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Synopsis Of

Development of Resilient Supply Chain Through Intelligent Risk Management Mechanism

A Thesis

To be submitted by

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Of

DOCTOR OF PHILOSOPHY

1 Abstract

The global pandemic COVID-19 unveils the transformation of the supply chain (SC) to be more resilient, visible, and responsive against unprecedented events like natural disasters, demand fluctuation and government policy changes. Identifying and assessing these risks are the most significant phases since they provide the decisions regarding the development of mitigation strategies. The earlier risk quantification methods make timely decision-making more complex due to their inability in providing early warning. Also, the SC managers have begun to focus on decision-making with the help of available data sources to achieve a proactive and predictive intelligent risk management mechanism. In this view, a framework is proposed that integrates data analytics, simulation, and optimization to attain a holistic risk management mechanism. To begin with, we exploit a text mining-based risk identification model that retrieves the information using Twitter streaming API from online SC-related forums like 'Supply Chain Dive', 'Supply Chain Brain', 'Supply Chain Digest'. The model comprises five modules as risk categorization, data extraction, preprocessing, string matching, and content analysis. The outcomes carry valuable insights about some contemporary SC issues due to the pandemic during the year 2021.
In addition, the subsequent risks derive from risk propagation to other nodes (i.e., ripple effect) is considered as a significant stressor of SCs. Hence, ripple effect visualization, modeling, quantification, and control have become promising avenues in risk assessment. Towards this direction, we attempt to analyze the ripple effect of an intertwined supply network (ISN) that comprises automobile, consumer electronics, and medical device SCs using the system dynamics concept. The model aims to demonstrate the varying impacts of semiconductor shortages on different SCs as an example. The visual representation of the risk propagation can help the researchers to understand the impact of the risk propagation and the significance of faster decision-making. Future research will extend to represent a digital twin for identifying potential risks through social media analytics, assessing risk propagation, and optimizing the mitigation strategies respectively.

2 Objectives

The major objectives of the research are following.

- To conduct the systematic review of the existing literature to understand the missing aspects to exploit the unexplored potential of AI in SCRM.
- To develop an intelligent risk management framework concerning deep disruptions.
- To investigate the influencing factors and their interdependencies to attain proactive risk identifiction mechanisms.
- To develop a risk identification model using data mining that extracts recent social media data related to SC to understand the contemporary risks.
- To analyze the risk propagation across various nodes of intertwined supply networks through sytem dynamics simulation.

3 Existing Gaps Which Were Bridged

Among the number of missing aspects identified through systematic literature review, the following significant gaps were bridged in the research.

Table 1: Existing gaps which were bridged

Gaps from the literature	**Research contributions**
Risk management	
• Holistic risk management approaches (Fan and Stevenson (2018); Baryannis *et al.* (2019)) • Hybrid quantitative models (Vishnu *et al.* (2019); Baryannis *et al.* (2019)) • Proactive risk management through SC digitalization (Ivanov *et al.* (2019); Toorajipour *et al.* (2021))	The objective of the proposed framework is the conception of a proactive, resilient SC design against severe disruptions. It is built on integrating data analytics, MCDM and simulation. The data analytics part of the model aims at risk identification using the unstructured data from social media. The simulation-optimization part of the system is intended for illustrating the risk propagation across the SC and followed by enhancing performance.
Risk identification	
• Lack of continuous monitoring (Su and Chen (2018);Aboutorab *et al.* (2021)) • Multi-view on different risk types (Chu *et al.* (2020); Eligüzel *et al.* (2020)) • Frequency quantification (Aboutorab *et al.* (2021); Kumar *et al.* (2021))	The presented methodology investigates the contemporary SC risks through text mining. Continuous monitoring of the neutral, negative tweets supports spotting of new threats. The FP-growth algorithm results provide the opportunity for decision-makers to prioritize the significant risks. In addition, this study includes multiple viewpoints on SC risks (supply, demand, quality, environmental, logistics, and political) to identify the threats.
Risk assessment	
• Scarcity of ripple effect visualization (Ivanov *et al.* (2019); Ghadge *et al.* (2022)) • Ripple effect assessment of ISNs (Ivanov and Dolgui (2021)) • Stress testing for faster decision-making (Ivanov *et al.* (2019)); Dolgui and Ivanov (2021))	The model provides visualizing the the risk propagation in ISNs. It supports SC experts in identifying and recognizing the weaker nodes in the SC networks. The simulation findings can help the researchers to understand the dynamic nature of the risk propagation and the significance of stress testing for faster decision-making. The visual representation of risk profile is beneficial for understanding the acceleration of the risk propagation in SC networks.

4 Most Important Contributions

4.1 Factors influencing proactive risk identification mechanism

As the primary stage of SCRM, risk identification is receiving significant attention in recent years due to the global pandemic. In the existing literature, most studies illustrated the identification of risks that may occur through historic data. However, they failed to consider the external drivers like natural disasters, COVID-19 etc., to determine the impact of the disruption. In addition, the models demonstrate the risk drivers related to specific types which leads to the process of decision-making being more complex and inaccurate (Chu *et al.* (2020)). Furthermore, the extant methodologies are lacking in considering the risk interdependencies, multi-viewpoints in risk categorization, and risk quantification to achieve continuous monitoring. Finally, the conventional risk identification approaches are not suitable for providing early warning in the present data-driven society (Aboutorab *et al.* (2021)). In this view, this study aims at determining the necessary and sufficient factors to achieve a proactive risk identification mechanism. Figure 1 portrays the combinations of solutions obtained through qualitative comparative analysis.

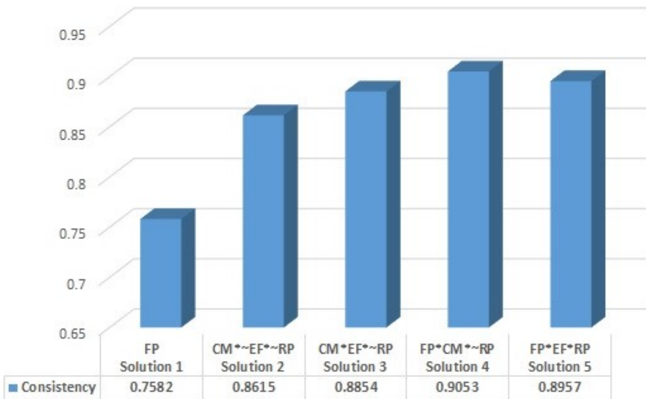

Figure 1: Interpretation of fsQCA solutions

Among the five solutions presented, solution 4 provides the maximum consistency which represents the better configuration. The higher value of overall consistency (0.8862) confirms the necessity of the given combinations to attain a proactive risk identification mechanism. As expected, continuous monitoring plays a crucial role in the successful implementation of the risk identification process.

4.2 Supply chain risk identification through text mining

Considering the factors addressed in the previous section, a model for analyzing the social media data to understand the potential SC risk factors in real-time is proposed. The text mining-based model retrieves the information using Twitter streaming API from online SC forums. This study presents the significance of real-time risk identification using online SC platforms like ‘Supply Chain Dive’, ‘Supply Chain Brain’, ‘Supply Chain Digest’. The objectives of this investigation are i) developing a model for risk identification using text-mining, ii) implementing the model with up-to-date information to understand contemporary risks iii) exploiting the extensive social-media data to improve decision-making faster. The results highlight the significant role of data analytics in achieving accurate decision-making. The findings illustrate the notable current SC issues such as shortages of semiconductors in automotive industries, port congestion, the lead time increase, and production shutdown (refer to Figure 2). It has been observed that the impact of the semiconductor shortages disrupts different global SCs, and it could extend until at least 2023 (Ivanov *et al.* (2019)). This risk forces automobile industries like Ford to shut down production at multiple plants. Similarly, port congestion is also a frequently occurring risk that may lead to delivery delay, backlogged orders, and lead time increase. Also, the sentiment distribution (Figure 3) bigram analysis (Figure 4) of the extracted tweets could be a risk signal. Continuous monitoring of the neutral, negative tweets supports spotting of new threats and understanding the scale of risk propagation. Further assessment can lead to developing proactive strategies against the mentioned risks for avoiding long-term impact.

Month	Issue	Future trend
February	Shortages of semiconductors in automotive industries	Up ∆
March	Port congestion due to Suez canal blockage	Stable
April	Production shutdown due to lockdown	Stable
June	Port congestion across Yantian (China)	Stable
July	Lead time at high and accelerating	Up ∆
October	Port delays across U.S	Up ∆
November	Resin shortages	Up ∆

Figure 2: SC issues in 2021

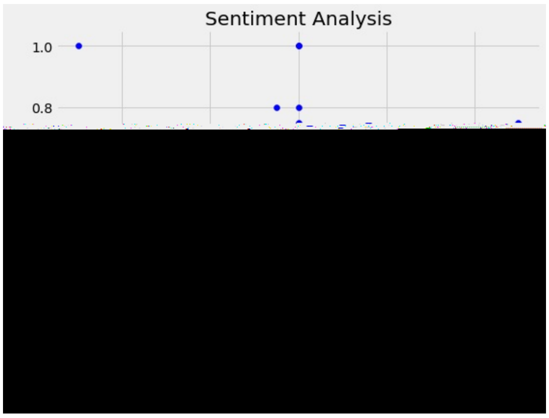

Figure 3: Sentiment analysis

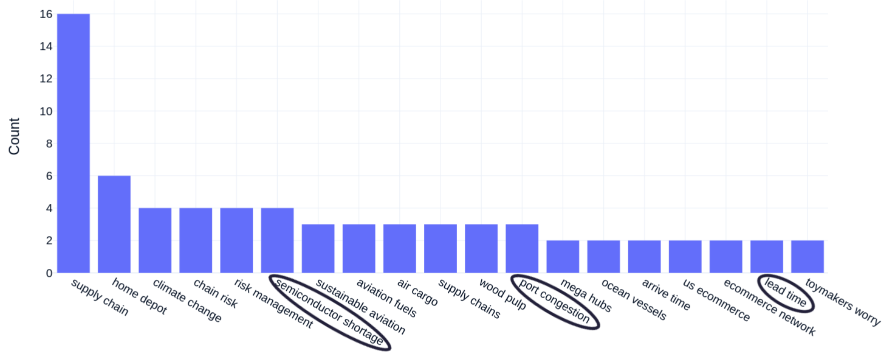

Figure 4: Bigram analysis

The findings fill some notable gaps. Our study provides contemporary findings using recent information (i.e., Twitter). Though studies in the literature applied Twitter data (Su and Chen (2018) for supplier selection; Eligüzel *et al.* (2020) for disaster management), they focus only on a particular risk factor. By contrast, this study includes multiple viewpoints on SC risks to identify the threats. Moreover, there is no previous research that incorporates association rule mining (ARM) techniques in SCRM. This study enabled frequency quantification to identify the most important risk factor for assessment.

4.3 Prioritizing the contemporary risks

This investigation involves integrating data mining and MCDM techniques to eliminate the experts' survey for ranking the risks. Due to the gradual maturation of data analysis and information growth within organizations, the integration of machine learning/data mining in industries is gaining attention recently. On the other hand, MCDM is concerned with handling classification, ranking, and sorting based on multiple attributes. Therefore, integrating data mining with MCDM techniques to develop hybrid decision-making frameworks can exploit the benefits of both domains (Deepu and Ravi (2021)). In this study, Neutrosophic-AHP is applied for calculating the weights, while Neutrosophic-TOPSIS is applied for ranking the most significant risk factors related to SC. Based on the results obtained by FP-growth algorithm, the decision matrix was determined. Further, the Euclidean distances are determined through constructing weighted decision matrix to rank the critical issues. The results of SC ranks and degree of closeness are presented in Table 2. The results indicate the top three significant risk factors in the year 2021 as Shortages of semiconductors (R1), Port congestion (R2), and Lead time acceleration (R4).

Table 2: Ranking of identified SC risks

SC risks	$\mathbf{d}^{+}{}_i$	$\mathbf{d}^{-}{}_i$	$\mathbf{d}^{+}{}_i + \mathbf{d}^{-}{}_i$	$\mathbf{c}_i$	**Rank**
Semiconductor shortages	0.006	0.106	0.112	0.946	1
Port congestion	0.011	0.087	0.098	0.887	2
Production shutdown	0.098	0.029	0.127	0.228	5
Lead time acceleration	0.043	0.074	0.117	0.632	3
Resin shortages	0.051	0.040	0.091	0.439	4

4.4 Ripple effect assessment of intertwined supply networks through system dynamics

The subsequent risks derived from risk propagation are considered significant stressors. Therefore, it is essential to understand the dynamic nature of risks cascading across the SC nodes. As we understood from the previous results, the sudden interruption of semiconductor supply disrupts different global SCs. This disruption highlights the salience of combining SC networks to provide the service to society. Towards this direction, we attempt to analyze the ripple effect of an intertwined supply network that comprises automobile, consumer electronics, and medical device SCs using the system dynamics concept. The model aims to demonstrate the varying impacts of semiconductor shortages on different SCs. The results highlight the significant impact on automobile firms due to the demand surge in consumer electronics. In addition, the capacity disruptions in semiconductor SC leads to production and distribution disruptions in the interconnected SCs. The visual representation of the risk propagation can help the researchers to understand the acceleration of the risk propagation and the significance of stress testing for faster decision-making. The model captured the variations in considered variables as vulnerabilities that disrupt the entire system. For instance, the deviations between the expected distribution and the actual received quantity highlight a risk inducing production or distribution risk in the system. Similarly, the risks related to other entities in the ISN can be derived using the interrelationships.

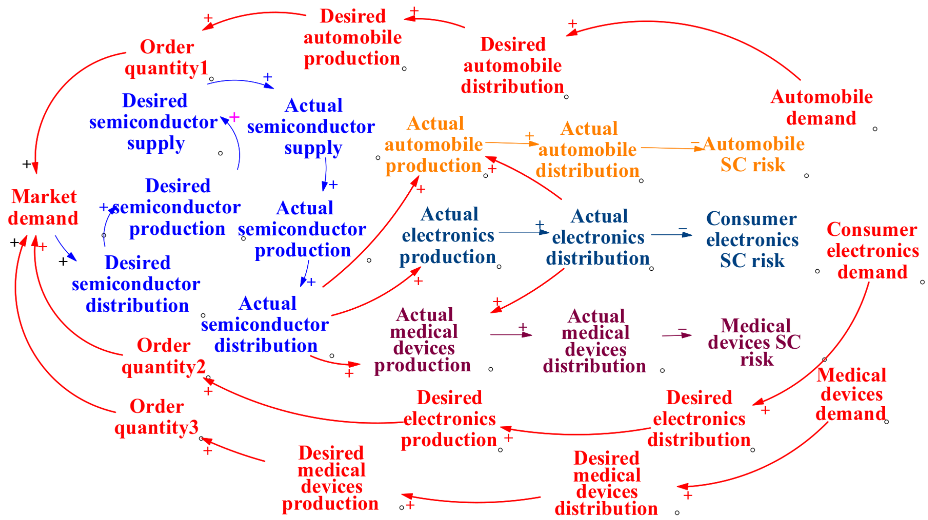

Figure 5: Causal loop diagram

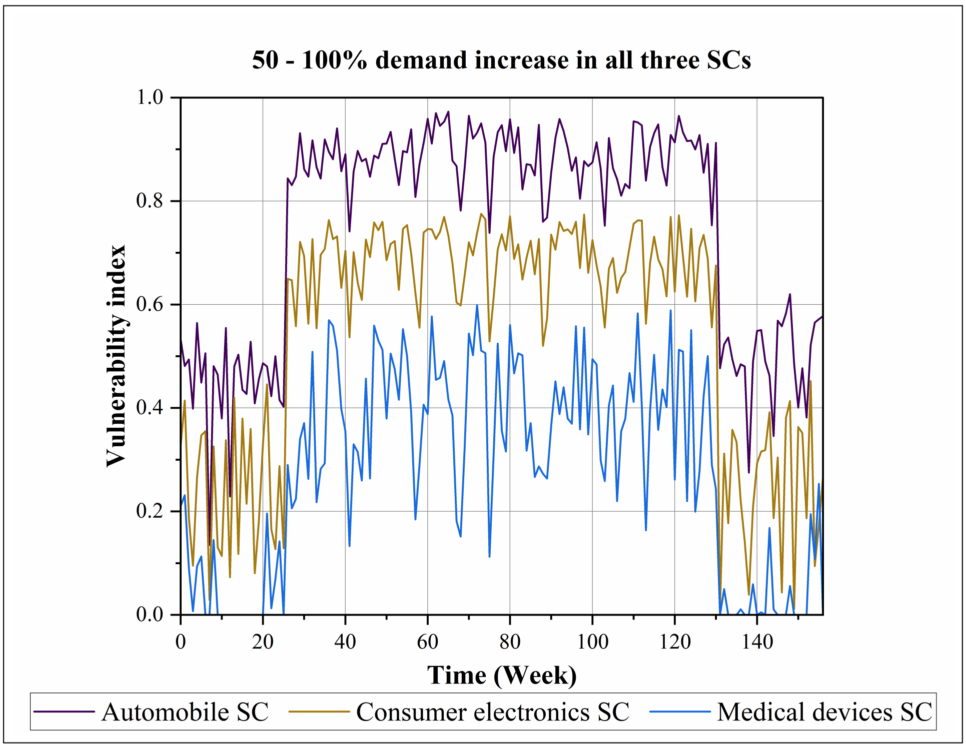

Figure 6: Impact of sudden demand increase in SCs

Figure 5 illustrates the causal loop diagram of the model with the primary variables and parameters. Three different SCs related to semiconductor applications were tried to capture the propagation of intertwined risks. As one of the important outcomes, Figure 6 helps to understand the automotive and electronics industries have been adversely affected due to the unprecedented shortages of semiconductor devices. The unexpected market demand increase in automobile industries after the pandemic shock leads to the SC being more vulnerable. Further, the ripple effect triggers lead time increase, delivery delays, and production shut down in the respective industries. Therefore, multiple disruptions create larger propagation across ISN compared to individual disruption. The industries should keep up with the demand variation to maximize the expected service level and SC continuity. As the demand grows, capacity expansion, the size, and timing of the expansions are crucial (Suryani *et al.* (2010)). Hence, the global pandemic and chip shortages confirm that SC stress testing and deriving proactive strategies become captivating factors among researchers to navigating the changes and staying resilient.

4.5 Continuous risk monitoring

A resilient SC designed using potential data analytics allows monitoring the internal as well as external risk factors. This can be executed at the beginning as a pre-warning approach and after the risk mitigation as continuous monitoring to observe the progression of the critical risks. Through exploiting the risk identification model, we retrieved the tweets using Twitter streaming API from 14 different online SC platforms [1]. The tweets from January 2021 to December 2022 have been imported as input sources. To understand the path of risk factors, a month-wise analysis was conducted.

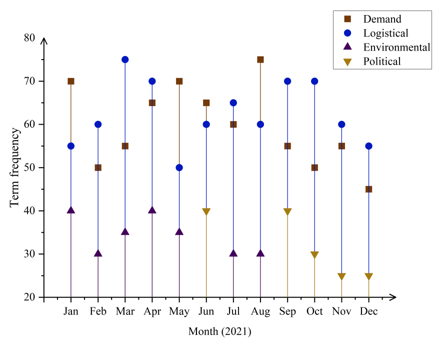

Figure 7: Top three risk categories in 2021

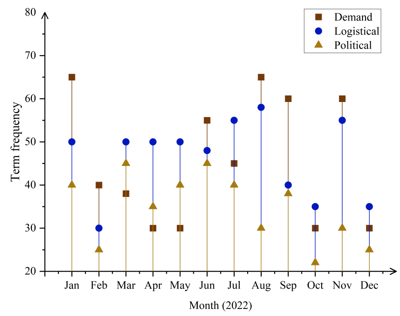

Figure 8: Top three risk categories in 2022

As an outcome of string-matching results, the total number of strings related to SC risks can be categorized. This section highlights the major types of risks observed in various months during 2021 and 2022. Figure 7 and 8 shows the top three risk categories in the years 2021 and 2022 respectively. Recent reports from online SC platforms are highlighting that the issues such as cyber-attacks, labor shortages, increase in transportation costs, Chinese manufacturer disruptions and inventory visibility will be critical in the year 2023.

[1]*Supply chain dive, Supply chain digest, Supply chain brain, Supply chain matters, Supply chain management review, Supply chain quarterly, Supply management, Supply wisdom, Logistics management, Risk management, Risk ledger, Logistics management, Institute of risk management, SAP digital supply chain*

5 Conclusions

This investigation comprises the following significant phases.

- To begin with, the important factors that influence proactive risk management and their causal relationships highlighted the significance of continuous monitoring in SCRM.
- As a continuation, identifying the contemporary SC risks induced by COVID-19. The proposed framework exploits the potential of text mining to identify the risk factors through Twitter data.
- In addition, proposing an ISN using SD concept to assess the risk propagation of semiconductor shortages across the supply chain network. This simulation model enabled quantification and visualization of the ripple effect in terms of vulnerability index.
- Furthermore, the results of risk monitoring indicate the significance of continuous monitoring to spot new emerging threats for achieving better preparedness in managing the impact.
- The investigation can be extended to SC stress testing, developing recovery policies. In addition, optimizing the strategies to enhance the service level can provide digital twin-based intelligent risk management framework.

6 Organization of the Thesis

The proposed outline of the thesis is as follows:

(a) Chapter 1: Introduction

(b) Chapter 2: Literature review

(c) Chapter 3: An integrative framework for intelligent risk management

(d) Chapter 4: Qualitative comparative analysis to identify influencing factors of proactive risk identification

(e) Chapter 5: Supply chain risk identification - A real-time data mining approach

(f) Chapter 6: Ranking of contemporary supply chain risks

(g) Chapter 7: Ripple effect assessment on intertwined supply networks

(h) Chapter 8: Conclusion and Future scope

7 List of Publications

Journals

(a) Deiva Ganesh A., and Kalpana P. (2022), "Supply chain risk identification: a real-time data-mining approach", *Industrial Management and Data systems*, Vol. 122, No. 5, pp. 1333-1354. Doi:10.1108/IMDS-11-2021-0719.

(b) Deiva Ganesh A., and Kalpana P. (2022), “Future of artificial intelligence and its influence on supply chain risk management–A systematic review”, *Computers and Industrial Engineering*, Vol. 169, p.108206. Doi:10.1016/j.cie.2022.108206.

(c) Deiva Ganesh A., and Kalpana P. “An integrated ARM – Neutrosophic AHP – TOPSIS approach for ranking contemporary supply chain risks”, *International Journal of Information Technology and Decision Making*.(Revision submitted).

(d) Deiva Ganesh, A., and Kalpana, P. “Factors influencing proactive risk identification”, *International Journal of Disaster Risk Reduction*.(Revision submitted).

Conferences

(a) Deiva Ganesh A., and Kalpana P. (2020), "Supply Chain Risk Management: Impact of AI and challenges in managing the disruptions during the current pandemic COVID - 19", *SOM Doctoral Colloquium organized by XLRI*, Jamshedpur.

(b) Deiva Ganesh A., and Kalpana P. (2022), “Stress testing and assessment on ripple effect due to contemporary supply chain risks: A system dynamics approach”, *International Conference on Advanced Research in Supply Chain Management*, Stockholm, Sweden.

Book chapters

(a) Deiva Ganesh A., and Kalpana P. (2022) “Digital twins – a state of the art from Industry 4.0 perspective”, Intelligent Analytics for Industry 4.0 Applications, IA14A-CRC Press, Taylor and Francis.

(b) Rajkumar K., Kalpana P., and Deiva Ganesh A. (2022) “Sustainability in manufacturing”, Progress in sustainable manufacturing, Springer.

References

1. **Aboutorab, H.**, **O. K. Hussain**, **M. Saberi**, **F. K. Hussain**, and **E. Chang** (2021). A survey on the suitability of risk identification techniques in the current networked environment. *Journal of Network and Computer Applications*, **178**, 102984.

2. **Baryannis, G.**, **S. Validi**, **S. Dani**, and **G. Antoniou** (2019). Supply chain risk management and artificial intelligence: state of the art and future research directions. *International Journal of Production Research*, **57**(7), 2179–2202.

3. **Chu, C.-Y.**, **K. Park**, and **G. E. Kremer** (2020). A global supply chain risk management framework: An application of text-mining to identify region-specific supply chain risks. *Advanced Engineering Informatics*, **45**, 101053.

4. **Deepu, T.** and **V. Ravi** (2021). Supply chain digitalization: An integrated mcdm approach for inter-organizational information systems selection in an electronic supply chain. *International Journal of Information Management Data Insights*, **1**(2), 100038.

5. **Dolgui, A.** and **D. Ivanov** (2021). Ripple effect and supply chain disruption management: new trends and research directions. *International Journal of Production Research*, **59**(1), 102–109.

6. **Eligüzel, N.**, **C. Çetinkaya**, and **T. Dereli** (2020). Comparison of different machine learning techniques on location extraction by utilizing geo-tagged tweets: A case study. *Advanced Engineering Informatics*, **46**, 101151.

7. **Fan, Y.** and **M. Stevenson** (2018). A review of supply chain risk management: definition, theory, and research agenda. *International journal of physical distribution & logistics management*.

8. **Ghadge, A.**, **M. Er**, **D. Ivanov**, and **A. Chaudhuri** (2022). Visualisation of ripple effect in supply chains under long-term, simultaneous disruptions: a system dynamics approach. *International Journal of Production Research*, **60**(20), 6173–6186.

9. **Ivanov, D.** and **A. Dolgui** (2021). Or-methods for coping with the ripple effect in supply chains during covid-19 pandemic: Managerial insights and research implications. *International Journal of Production Economics*, **232**, 107921.

10. **Ivanov, D.**, **A. Dolgui**, **A. Das**, and **B. Sokolov** (2019). Digital supply chain twins: Managing the ripple effect, resilience, and disruption risks by data-driven optimization, simulation, and visibility. *Handbook of ripple effects in the supply chain*, 309–332.

11. **Kumar, S.**, **A. K. Kar**, and **P. V. Ilavarasan** (2021). Applications of text mining in services management: A systematic literature review. *International Journal of Information Management Data Insights*, **1**(1), 100008.

12. **Su, C.-J.** and **Y.-A. Chen** (2018). Risk assessment for global supplier selection using text mining. *Computers & Electrical Engineering*, **68**, 140–155.

13. **Suryani, E.**, **S.-Y. Chou**, **R. Hartono**, and **C.-H. Chen** (2010). Demand scenario analysis and planned capacity expansion: A system dynamics framework. *Simulation modelling practice and theory*, **18**(6), 732–751.

14. **Toorajipour, R.**, **V. Sohrabpour**, **A. Nazarpour**, **P. Oghazi**, and **M. Fischl** (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, **122**, 502–517.

15. **Vishnu, C.**, **R. Sridharan**, and **P. R. Kumar** (2019). Supply chain risk management: models and methods. *International Journal of Management and Decision Making*, **18**(1), 31–75.