Visualising Industry Network-based Supply Chain Risks for Informed Opportunity Management

Ming Zhao
School of Business
UNSW Canberra
Canberra, Australian Capital Territory, Australia
ming.zhao@unsw.edu.au

Omar Hussain
School of Business
UNSW Canberra
Canberra, Australian Capital Territory, Australia
o.hussain@unsw.edu.au

Abstract

This paper presents an extension of the LARD-SC (LLMs for Automated Risk Detection in Supply Chains) framework to support not only reactive risk mitigation but also proactive opportunity identification across broader industry networks. By integrating structured supplier data with real-time, unstructured information streams from news feeds, the LARD-SC framework applies GPT-4o to identify, categorise, and visualise risk signals to create a unified, dynamic risk landscape for focal companies to visualise their globally dispersed supply chains. We demonstrate LARD-SC's capability using Apple as a case study, leveraging its supply chain data to visualise and classify risks impacting its supply chain. Beyond reducing risk exposure, we then demonstrate how the LARD-SC framework can be used by the focal company to create opportunity-driven foresight. This can be used to enable strategic planning and competitive advantage by anticipating disruptions and acting ahead of rivals.

ACM Reference Format:

Ming Zhao and Omar Hussain. 2025. Visualising Industry Network-based Supply Chain Risks for Informed Opportunity Management. In *Proceedings of the 1st Workshop on "AI for Supply Chain: Today and Future" @ 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V.2 (KDD '25), August 3, 2025, Toronto, ON, Canada.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/XXXXXX.XXXXXX

1 Motivation of the paper

The increasing globalization of markets, intensification of competition, and heightened focus on customer satisfaction are widely recognized as key drivers behind the growing scholarly and managerial interest in supply chain management (SCM). Within this competitive landscape, the profitability of the focal firm—defined as the entity identified by consumers as accountable for a product or service and responsible for coordinating material and information flows—depends significantly on its capacity to manage complex inter-organisational relationships. From the perspective of the focal firm, supply chain visibility (SCV), particularly regarding dependencies on upstream suppliers, has emerged as a critical concern within SCM research, given its substantial influence on overall supply chain performance. Recent global disruptions, such as the Covid-19 pandemic, have exposed the vulnerabilities associated with limited SCV, including constrained visibility upstream toward suppliers and downstream toward customers. Beyond immediate supply chain partners, focal firms often lack insight into the operations of lower-tier suppliers, resulting in disruptions to material availability, delivery schedules, productivity, and revenue generation. In addition to adversely impacting operational performance, reduced SCV undermines the capacity to foster supply chain resilience. Consequently, the need to manage disruptions within globally distributed supply networks has underscored the strategic importance of enhancing SCV to ensure sustainable and competitive business performance.

In response to these gaps, our previous work [1, 2] proposed and developed the LARD-SC (LLMs for Automated Risk Detection in Supply Chains) framework. LARD-SC integrates state-of-the-art LLMs and graph-based data visualisation to autonomously collect, analyse, and classify risk events from vast pools of unstructured textual data (e.g., online news articles). Specifically, LARC-SC:

- Automates risk detection across a globally dispersed supply chain network using LLMs.
- Structures and classifies identified risks according to the established Cambridge Taxonomy of Business Risks (CTBR) [3] so that strategic decisions can be effectively prioritised, and
- Visualises and explores these risks interactively, enabling supply chain managers to respond to risks impacting their geographically dispersed supply chain network in a timely and data-driven manner.

However, while LARD-SC offers valuable support to risk managers in identifying and mitigating risks specific to their own supply chains, its capabilities can be further extended to facilitate proactive and informed opportunity management across the broader industry network. This shift from risk mitigation to strategic opportunity identification enables focal companies not only to safeguard operations but also to gain a competitive edge. For instance, consider Apple as a focal company operating within the technology industry network. By leveraging LARD-SC to pre-identify risks that may affect the wider industry—such as emerging geopolitical tensions, regulatory changes, or supplier vulnerabilities—Apple could anticipate potential disruptions before they materialise. More importantly, it could translate this foresight into strategic action, such as securing alternative suppliers, innovating product designs, or entering new markets, thereby capturing a greater market share ahead of competitors who may still be reacting to unfolding events. In this paper, we refer to this expanded capability as an opportunity identification framework, designed to enhance the performance of

KDD '25, Toronto, ON, Canada.

ACM ISBN 979-8-4007-1454-2/25/08
https://doi.org/10.1145/XXXXXX.XXXXXX

supply chain networks by enabling focal firms to pre-emptively recognize and act on strategic opportunities embedded within risk signals—ultimately informing higher-level decision-making and fostering long-term competitive advantage.

In this paper, we present the results from such an opportunity identification framework by taking Apple as the focal company. The structure of the paper is as follows. In Section 2 we present the LARD-SC framework. The results from the framework are presented in Section 3. Section 4 presents how the analysis can be used by risk managers to determine the opportunities that they can utilize when risks specific to an industry are identified. Section 5 concludes the paper with a discussion on future work.

2 The LARD-SC Framework

As shown in Figure 1, LARD-SC is an overarching framework that develops and integrates three sub-frameworks, namely DCV-RA (Data Collection and Visualisation for Risk Analysis), LLM-RI (Large Language Model-based approach for Risk Identification) and LLM-RC (Large Language Model-based approach for Risk Classification) for automated risk identification, risk classification, and interactive visualisation of the detected risks. The details of each sub-framework in the LARD-SC framework are as follows:

DCV-RA: DCV-RA is the first sub-framework of the LARD-SC framework that presents the risk information intuitively and interactively. This interactive functionality empowers risk managers to navigate vast data sets effectively, fostering better alignment between risk assessments and organisational strategies. The LARD-SC framework uses the DCV-RA sub-framework in two phases, namely the pre-analysis phase and the post-analysis phase. In the pre-analysis phase, the DCV-RA sub-framework assists the risk manager in initialising the LARD-SC framework on their globally dispersed SC. The following tasks are performed in this phase:

- Configuring the analysis of the LARD-SC framework with the focal company's supply chain details and the suppliers' information.
- Collecting the news articles associated to the suppliers of the focal company.
- Visualising the focal company's geographically spread supply chain network with supplier nodes and their interrelations.

In the post-analysis phase, the DCV-RA sub-framework builds on the outputs of the LLM-RI and LLM-RC sub-frameworks and performs the following tasks:

- Enhances the visualised supply chain network of the focal company with risk events impacting its operations. This is done by capturing the risks impacting its suppliers and their impact on the focal company's operations.
- Through real-time graph representations, enable risk managers to filter, explore, and scrutinise events by region, supplier, or risk category. This enables them to quickly identify and respond to potential disruptions impacting any node of their supply chain network.

LLM-RI: is the second sub-framework of the LARD-SC framework. The LLM-RI sub-framework focuses on automating the discovery of emerging risk events across a focal company's geographically dispersed supply chain. By employing LLMs, it efficiently processes unstructured data (e.g., news articles) and provides real-time risk identification and assessment, alerting the risk managers of the focal company to potential disruptions. As shown in Figure 1, the output of this sub-framework assists the risk managers of a focal company in visualising its geographically spread supply chain network with the determined risks impacting it and its suppliers with their impact. A brief description of the LLM-RI sub-framework is as follows:

- Input: List of focal company's geographically dispersed suppliers.
- Input: Automated feeds of textual data from news outlets and other publicly available sources (e.g., newspapers, blogs, social media).
- Output: A set of identified risk events for each supplier, annotated with a short descriptive summary.
- Output: Likelihood ratings (e.g., low likelihood, moderate likelihood, high likelihood) indicating how probable it is that each event will materialise.
- Output: Impact ratings (e.g., low impact, moderate impact, high impact) specifying the severity of potential disruptions.

LLM-RC: is the third sub-framework of the LARD-SC framework. After LLM-RI identifies potential risks, the LLM-RC sub-framework assists in the classification of the identified risk events according to the focal company's interests. By utilising advanced embedding techniques, such as sentence-t5-base, LLM-RC aligns risk events with CTBR-defined risk class labels (e.g., financial, geopolitical). The CTBR's hierarchical structure, encompassing risk classes, families, and types, enables precise categorisation and prioritisation of risks, distinguishing between general classes (e.g., financial) and more specific families and types (e.g., economic outlook > recession). Organising risk events by category allows risk managers to focus on specific threat domains (e.g., financial instability, geopolitical uncertainties, environmental contingencies). A brief description of the LLM-RC sub-framework is as follows:

- Input: A repository of risk events (e.g., textual descriptions, likelihood/impact ratings) generated by the LLM-RI sub-framework.
- Input: The CTBR encompassing classes, families, and types of business disruptions.
- Input: A pre-trained sentence embedding model (e.g., sentence-t5-base) tailored for semantic similarity assessments.
- Output: CTBR-based labels for each risk event (e.g., Financial > Economic Outlook > Recession).
- Output: Enhanced metadata clarifying the rationale for each assignment, via semantic similarity scores or LLM-generated justifications.
- Output: A structured database that aligns each identified risk with a standardised taxonomy node, facilitating queries and analytics.

3 Results

To demonstrate the results and comprehensive functionality of the LARD-SC framework, Apple is employed as the focal company. This is because of the ease in which suppler data related to Apple was available [4], which is needed for the LARD-SC data for the modelling of Apple's supply chain network. Additionally, according

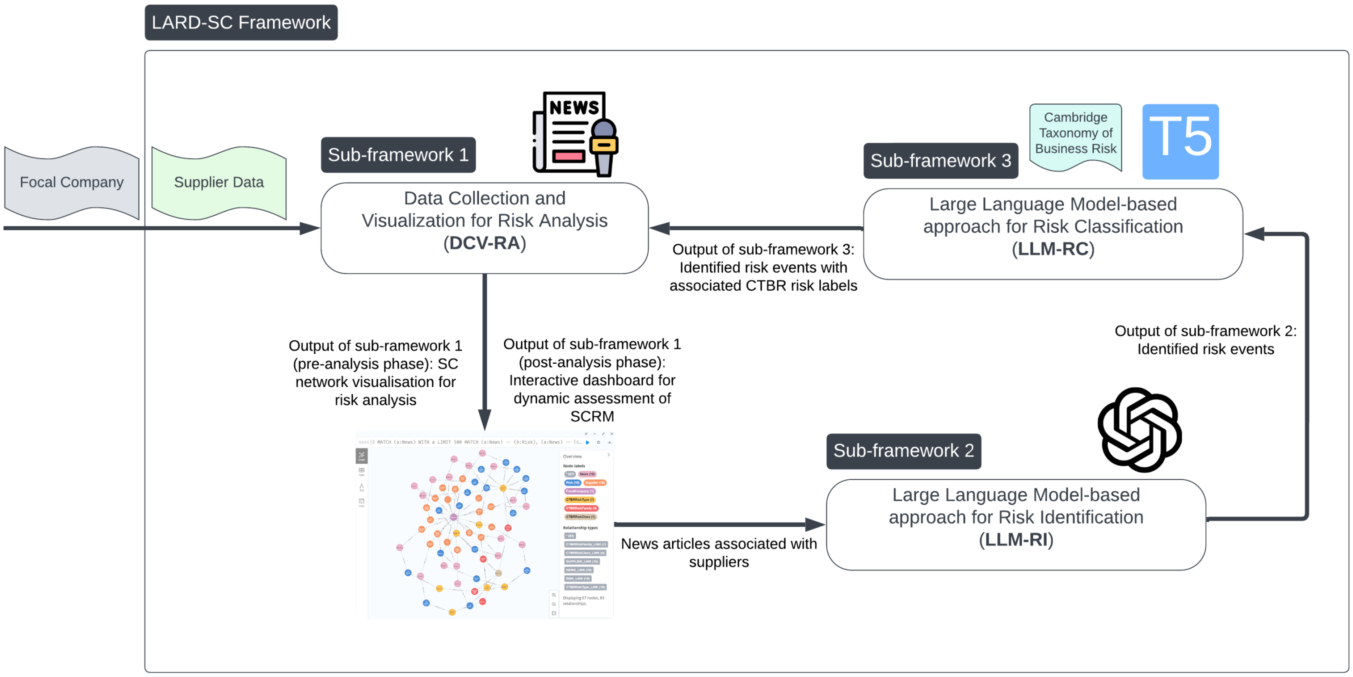

Figure 1: showing the conceptual architecture of the LARD-SC framework

to the Global Industry Classification Standard (GICS) [5], Apple is classified under the Technology sector and the Consumer Electronics industry. Companies within the Technology sector across various industries were collected using the Financial Modeling Prep (FMP) API [6] to establish the industry network for Apple. This returned over 900 entities across multiple exchanges. We sampled 95 companies across nine different industries, in addition to the existing 188 of Apple's tier-1 suppliers, as shown in Figure 2. Associated news articles were collected for each company using Alpha Vantage News APIs [7]. Function calling with predefined prompts and schema leveraged GPT 4o [8] to identify potential risk events from the collected news articles. CTBR [3] along with the sentence t5 base embedding model [9] was then employed to further classify each risk event. Finally, these results were ingested into a Neo4j graph database [10] and rendered via Neo4j Browser for risk manager analysis.

Figure 3 shows various companies categorised by whether they belong to the same or different industries within the Technology sector by using the green nodes, and Apple's tier-1 suppliers by using the purple nodes. For each company or supplier, LARD-SC framework also parses for news articles related to them and then appends it to them in the figure. These news articles are represented by orange nodes in Figure 3. The collected news articles are linked to 99 instances of CTBR labels. This representation assists Apple's risk managers in having a complete view of their global supply chain along with the different risk events that are currently impacting their suppliers.

Figure 4 shows the details of each news article captured by the LARD-SC framework. As can be seen from the figure, the framework gives an explanation of the reason why a particular news article

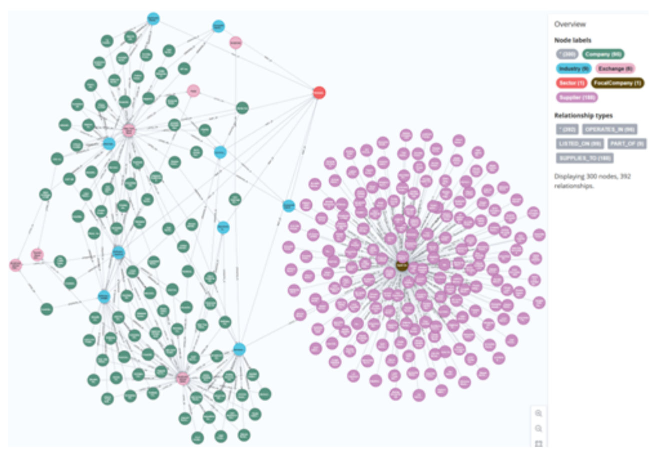

Figure 2: demonstrates Apple's industry network on the left and its supply chain network on the right

was linked to a particular supplier. It also shows the impact of the risk which this news article refers to along with the likelihood of the impact. This enables the risk manager to determine the severity of the risks impacting its supplier base that will be beneficial in making an informed decision about risk management.

Figure 5 shows the specific details of each captured news article linked to a supplier.

The risk manager can now query the LARD-SC framework's output to get specific responses related to different suppliers. For example, if the aim is to return with news, risks and CTBR labels

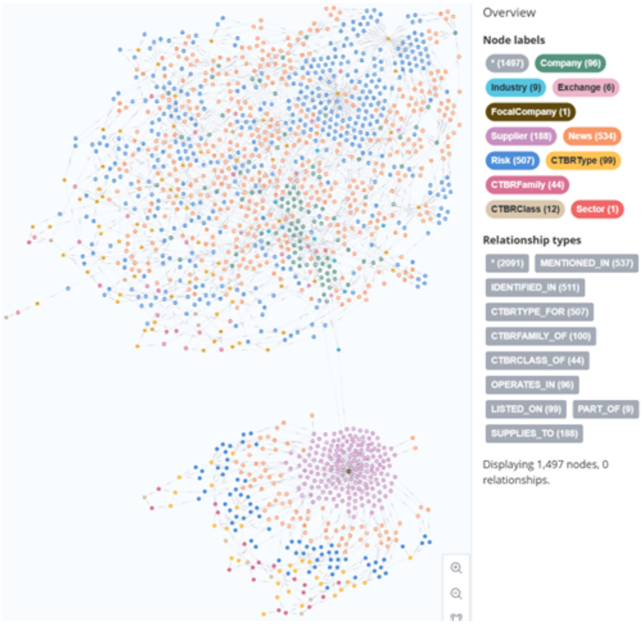

Figure 3: shows the complete view of Apple's industry network at the top and its supply chain network at the bottom

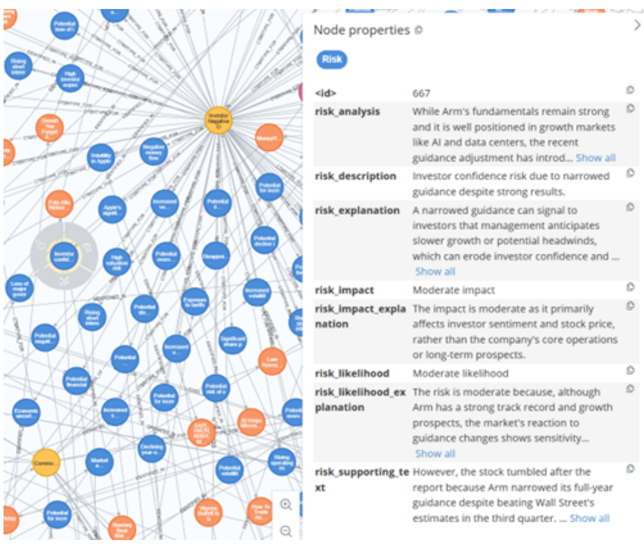

Figure 4: shows the details of the risk events impacting a supplier node

related to Cisco Systems, Inc, Figure 6 shows the output of the LARD-SC framework using the following query:

```
MATCH (a:Company {name:"Cisco Systems, Inc."})-[:
     MENTIONED_IN*1..2]-(b:News)-[:IDENTIFIED_IN*1..2]-(c:
     Risk)-[:CTBRTYPE_FOR*1..2]-(d:CTBRType)-[:CTBRFAMILY_OF
     ]-(e:CTBRFamily)-[:CTBRCLASS_OF]-(f:CTBRClass)
RETURN a, b, c, d, e, f
```

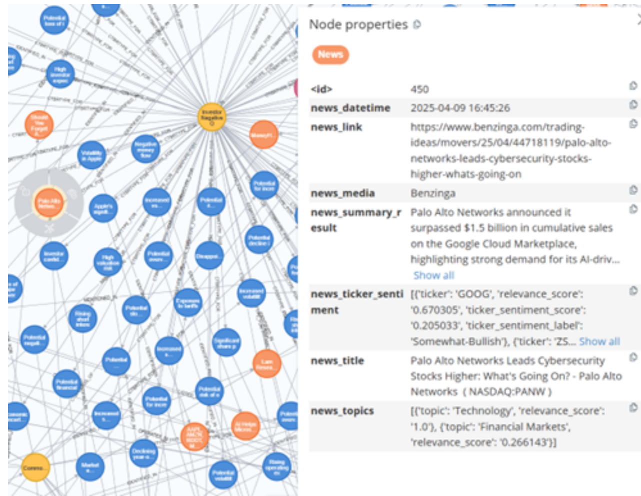

Figure 5: shows the metadata of the captured news articles

From the figure, it can be seen that there are ten risk events returned from ten shortlisted news articles that correspond to 3 classes of CTBR and 7 labels. This enables the risk manager to accurately zoom in on any specific risk events that are of concern and ascertain what possible impact they may have on the operations.

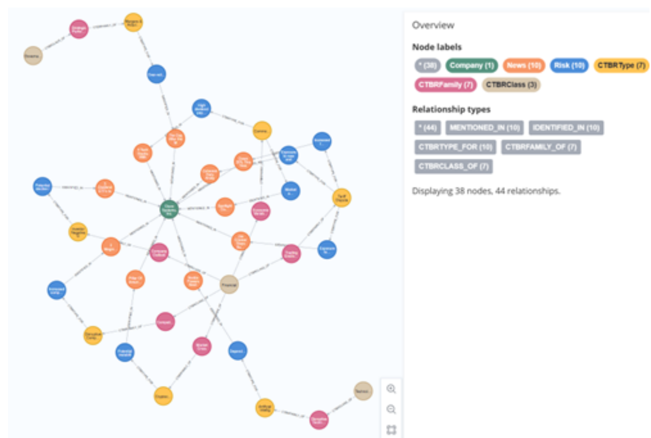

Figure 6: shows the output of the LARD-SC specific to a supplier node

For example, if risk manager wants to determine which of its suppliers are currently impacted by the risk class Tariff Dispute, then by using the below query, as shown in Figure 7 it can be seen that there are currently 24 companies This enables the risk manager to accurately zoom in on any specific risk events that are of concern and ascertain what suppliers are impacted by it. This analysis can also be used to determine the possible impact they may have on the operations.

```
MATCH (a:News) -- (b:Risk), (a:News) -- (c:Company), (b:Risk
     ) -- (d:CTBRType {risk_type: "Tariff Dispute"}), (d:
     CTBRType) -- (e:CTBRFamily), (e:CTBRFamily) -- (f:
     CTBRClass)
```

```
RETURN a, b, c, d, e, f
```

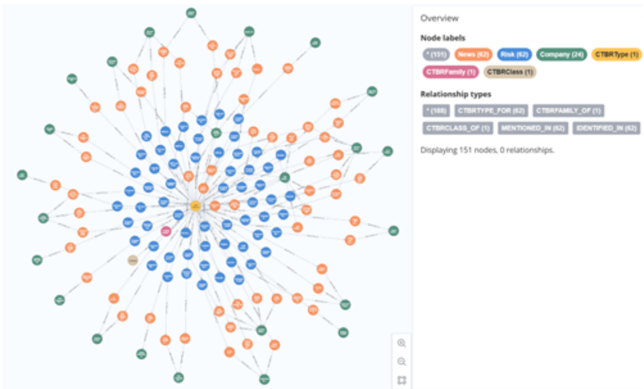

Figure 7: shows the output of the LARD-SC specific to a CTBR risk class

Figure 8 shows to the risk manager which risks events have a likelihood level of high and what CTBR risk nodes to they belong to by using the query below. The same analysis can be done for nodes that have a high impact in terms of the risk occurrence.

```
MATCH (a:Risk {risk_likelihood: "High likelihood"})--(b:
     CTBRType)--(c:CTBRFamily)--(d:CTBRClass)
RETURN a,b,c,d
```

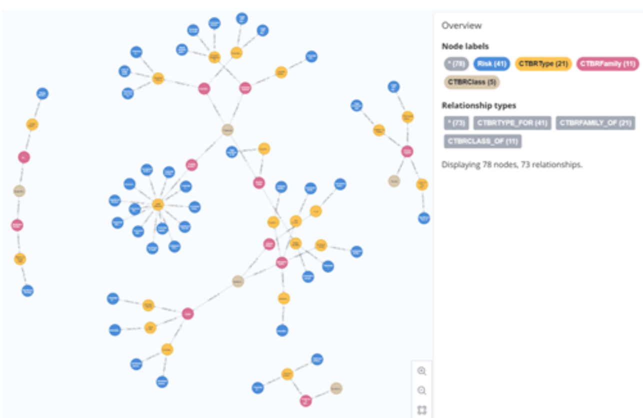

Figure 8: shows which risk events have a likelihood of high and to which supplier are they related

4 Discussion

As demonstrated in the previous section, the LARD-SC framework offers a robust and scalable architecture that seamlessly integrates structured internal datasets from a focal company's supplier base with dynamic external data sources—most notably, real-time feeds from automated Google News and Alpha Vantage alerts. This architectural synthesis creates a unified and responsive information environment, significantly reducing the long-standing issue of data silos and enabling the continuous, real-time updating of supplier-specific risk intelligence. Crucially, the LARD-SC framework also showcases the applied utility of GPT-4o, a cutting-edge large language model, in interpreting and extracting meaningful patterns from unstructured textual data. This capability is instrumental in identifying subtle, emerging, or context-specific risk indicators that would likely be overlooked by conventional rule-based systems.

The value of the LARD-SC framework extends beyond reactive risk management by equipping focal firms with strategic foresight for identifying opportunities across their broader industry networks. For example, in the case of a technology company like Apple, the framework visualises risks affecting its supplier network—many of whom, such as Cisco Systems, may also supply Apple's competitors. Insights from the framework (e.g., Figure 6) enable Apple's risk managers to assess the nature and severity of risks impacting shared suppliers and proactively develop strategies—such as diversifying sources or renegotiating terms—before competitors respond. This anticipatory approach not only reduces exposure but also creates opportunities to gain a competitive edge. More broadly, opportunity-based foresight transforms supply chain management into a strategic function. By identifying emerging risks, supplier vulnerabilities, or geopolitical shifts early, firms can act decisively and secure first-mover advantages. This supports the design of agile, resilient supply chains that adapt to disruption while capitalizing on gaps in the market. With enhanced visibility into future possibilities, firms can prioritize high-impact investments in innovation, partnerships, or digital capabilities—ultimately positioning the supply chain as a driver of long-term value, growth, and strategic resilience.

5 Conclusion

This paper has introduced an extended application of the LARD-SC framework that empowers focal firms to visualise and manage supply chain risks not only within their immediate networks but also across broader industry ecosystems. By integrating LLM-powered risk detection and classification with graph-based visualisation, the framework enables real-time, supplier-level insights that are both actionable and strategically valuable. The Apple case study illustrates how companies can proactively identify shared supplier risks and leverage this intelligence to anticipate disruptions, formu late adaptive strategies, and secure competitive advantages. This shift from reactive to opportunity-based foresight marks a critical evolution in supply chain risk management, reframing it as a strategic function that contributes to resilience, innovation, and long-term market leadership. Future work will explore the integration of predictive analytics and cross-industry intelligence to further enhance the framework's decision-support capabilities.

References

[1] Ming Zhao, Omar Hussain, Yu Zhang, and Morteza Saberi. 2024. Optimizing supply chain risk management: an integrated framework leveraging large language models. In *2024 IEEE Conference on Artificial Intelligence (CAI)*. IEEE, 1057–1062.

[2] Ming Zhao, Omar Hussain, Yu Zhang, Morteza Saberi, and Abderrahmane Leshob. 2024. Enhancing supply chain risk management with large language models: software prototyping and interactive visualization. In *2024 IEEE International Conference on e-Business Engineering (ICEBE)*. IEEE, 284–291.

[3] Cambridge Centre for Risk Studies. 2019. Cambridge Taxonomy of Business Risks. Tech. rep. Cambridge Centre for Risk Studies.

[4] Apple Inc. 2021. Apple Supplier List. Tech. rep. Supplier Responsibility Report. Apple Inc. https://www.apple.com/au/supplier-responsibility/pdf/Apple-Supplier-List.pdf.
[5] MSCI and Standard & Poor's. 2024. Global Industry Classification Standard (GICS®) Methodology. Tech. rep. MSCI Inc. and S&P Dow Jones Indices.
[6] Financial Modeling Prep. 2025. Free stock market api and financial statements api. https://site.financialmodelingprep.com/developer/docs/stable.
[7] Alpha Vantage. 2025. Alpha vantage api documentation. https://www.alphavantage.co/documentation/.
[8] OpenAI. 2024. Gpt 4o. https://openai.com/index/hello-gpt-4o/.
[9] Jianmo Ni, Gustavo Hernandez Abrego, Noah Constant, Ji Ma, Keith B Hall, Daniel Cer, and Yinfei Yang. 2021. Sentence-t5: scalable sentence encoders from pre-trained text-to-text models. *arXiv preprint arXiv:2108.08877*.
[10] Neo4j. 2024. Neo4j graph database platform. https://neo4j.com/product/neo4j-graph-database/.