nodes are CEs. This paper emphasises that the early identification of any of these CEs can help in the early detection of the risk event and the organization can proactively implement any preventive actions it deems necessary to take. Thus, constructing a network of CEs that may lead to specific risks is an important first step.

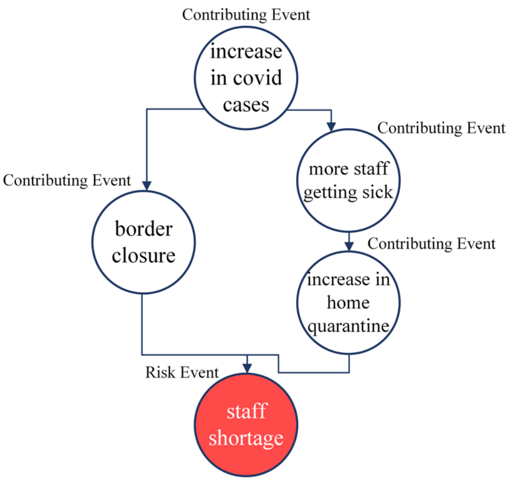

Fig. 1 CEs leading to the occurrence of a risk event

To achieve this aim, in this paper, we propose an artificial intelligence (AI)-based framework named Contributing Event-based Risk Identification and Assessment (CERIA) for supply chains. CERIA comprises two steps: (a) it builds a causal relationship between a risk event and its CEs by analyzing past news data and utilizing a Bayesian network (BN) to map these relationships, and (b) it continuously monitors the daily news to detect the occurrence of these CEs. After identifying the occurrence of a CE in the daily news, CERIA evaluates its likelihood of occurrence and integrates it into the BN, which calculates the probability of the occurrence of the potential risk event. This paper focuses on CERIA's second step, identifying the occurrence of CEs in news sources. Many researchers have tackled this problem by developing data-processing AI models that identify the events in a sentence. For these models to work, they need huge preprocessed or annotated data, to train themselves before being applied to real-world data, otherwise they will not have meaningful output. While having training data is achievable if these methods aim to ascertain a commonly occurring risk event (which may be limited in number), it is impracticable when they need to be applied to multiple CEs, particularly when these risk events are previously unknown. This may be due to various reasons, the primary one being the lack of data related to these CEs on which the data-processing AI models can be trained. This paper addresses this problem by utilizing the notion of *seed phrases* related to the CEs. Seed phrases are keywords related to the CEs that are utilised to find relevant news articles for that particular CE. Our proposed approach, which we term a Lightweight Unsupervised Event Identification (LUEI) framework, addresses this gap by developing a lightweight and unsupervised method that does not require such a large amount of preprocessing to achieve results. The research question addressed in this paper is:

Given an established causal relationship between a risk event and its CEs, how can the occurrences of these CEs in real-world news articles be determined without any training data?

To demonstrate the working of the LUEI framework, we consider a case scenario where the supply chain manager considers *delivery delays* as the risk event of interest. Using the first part of CERIA, the supply chain manager identifies *increase in COVID-19 cases*, *Australian Football League (AFL) matches* leading to *road closures,* s *hortage of airport staff*, and *construction workers' strike* (both leading to *road closures*) as the CEs leading to *delivery delays*. Using advanced AI-based methods, the LUEI framework ascertains the occurrence of an event in real-world news articles. So, the competency requirements that we define to analyse the effectiveness of the LUEI framework are:

1.1 Competency Requirements to Address the Research Question

1- How does the LUEI framework identify the seed phrases related to a CE?
2- How effective is the LUEI framework in identifying the occurrences of an event in the real world by monitoring and analyzing news articles?

The remainder of the paper is organized as follows. Section 2 discusses the related work. Section 3 details the CERIA framework and its different modules. In

Section 4, we delve into the methodology of the LUEI framework. Section 5 presents the results of the LUEI framework and compares its efficiency with other approaches of selecting news that contain the event of interest. Section 6 demonstrates how the LUEI framework answers the competency questions. Section 7 concludes the paper with a discussion on future work.

2 Related Work

Event extraction is part of information retrieval, one of the Natural Language Processing (NLP) applications [12]. The goal of event extraction from text is to detect any instance of the event and its type and attributes. To extract events, researchers aim to identify the event and its related information, which is the answer to the 5W1H questions (i.e. who, when, where, what, why, how) related to that event [12]. Leban, Fortuna, Brank and Grobelnik [13] developed an approach to detect events in news articles by clustering the news that mentions them. The clustering model is trained using manually labelled data. To detect the events in each cluster, the name entities are extracted, and based on their frequency of use, they are weighted. One of the important parts of the learning process in deep learning and machine learning techniques is the training data. Chen, Xu, Liu, Zeng and Zhao [14] developed an event extraction method to automatically extract lexical-level and sentence-level learning features and then pass this training data to the neural network. In this way, the human effort required to preprocess the data is reduced. The authors also developed a dynamic multi-pooling convolutional neural network (DMCNN) for event extraction. Other researchers such as Yang, Feng, Qiao, Kan and Li [15] used the BERT pre-trained language model, which automatically generates training data instead of manually annotated data. They also proposed a method for overcoming the role overlap problem. Zhang et al. [16] introduced a multi-task learning approach to address the challenges of data scarcity and the under-utilization of training data in event detection. This approach effectively harnesses additional knowledge. To be more precise, the authors introduce two methods for integrating a bi-directional neural language model at both the word and character levels.

Han, Huang and Liu [17] proposed a method for news recommendation. They proposed a model for event extraction and then used the trained model for news recommendation. Zhukov, Andrianova and Trifonova [18] proposed a method that can predict the events in news feeds based on an analysis of the dynamic characters of the events. However, it does not identify or detect the occurrence of an event. Bhokare, Sonawane and Sonawane [19] focused on financial event detection using classification. However, this, too, requires data for the model to train on it first. Other researchers used other text sources, such as social network data for event identification using text features and long short-term memory (LSTM), multi-task learning (MTL) or locality sensitive hashing (LSH) methods for training their proposed model [20–23]. While these approaches use different methods, they have a common goal: identifying events in a sentence. This is done using preprocessed data manually curated or generated by a system. In both scenarios, the availability of training data is crucial for achieving meaningful results. In scenarios where this is not possible,

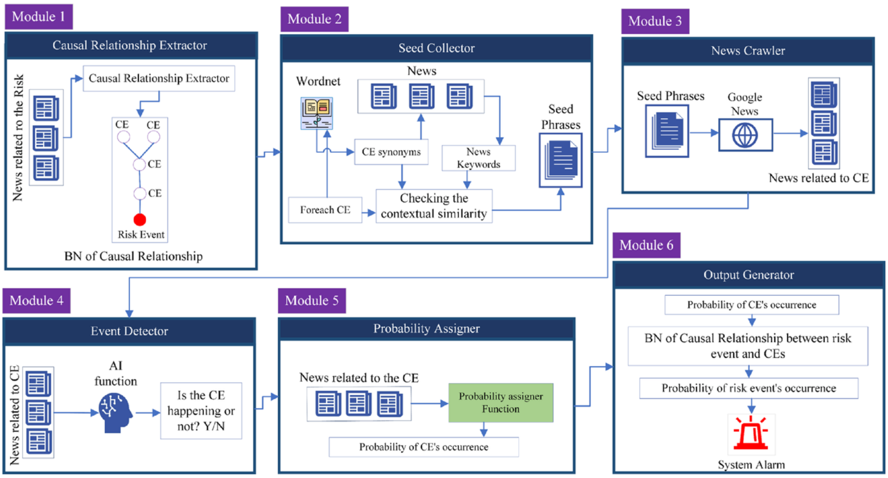

Fig. 2 CERIA framework (Recreated from [27])

these methods fail. The proposed LUEI framework addresses this by recognizing the occurrence of events with only the event's name as input. We evaluated the proposed LUEI framework in two different ways. In the first approach, we compared the shortlisted news given by the LUEI framework (by using the determined seed phrases for the searching event) with those shortlisted news articles when only the name of the event or the name, along with its synonyms, were used. In the second approach, we compared the final output of the LUEI framework with two other approaches from the literature namely EventRegistry and Aylien. This has been explained in section 5 after explaining the LUEI framework.

3 CERIA Framework

Figure 2 illustrates the CERIA framework architecture comprising different modules. We first define the key terms before explaining the different modules of the CERIA framework.

3.1 Key Terms

3.1.1 Risk Event

A risk event is any unexpected event that can negatively affect supply chains and cause disruptions. As shown in Fig. 1, staff shortage can be a risk event in the supply chain.

3.1.2 Contributing Events (CEs)

CEs are those events that can either occur before a risk event or are a precursor to it. As shown in Fig. 1, events such as *an increase in COVID cases*, *more staff getting sick* and *an increase in home quarantine* are events that lead to the risk event of *staff shortage*. These events are termed CEs to the risk event.

3.1.3 Seed Phrases

Seed phrases refer to an event's variant names. For example, "fall" is a variant of "autumn". Similarly, "strike" is a variant of "industrial action". Fall and strike are members of the seed phrases set for autumn and industrial action, respectively and are used when news about autumn and industrial action is being searched for. This is crucial as they uncover a broader range of news articles about a specific event.

3.1.4 Bayesian Networks (BNs)

BNs are mathematical models representing the interaction between variables with cause-effect connections. Such models explicitly represent the uncertain information and propagate this uncertainty to generate the model outputs [24, 25].

3.1.5 Natural Language Processing (NLP)

NLP techniques are machine learning methods that assist machines to process text in a similar way to a human.

3.1.6 Large Language Model (LLM)

LLMs are models that are trained on large amounts of data and can perform NLP-related tasks with a high level of accuracy [26].

3.2 Modules of the CERIA Framework

3.2.1 Causal Relationship Extractor Module

As shown in Fig. 2, the first module of CERIA is the Causal Relationship Extractor which builds the causal relationships between the CEs and risk events. This is done by analyzing historical news related to risk events and identifying the key CEs leading to that risk event. The details of this module are as follows:

<u>Input of this module:</u> Risk events for which the risk manager wants to build a BN.

<u>Output of this module:</u> The BN of causal relationship between risk event and CEs.

<u>Process to achieve it:</u> AI techniques that analyse news to find the causal relationships between the risk event and the CEs.

3.2.2 Seed Collector Module

Seed Collector is the second module of CERIA. For each CE, this module generates its seed phrases. This step is crucial as different instances of a CE can be used to refer to it in news articles. For instance, "fall" might also be called "autumn". So, this module generates the seed phrases for each CE, aiding in their subsequent identification in news articles. The details of this module are as follows:

Input of this module: The CEs.

Output of this module: Seed phrases for each CE.

Process to achieve it: Different NLP techniques to analyze news articles from the previous 3 years.

3.2.3 News Crawler Module

News Crawler is the third module of CERIA. This module utilizes the seed phrases for each CE to search for relevant news articles on Google News, a prominent online news aggregator. The details of this module are as follows:

Input of this module: The seed phrases of each CE.

Output of this module: News articles which mention the CE.

Process to achieve it: Application Programming Interface (API) for searching Google news.

3.2.4 Event Detector Module

The Event Detector Module is the fourth module of CERIA. This module analyzes each news article from the previous module to ascertain whether it relates to the occurrence of the CEs. This module returns a binary value of 0 or 1. A value of 1 means that the event is recognized to be happening, while 0 indicates the reverse. The details of this module are as follows:

Input of this module: News articles from the previous module.

Output of this module: The binary value of occurrence of a CE.

Process to achieve it: AI techniques and LLMs to analyse the news articles.

3.2.5 Probability Assigner Module

The Probability Assigner Module is the fifth module of CERIA [27]. If a CE is identified as occurring, this module will process the relevant news articles collected in the News Crawler Module and analyze them to assign them a probability score of occurring. The details of this module are as follows:

Input of this module: CEs marked with a label of 1, indicating they are occurring.

Output of this module: the probability of the occurrence of the CE.

Process to achieve it: analyzing the news list related to the CE

Table 1 Inputs/Outputs and Processes of the different modules of the CERIA framework

Module	Input	Output	Process
Causal Relationship Extractor	Risk event	BN of causal relationship	AI techniques to find the causal relationships between events
Seed Collector	The CEs	Seed phrases for each CE	NLP techniques to analyze news articles from the previous 3 years
News Crawler	The seed phrases for each CE	News articles which mention the CE as happening	API for searching Google news
Event Detector	News articles from News Crawler module	The binary value of occurrence of a CE	AI techniques and LLMs to analyse the news articles
Probability Assigner	CEs marked with a label of 1	The probability of the occurrence of the CE	Analyzing the news list related to the CE
Output Generator	CEs with a probability of occurrence	Probability of occurrence of the risk event	Propagating the probability in BN

3.2.6 Output Generator Module

The Output Generation Module is the sixth and last module of CERIA. This module integrates the probability of the occurrence's score ascertained for each CE in the BN to generate CERIA's final output, the probability of the risk event occurring. The details of this module are as follows:

Input of this module: CEs with a probability of occurrence.

Output of this module: Probability of occurrence of the risk event.

Process to achieve it: Propagating the probability in BN.

Table 1 shows input, output and the process of each module in summary. As discussed in Sect. 1, this paper focuses on CERIA's step of identifying the occurrences of CEs from news sources. So, it assumes that the Causal Relationship Extractor module has determined the causal relationship of the risk event of interest with its corresponding CEs. To identify their occurrence, these CEs will be given as the input to CERIA's second module, followed by modules 3 and 4. The LUEI framework encompasses modules 2, 3 and 4. Figure 3 shows the hierarchy of CERIA and LUEI framework.

4 Working Details of the LUEI Framework

Figure 4 shows our LUEI framework which automatically discovers news articles related to the predefined CEs and identifies the occurrence of the CE by analyzing the news. The proposed framework incorporates Modules 2, 3 and 4 of the CERIA framework. The first module, Seed Collector, uses WordNet and news articles from

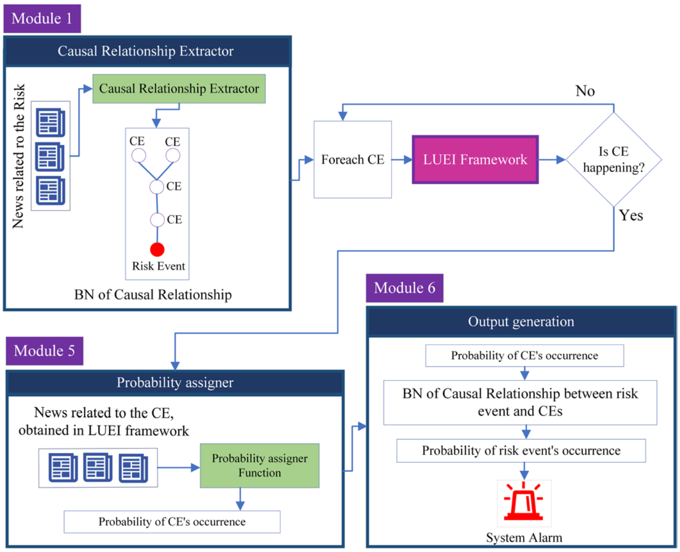

Fig. 3 Relationship between LUEI and CERIA framework

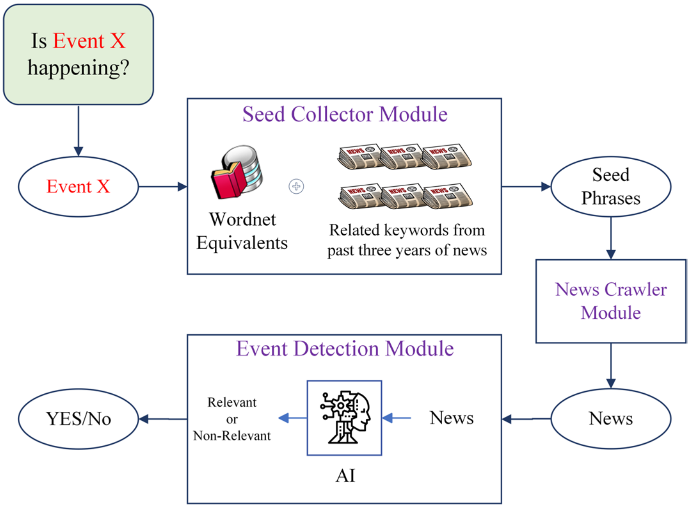

Fig. 4 LUEI framework

the past 3 years to generate a set of phrases, termed *Seed* – *Phrases*, related to the CE. The second module, News Crawler, uses the *Seed* – *Phrases* to search for news articles that are related to the CE. We utilize Google News as the news source in this research. However, it is important to note that the presence of the *Seed* – *Phrases* in the body of the news does not guarantee that it relates to the CE. So, Event Detector is the fourth module that thoroughly analyses the news article's content to determine if it relates to the CE. In this section, we comprehensively explain the workings of each module in the proposed method.

4.1 Seed Collector Module

To conduct a comprehensive search on Google News for each event, we must avoid restricting our search to a specific term. This is done to ensure that other contextually relevant news articles are not missed if they do not contain the exact keyword used in the search. Therefore, for each CE, we need a set of appropriate phrases known as *Seed* – *Phrases* that are contextually similar to the name of the CE. For instance, "industrial action" is equivalent to "strike". If we only use the keyword "strike" for the search, we may overlook news articles that do not contain the word "strike" but instead include the phrase "industrial action." Hence, "industrial action" should be included as one of the *Seed* – *Phrases* for the event "strike." The Seed Collector module determines the *Seed* – *Phrases* for each CE and has two steps, explained as follows:

4.1.1 Step 1. Finding the Equivalent Phrases of a CE Using WordNet

This step utilizes WordNet to identify each CE's synonyms or equivalent phrases in two sub-steps:

Step 1.1: Generating initial *Seed – Phrases* for the CE's name using WordNet: Since WordNet only provides synonyms for individual words, we divide the name of each CE into its constituent words. For example, if our event of interest is "staff shortage", then we consider "staff" and "shortage" separately. So the output of this process for the event "staff shortage" is: "staff" + "shortage". After this, WordNet is used to find the synonyms for each word. For example, the synonyms for "staff" would be "staff", "faculty", and "stave", and for "shortage," it would be "shortage", "deficit", "shortfall", "dearth" and "famine". By maintaining the word order in each CE's name, we merge all the synonyms to generate new equivalents for each CE. This involves considering all possible combinations of words. For example, the output of this step encompasses various combinations and consists of phrases such as "staff shortage", "staff deficit", "staff shortfall", "staff dearth", "staff famine", "stave shortfall", "stave dearth", and "stave famine". All these terms are added to the *Seed – Phrases* set. The size of this set is $\prod_{\mathrm{i}=1}^{\mathrm{n}} m_i$, where n refers to the number of words in the CE's name and m_i refers to the number of equivalents for the i^{th} word returned by WordNet. $Seed - Phrase_j$ is defined as j^{th} seed-phrase in the *Seed – Phrases* set. It is important to note that not all equivalents provided by WordNet carry the same contextual meaning we seek. Therefore, a filtering process is necessary, which is undertaken in Step 1.2.

Step 1.2. Pruning the initial *Seed – Phrases* set using semantic similarity to the CE's name: Some phrases created in Step 1.1 may not be semantically equal to the event's name. For example, the words "stave shortage" or "stave deficit" are contextually different to the CE of "staff shortage" because stave means a wooden log and semantically doesn't have the same meaning as the CE's name and should be omitted. We use SBERT sentence embedding [28] for the embedding process and then cosine similarity to compute the semantic similarity between the equivalents and the CE's name. Multiple pre-trained sentence embedding models are available for this purpose. Since the length of the query (equivalent - new phrase) and the length of the passage (CE's name) are similar, a symmetric semantic search model is utilized. Three different models were tested, and the "multi-qa-mpnet-base-dot-v1" model was the most suitable for this task, as it is specifically designed for a symmetric semantic search. The cosine similarity between the vectors generated for each equivalent phrase and the CE is calculated to determine their similarity. Ultimately, only the equivalents with a similarity score of 0.8 or higher are selected as equivalent phrases for the event's name. Algorithm 1 shows the working process of Step 1.2. The working process of Step 1, including its sub-steps, is illustrated in Fig. 5 for the event "Staff Shortage".

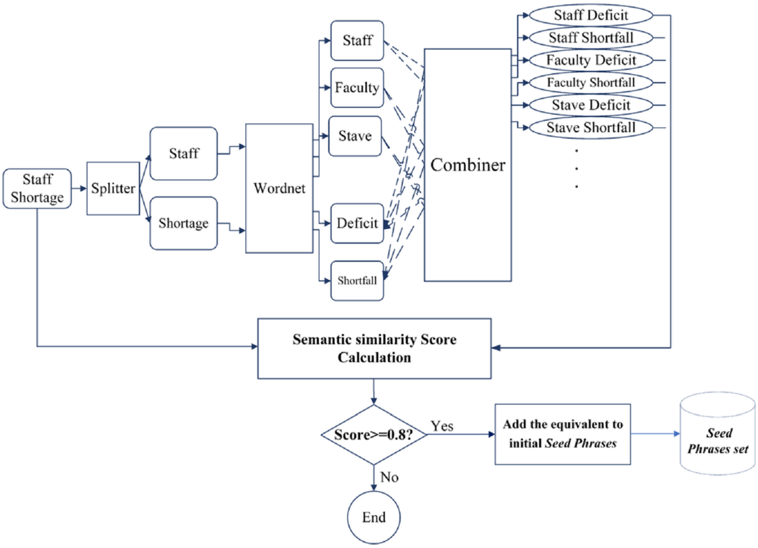

Fig. 5 Working process of Step 1 of the Seed Collector module for the event: "Staff Shortage"

Algorithm 1 (offline mode). Pruning the initial Seed-Phrases for event's name by using semantic similarity

	Input: Initial $Seed - Phrases$
	Output: Initial $Seed - Phrases$
1	For j=1:k
2	If Cosine_Similarity(SBERT($Seed - Phrase_j$),
3	SBERT(event's name)) <0.8:
4	Remove $Seed - Phrase_j$ from $Seed - Phrases$
5	Return $Seed - Phrases$

4.1.2 Step 2. Adding More Related Phrases to *Seed* − *Phrases* Set by Analyzing News from the Past 3 Years

In this step, we use the pruned *Seed* − *Phrases* set to conduct a targeted search for them in Google News for the past 3 years. This is to achieve two aims. The first aim is to ensure the seed phrase is relevant and returns at least one news article from the past 3 years. Including news from more than 3 years ago would collect outdated phrases, potentially incorporating those no longer in use. On the other hand, limiting the analysis to a period shorter than 3 years may result in losing important recent seed phrases. Thus, the search period of 3 years is considered as it is recent enough to reflect current trends and terminologies yet sufficient to observe evolving patterns and recurring themes in news events.

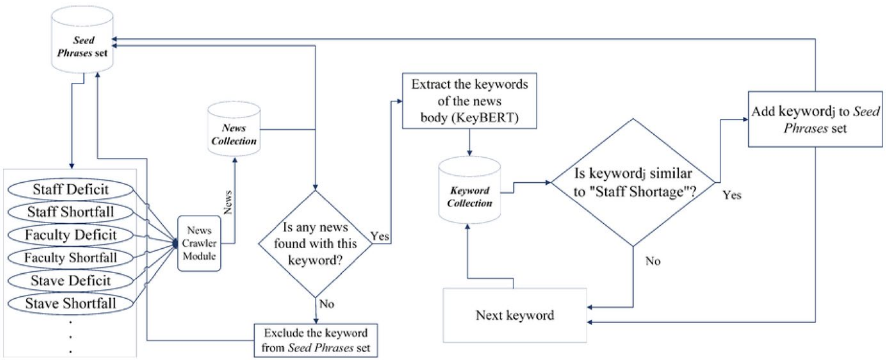

Fig. 6 Step 2 of Seed Collector module for the event: "Staff Shortage"

The second aim is to find more terms related to the event's name to expand the search scope. To achieve the first aim, news articles are searched for each phrase from the $Seed - Phrases$. The obtained collection of news articles is referred to as $News - Collection$. If no news articles are found for a certain phrase from the $Seed - Phrases$, that phrase is excluded from the final $Seed - Phrases$ set. However, if any news articles are discovered to contain a particular phrase, that phrase will remain in the final $Seed - Phrases$ set. The matched news articles related to each phrase are analyzed to extract their keywords by using KeyBERT [29], which identifies the most important phrases within a document. Each extracted keyword's cosine similarity with CE's name is calculated using symmetric semantic similarity. As shown in our previous work [30], it was observed that all the equivalents with a similarity score of equal to or more than 0.8 have the same meaning as the main phrase. So, we chose 0.8 as the threshold to consider that equivalent as the seed phrase. Therefore, if the similarity between the extracted keyword and CE's name is equal to or greater than 0.8, and the keyword does not already exist in the $Seed - Phrases$ set, it is added to the $Seed - Phrases$ set (see Fig. 6). Algorithm 2 shows the pseudocode for updating the $Seed - Phrases$ set using the past 3 years' history of news articles. For example, for the event "construction workers hold strike", "construction workers hold industrial action" is one of the seed phrases added to the $Seed - Phrases$ set in Step 1.1. By using this seed phrase as the search query, a collection of news articles ($News - Collection$) is built. For each news article ($News_j$) in $News - Collection$, a list of keywords is extracted and stored in $Keyword\_Collection_j$. For each $keyword_k$ in $Keyword\_Collection_j$, its semantic similarity with the event's name is determined using the process described in Step 1.2, and if it is greater than the threshold, it is added to the $Seed - Phrases$ set.

Algorithm 2 (offline mode). Adding more related phrases to Seed – Phrases

```
Input: Initial Seed – Phrases, News_Collection
Output: Updated Seed – Phrases
For i=1:n
    If Count(News_Collection_i) == 0:
        Remove Seed – phrase_i from Seed – Phrases
    Else
    Foreach News_j in News_Collection_i:
        Keyword_Collection_j=
        KeyBERT(News_j)
        Foreach keyword_k in Keyword_Collection_j:
            If Cosine_Similarity(SBERT(event's name)),
                SBERT(keyword_k))>=0.8:
                    Add keyword_k to Seed – Phrases
Return Seed – Phrases
```

Once the Seed-Collector finishes collecting the seed phrases, the *Seed – Phrases* set is passed on to the next module called the "News Crawler" module to find the pertinent news articles related to each event within the specified time frame.

4.2 News Crawler Module

As previously discussed, we use the Google News search engine as the source of news. To crawl the news in Google News, we use the pygooglenews API (https://pypi.org/project/pygooglenews/). This API gets some parameters as input such as, keyword, date, language and country, and returns the news which match the parameters. These news are extracted from Google News search engine. The output of the "News Crawler" module is the news articles that contain phrases from the *Seed – Phrase* set. However, these may be in different combinations. For instance, if we search for the phrase "increase in COVID cases," the search results include news articles that mention the words "increase", "in", "COVID" and "cases" in the body of the article or, in some cases, news articles that don't have these keywords in their body, but some of the words appear somewhere in the margin of the news. Although enclosing the search phrase in double quotation marks to retrieve exact matches is possible, this approach may yield limited results. We may also get news articles with different meanings to the CE's name. For example, if we search for "staff shortage," we might come across news articles that discuss improving staff performance in one paragraph and address a shortage of tools or equipment in the workplace in another. Although both words of the search phrase are present in the news article, the article itself may not be relevant to the desired CE. To filter out such noisy data from our news collection, the next module analyzes each news article, based on which it will decide whether the event of interest is happening.

4.3 Event Detector Module

This module aims to filter out news articles which are irrelevant to the CE's name. This is done by utilizing the SBERT sentence embedding technique and the "multi-qa-MiniLM-L6-cos-v1" pre-trained model to convert the entire text of a news article into a vector. The same process is applied to the event of interest. Semantic search is then performed by calculating the cosine similarity between the two vectors. If the semantic similarity is more than 0.5, then the news article is considered to relate to CE. For example, for the event, "staff shortage", this module converts the news article related to that term into a vector along with the term "staff shortage". The cosine similarity between these vectors is then computed, and if it is more than 0.5, it is considered relevant. We selected the threshold 0.5 by examining over 1000 news articles for four CEs and determined the threshold level that gives the correct matching results. The output of this module is a binary label with values "0" and "1." News articles labeled "1" indicate that they suggest the event is mentioned in the news article as either happening or will happen, while those labeled "0" are recognized as non-relevant news articles that do not pertain to the event. Clearly, when the system designates at least one event as "1," it implies a positive occurrence of that event. The risk manager can use this information for further analysis. For events identified as relevant, the CERIA assigns a probability score for their occurrence. This score is then utilized in the BN to evaluate the probability of the risk event happening.

The next section discusses the experiments we performed to demonstrate the effectiveness of the proposed approach.

5 Results and Evaluation

To evaluate the performance of the LUEI framework, we evaluated the Seed Collector module, followed by the News Crawler module. Then, using the results generated by these modules, we evaluated the performance of the Event Detector Module in two different ways. Firt we made the evaluation against manual approach in which we used the output of Google search news. In the second approach we compared the output of LUEI framework with other two frameworks. In both scenarios we used expert knowledge. To conduct the first approach of evaluation we have considered four CEs, namely **"Increase In COVID Cases"**, **"AFL Matches Happening"**, **"Airport Staff Shortage"** and **"Construction Workers Hold Strike"** which lead to the risk event of "Delay in Delivery". We aim to evaluate the performance of the LUEI framework and assess its ability to recognize the relevant news related to these CEs and separate the non-relevant ones. As mentioned in the previous section, Step 1 of the Seed Collector module consists of two steps. Step 1.1 involves extracting WordNet equivalents for the CE's name. After completing this step for the CE "Increase in Covid cases", 1537 equivalents were identified for the CE's name. Step 1.2 calculated the semantic similarity between the equivalents and the CE's name, a snapshot of which is shown in Table 2 for the CE "Increase in COVID Cases". Only equivalents with a semantic similarity score of 0.8 or higher with the CE's name were added to the initial $Seed - Phrases$ set. The initial $Seed - Phrases$ set was used in Step 2 to generate the final $Seed - Phrases$ set as shown in Tables 3, 4, 5 and 6. These terms are later used to search for news articles related to CEs.

In the first approach of evaluation we demonstrate the effectiveness of the LUEI framework in searching for the CEs by conducting three experiments. In the first

Table 2 A snapshot of the outcome of step 1 of the Seed Collector module for the event "Increase in Covid cases"

WordNet equivalents	Semantic similarity
Increase in covid instance	0.87
Increase inward covid character	0.68
Addition inward covid cause	0.63
Addition inward covid suit	0.53
Gain indium covid typeface	0.35
Step-up indium covid pillow_slip	0.16
Step-up indium covid showcase	0.2
Increase inch covid instance	0.7
Growth indium covid suit	0.46
Addition indium covid slip	0.28

Table 3 Final seed-phrase set for event: "Increase in Covid cases"

Increase in covid instances	Steep increase in coronavirus infections
Increase in covid cases	Growth in covid cases
Rise in coronavirus cases	Covid cases risen

Table 4 Final seed-phrase set for event: "AFL Matches Happening"

AFL match happening	AFL match occurrence
Aflw matches happening	Teams afl play
Aflw match happening	Aflw game
Afl match starting	Matches week afl
Aflw showdown	Aflw showdown slated
Blockbuster afl match	Afl season fixture
Rivalries going afl	Afl showdown game
Afl championship match	Live AFL contests
Playing AFL encounters	In-session AFL bouts
In-play AFL confrontations	Unfolding AFL games
Present AFL competitions	Currently playing AFL matchups
Real-time AFL battles	On-field AFL confrontations
Running AFL showdowns	Happening AFL face-offs

Table 5 Final seed-phrase set for event: "Airport Staff Shortage"

Airport staff deficit	Airport staff shortage
Airport staff shortfall	Insufficient staffing airports
Airport labor shortage	Inadequate airport staff
Dearth of airport staff	

Table 6 Final seed-phrase set for event: "Construction Workers Hold Strike"

Construction worker hold strike	Building worker strike
Structure worker strike	Construction workers protest
Building site worker industrial action	Construction labor unrest

experiment (termed Single Keyword), we used only the CE's name, for example, "increase in Covid cases", as the keyword for searching the relevant news. Two experts labelled the news as relevant or non-relevant on the returned results. In the second experiment (termed Keyword + WordNet Equivalent), we used the CE's name and its equivalents created in Step 1 of the Seed Collector module to search for relevant news. We again asked the two experts to label the news as relevant or non-relevant on the returned results. In the third experiment (termed LUEI), we used the final $Seed - Phrases$ set generated by LUEI framework to search for news related to the CE. As explained in Section 4.3, the LUEI framework classifies the news articles into two categories: "0" (non-relevant), indicating that the news does not mention the event as likely to happen, and "1" (relevant) indicating that the shortlisted news refers to the CE as occurring. We again asked the two experts to label the news as relevant or non-relevant on the returned results. Once the labelling by the experts on the different sets of experiments was done, the True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) of each method were computed (see Tables 7, 8, 9 and 10). The semantics of the measures are as follows:

- TP: This measure shows the number of news articles a model recommended and confirmed by both experts as relevant.
- FP: This measure shows the number of news articles a model recommended but labelled by any one of the experts as irrelevant.

Table 7 Confusion matrix for "Increase In Covid Cases"

Category	Single Keyword	Keyword + WordNet Equivalents	LUEI framework
TP	6	23	60
FP	13	207	4
TN	0	0	640
FN	68	56	8

Table 8 Confusion matrix for "AFL Matches Happening"

Category	Single keyword	Keyword + WordNet Equivalents	LUEI framework
TP	2	5	24
FP	8	14	2
TN	0	0	29
FN	24	21	2

Table 9 Confusion matrix for "Airport Staff Shortage"

Category	Single keyword	Keyword + WordNet Equivalents	LUEI framework
TP	4	7	11
FP	9	11	2
TN	0	0	25
FN	8	5	1

Table 10 Confusion matrix for "Construction Workers Hold Strike"

Category	Single keyword	Keyword + WordNet Equivalents	LUEI framework
TP	3	6	20
FP	10	23	7
TN	0	0	28
FN	17	14	0

- TN: This measure shows the number of news articles a model has recommended as irrelevant to the CE's name and that both experts have confirmed the news as irrelevant. In the first two categories of experiments (using "Single Keyword" or "Keyword + WordNet Equivalent"), this measure is always zero. This is because as we are using Google News for our search, it will only show us articles that it considers relevant, without any label. This is not the case in the third model that labels the news as relevant or irrelevant.
- FN: This measure shows the number of news articles that a model has not recommended as relevant to the CE's name but has been confirmed by both experts as relevant. For the first two categories of experiments (using "Single Keyword" or "Keyword + WordNet Equivalent"), this measure shows the number of news articles that were not shown by these methods as relevant but were marked as relevant by the third experiment and confirmed by both the experts. For the third experiment, this measure shows the number of news articles incorrectly labelled as non-relevant but marked as relevant by both experts. This also considers news articles shown as relevant in the first two experiments and confirmed by the experts but not shown as relevant in the third experiment.

Tables 11, 12, 13 and 14 show the evaluation metrics for each experiment. The results show that the proposed approach performs significantly better than only using the CE's name as the search keyword and/or the CE's name + synonyms. This is because the proposed approach, apart from just using the CE's name, expands its search scope by also using relevant terms. The number of FNs in the first and the second experiments (Tables 7, 8, 9 and 10) demonstrates this. Another advantage of the proposed approach is that it only shows news articles relevant to the CE. For example, as the CE's name is "increase in COVID cases", the first and second experiments show many news articles with COVID in them but do not specifically relate to an increase in COVID cases. This is shown in the number of FPs they have. The LUEI framework avoids this by only showing articles related to an increase in COVID cases, as shown by the number of FPs and TNs in its analysis. In other words, the proposed approach does not show a news article if it merely has the name of the CE. Hence, it has a higher accuracy, precision, recall and F1 score in determining the occurrence of the CE in the news articles. Tables 15 and 16 show the total confusion matrix and evaluation metrics for all the experiments.

Table 11 Evaluation metrics for different approaches for the event "Increase in COVID Cases"

Performance metric	Single keyword	Keyword + WordNet equivalents	LUEI framework
Accuracy	6.89%	8.04%	98.31%
Precision	31.75%	10%	93.75%
Recall	8.10%	29.11%	88.23%
F1 Score	12.90%	14.88%	90.90%

Table 12 Evaluation Metrics for Different Approaches for the Event "AFL Matches Happening"

Performance Metric	Single Keyword	Keyword + WordNet Equivalents	LUEI framework
Accuracy	5.88%	12.5%	92.98%
Precision	20%	26.32%	92.31%
Recall	7.69%	19.23%	92.31%
F1 Score	11.11%	22.22 %	92.31%

Table 13 Evaluation metrics for different approaches for the event "Airport Staff Shortage"

Performance metric	Single keyword	Keyword + WordNet Equivalents	LUEI framework
Accuracy	19.05%	30.43%	92.31%
Precision	30.77%	38.89%	84.62%
Recall	33.33%	58.33%	91.67%
F1 Score	32%	46.67%	88.0%

Table 14 Evaluation metrics for different approaches for the event "Construction Workers Hold Strike"

Performance metric	Single keyword	Keyword + WordNet Equivalents	LUEI framework
Accuracy	10%	13.95%	82.27%
Precision	23.08%	20.69%	74.04%
Recall	15 %	30%	100%
F1 Score	18.18 %	24.49 %	85.11%

Table 15 Total confusion matrix

Category	Single keyword	Keyword + WordNet equivalents	LUEI framework
TP	15	41	115
FP	40	255	15
TN	0	0	722
FN	117	96	11

Table 16 Total evaluation metrics

Performance Metric	Single Keyword	Keyword + WordNet Equivalents	LUEI framework
Accuracy	8.72%	10.46%	98.31%
Precision	27.27%	13.85%	93.75%
Recall	11.36%	29.93%	88.23%
F1 Score	16.04%	18.94%	90.90%

Table 17 Confusion matrix for different methods for the event "Increase in Covid Cases"

Category	LUEI	EventRegistery	Aylien
TP	15	6	4
FP	0	48	835
TN	53	0	0
FN	8	13	17

In the second approach of evaluation we demonstrate the superiority of the proposed LUEI framework, by comparing its results with that of EventRegistry [13], and Aylien (https://aylien.com/). We used each of the three models to determine the relevant news articles to the CE "increase in COVID cases" for a period of one day. EventRegistry returned 100 news articles, which was later reduced to 54 after deleting the duplicates. Aylien returned 839 news articles in total, whereas the LUEI framework, which used all seed phrases related to "increase in Covid cases" rather than just the phrase for finding the relevant news, returned 71 news articles. To determine the accuracy of the results, we asked experts to read the results from each approach and tag them based on their relevance to the "increase in COVID cases" or if they confirm that this event is happening. An article recognised by the experts as relevant to the CE was tagged as "true positive" (TP), whereas an irrelevant article was tagged as "false positive" (FP). Furthermore, if an article was identified as relevant by one framework and confirmed by the experts as a TP but did not appear in the output of another framework, it was tagged as a "false negative" (FN) for the latter. So, in other words, a news article that was not ranked as TP by a method but was confirmed

Table 18 Evaluation metrics for different methods for the event "increase in Covid cases"

Performance metric	LUEI	EventRegistery	Aylien
Accuracy	89.47%	8.96%	0.47%
Precision	100%	11.11%	0.48%
Recall	65.22%	31.58%	19.05%
F1 Score	78.95%	16.44%	0.91%

as a TP by the other methods was considered an FN for the former. As the LUEI framework categorizes news articles as relevant and irrelevant, they also have true negatives (TN) or false negatives (FN). However, this was not the case with the other two frameworks. Tables 17 and 18 presents the evaluation results. The results show that EventRegistry and Aylien generate significant noise as they return any news containing any part of the CE. When we attempted to search for the CE using double quotation marks, both frameworks returned only one result, which was also irrelevant. This was not the case with the proposed LUEI framework. It identified the occurrence of the CE with minimal steps in a large dataset by following its lightweight and unsupervised approach. The working of LUEI framework approach is versatile and not restricted to a particular domain as it is not trained on data from a specific field. Furthermore, it doesn't require an annotated dataset, and the risk manager only needs to input the CE's name for the framework to determine whether the event is occurring.

6 Efficacy of the LUEI Framework in Answering the Competency Question

This section demonstrates the effectiveness of the LUEI framework in detecting real-world events, aligning with the competency questions outlined in Sect. 1.1 as follows:

1-How does the LUEI framework identify the seed phrases related to a CE? The efficacy of the LUEI framework in aggregating seed phrases for each event, derived from news analysis, is substantiated by Tables 3 through 6. This approach enables the LUEI framework to broaden its search scope when mining news data. The augmentation of these seed phrases in search queries, as evidenced by Tables 7, 8, 9 and 10, significantly enhances the volume of the related news captured. This enhancement is essential in accurately detecting real-world events.

2- How effective is the LUEI framework in identifying the occurrences of an event in the real world by monitoring and analyzing news articles? Tables 11–18 present a comparative analysis, demonstrating the high efficiency of the LUEI framework in news labelling after using seed phrases. When compared to manual methods that employ either a single keyword or a combination of a keyword and its synonyms, or compared against other approaches like EventRegistery or Aylien, the LUEI framework's output closely mirrors expert opinions. This alignment with expert analysis underscores the primary objective of this research: to develop a system that can reliably and accurately identify real-world events with no training data available for these events.

7 Conclusion and Future Work

In this paper, we proposed the LUEI framework to identify the occurrence of events of interest. As opposed to existing models, LUEI is a lightweight and unsupervised approach that, without any training data, recommends news articles that are relevant to the search term of interest to the risk manager. As previously discussed, the LUEI framework is a part of the CERIA framework that quantifies the chance of the occurrence of risk events in supply chains by finding out the cause-and-effect relationship between the events that can lead to the occurrence of those risk events. In future work, we will develop an approach to model the cause-and-effect network of the risk events and analyze the daily news to quantify the probability of the occurrence of the risk event. We will also extend our experiments to demonstrate our proposed framework's effectiveness.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no Conflict of interest.

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