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A DATA-DRIVEN INTELLIGENT SUPPLY CHAIN DISRUPTION RESPONSE RECOMMENDER SYSTEM FRAMEWORK

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ABSTRACT

In light of the Industry 4.0 era, the global pandemic, and wars, interest in deploying digital technologies to increase supply chain resilience (SCRes) is rising. The utilization of recommender systems as a supply chain (SC) resilience measure is neglected, although these systems can enhance SC resilience. To address this problem, this research proposed a data-driven supply chain disruption response framework based on intelligent recommender system techniques and implemented the framework with a practical use case. The framework was validated by a System Dynamics (SD) model to demonstrate the effectiveness of the proposed system as a new communication scheme after a SC disruption, considering a demonstrative use case. Results show that the proposed framework can be implemented as an effective SC disruption mitigation measure in the SCRes response phase and help SC participants better react after the SC disruption.

1 INTRODUCTION

Supply chains (SC) are becoming more sophisticated and complex with globalization, result in more risks and uncertainty (Manners Bell 2017). Modern supply chains were designed in an era of lean management and globalization, and they now face the challenge of adapting to revolutionary trends such as the technological revolution (i.e., Industry 4.0), global pandemics (i.e., COVID-19), and wars. In light of the COVID-19 pandemic, researchers and practitioners have become increasingly interested in deploying digital technologies to increase supply chain resilience (Ivanov 2021).

SCRes means that an SC can recover from unexpected disruptions and regain or even improve its original performance. Companies might even achieve competitive advantages when they rebound more successfully than their rivals (Spieske and Birkel 2021). SCRes is a multidimensional and hierarchical structure with three primary dimensions: supply chain design quality, reactive and proactive capabilities (Chowdhury and Quaddus 2017). To comprehensively approach the resilience goal, SC systems must be designed to withstand disruptions (low vulnerability), respond (Chowdhury and Quaddus 2017), and recover from disruptions quickly and at a minimal cost (high recoverability) (Hosseini et al. 2019).

SCRes can be achieved by either creating redundancy or increasing flexibility (Sheffi and Rice Jr 2005) proactively or reactively (Cheng and Lu 2017) via internal or external collaboration (Ali et al. 2021) through (1) readiness, (2) response, (3) recovery, and (4) redesign stages (Hohenstein et al. 2015; Blackhurst et al. 2005). Hohenstein et al. (2015) classified SCRes based on ex-ante and post-ante disruptions. Specifically, an ex-ante strategy is a proactive approach consisting of redundancy and flexibility elements to create readiness, usually including capacity and inventory buffer, backup suppliers, and transportation channels (Ivanov et al. 2017). In contrast, a post-ante strategy is a reactive strategy employed in response to a disturbance. It involves the elements of agility, flexibility, and redundancy to recover and grow, such as multi-sourcing, product/process transformation, capacity expansion and regionalization (Ivanov et al. 2017; Hu and Ghadimi 2023).

SCRes is based on a two-dimensional structure: proactive aspect (including proactive network design) and reactive aspect (including network redesign) (Chowdhury and Quaddus 2017). Preparing ahead or taking proactive actions is the ground way of building a resilient supply chain in the first stage. However, the unknown unknowns, black swan events such as pandemics, extreme natural disasters, terrorist attacks or wars, lie outside the realm of regular expectations (Aven 2015). These events had severe, completely unforeseen impacts (Spieske and Birkel 2021). While the possibility of a disrupted event was not unknown, management protocols fell short of preparing for this 'tail-risk' scenario (O'Brien and MacAskill 2022). For instance, the rapidity of the COVID-19 disruption renders inappropriate proactive SCRes strategies such as readiness (Ali et al. 2021). In this case, proposing resilience strategies from the reactive aspect is essential, as ineffective or late deployment of (response) recovery actions resulted in long shortage periods (Hosseini and Ivanov 2022).

As the supply chain performance drops rapidly after disruption in a concise time frame indicated in Figure 1 (Sheffi and Rice Jr 2005), ineffective or late deployment of (response) recovery actions will result in long shortage periods (Hosseini and Ivanov 2022), which means minimum response time is essential for mitigating SC disruption. Therefore, shortening the time consumed in the response phrase (Hohenstein et al. 2015) can be one of the feasible SCRes strategies. However, studies on SC disruption risk mitigation from a 'reactive' aspect are limited (Ivanov et al. 2017; Hu and Ghadimi 2023). Of the three reactive phases, attempts to construct an agile supply chain to respond to the unexpected SC disruption are insufficient. This is the first research gap this study will bridge.

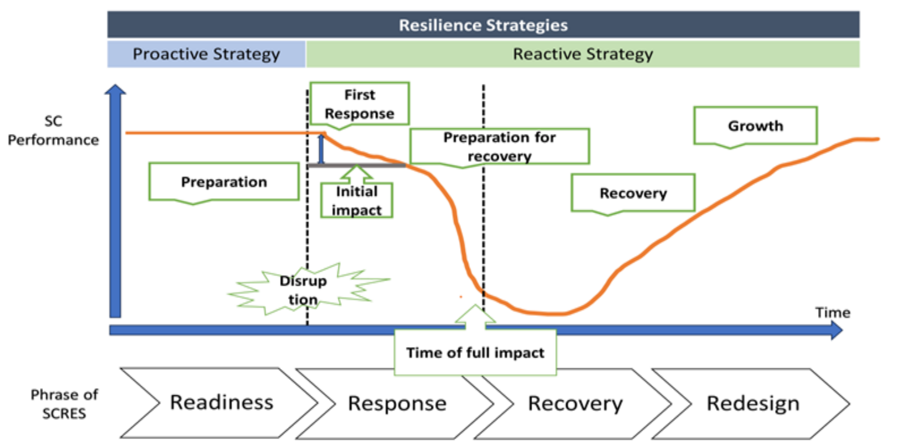

Figure 1: SC performance in different stages.

In the response phase Figure 1, companies will first access their internal resources to supplement the shortage, such as using inventory and capacity buffers (Ivanov et al. 2017). Hence, the SC performance drops relatively slowly after the initial response (Sheffi and Rice Jr 2005). When the internal resources run out, the SC performance drops quickly after the company's initial reaction because recovery preparation work, such as expanding capacity or adjusting processes (Ivanov et al. 2017), takes a relatively long time. The time interval between the first initial internal reaction stage and recovery stage makes the performance curve drop dramatically, as the internal buffer resource has run out and new supplementary owned by the same company are not yet to come. In this case, a fast searching, recommending, and visualizing tool to identify and illustrate external resources within the whole SC network is an ideal solution to tackle this problem. This research proposes that a real-time recommendation system can be utilized as the response system.

A recommender system (RS) is a tool that selects the most suitable items or services (Chiu et al. 2021) for an active user, considering existing information about the users and the items to predict each associated item/service utility (Dadouchi and Agard 2021) by filtering helpful information from a vast database pool

(Yassine et al. 2021). RS directly assists users in making decisions and satisfying their current information needs with accuracy, context, novelty, real-time, and diversity dynamics consideration (Rana and Jain 2015).

Resilience can be achieved by creating redundancy or increasing flexibility (Sheffi and Rice Jr 2005). An agile supply chain information system will achieve high supply chain flexibility (Gupta et al. 2019). The primary mechanism of leveraging a recommender system to enhance SCRes is that these systems can quickly overcome the challenges related to the incredible growth of information (Dadouchi and Agard 2021). Therefore, it can assist SC actors in making appropriate decisions to use the current network state without additional resources (Dadouchi and Agard 2021) in a concise time frame. The characteristics of fast detection and the use of available resources in the network can adequately help disrupted supply chain participants narrow the time gap between the response and recovery phases, achieving resilience in the first stage.

Not limited to only exploiting the information or knowledge naively, an intelligent recommender system (IRS) that employs artificial intelligence (AI) techniques (Borràs et al. 2014) has intelligent behavior with a set of capabilities such as information (knowledge) representation (clustering), learning, optimization and reasoning mechanisms (Borràs et al. 2014; Aguilar et al. 2017). The combination of these capabilities can exploit information (knowledge), update, and infer them (Aguilar et al. 2017). IRS can be applied in supply chain management (Pereira et al. 2022) to improve dealing speed (Sinha and Dhanalakshmi 2019) and capture dynamics (You et al. 2019). However, the application of recommender systems in the supply chain management domain is still in its infancy. Research on leveraging the IRS as a resilience tool for SC disruption risk mitigation is scant. This is the second research gap this study will address.

To our knowledge, there is a limited framework based on IRS techniques to respond to the SC disruption. The contribution of this research is twofold. This study not only enriches the knowledge of the SCRes research domain from the reactive aspect but also presents a new application domain for the IRS. The proposed framework based on RS techniques aimed to respond quickly to the SC disruption can optimize several objectives (Pachot et al. 2021) with careful consideration for remaining resources inside the available supply network, such as available capacity and inventory space, truck-load utilization (Dadouchi and Agard 2021), best transit routes (Wang et al. 2014) and human resources (Hargaden and Ryan 2015).

The remainder of this paper is organized as follows: A literature review was conducted in Section 2. It follows Section 3, which describes the proposed framework and recommender system, the steps for system implementation are explained and a practical use case is applied to illustrate the function of the proposed IRS. Section 4 validated the IRS framework as a new information-sharing scheme with a System Dynamics (SD) simulation. Finally, some remarks are concluded in Section 5.

2 LITERATURE REVIEW

Literature was studied based on three categorizations. (1) Aspects of proposed SCRes strategies, (2) Applied techniques, and (3) Phase of SCRes.

This body of literature summarizes that current research mainly focuses on developing SCRes strategies from the perspective of proactive factors. Mathematical models (Chen and Chen 2023; Caputo et al. 2023), simulation (Silva et al. 2023; Sani Mohammed et al. 2023) including digital twin (Ivanov 2023), and fuzzy logic (Belhadi et al. 2022) are widely used for SCRes assessment (Caputo et al. 2023; Sani Mohammed et al. 2023; Belhadi et al. 2022), resilient supplier selection (Mohammed et al. 2021; Cavalcante et al. 2019), resilient SC network design (Chen and Chen, 2023; Silva et al. 2023) and disruption impact evaluation (Tsiamas and Rahimifard 2021; Hosseini and Ivanov 2022). AI-based methods such as deep learning (Cuong et al. 2023) and artificial neural networks (Lorenc and Kuźnar 2021; Long et al. 2023) are applied to predict disruption. Table 1 illustrates the comparison between these studies.

Table 1: Comparison between research articles.

Reference	Action Aspect	Techniques	Phase of SCRes
(Belhadi et al. 2022)	Proactive	Fuzzy Wavelet Neural Network (FWNN)	Readiness
(Caputo et al. 2023)	Proactive	Mathematical Model	Readiness
(Cavalcante et al. 2019)	Proactive	Machine learning +Simulation	Readiness
(Chen and Chen 2023)	Proactive	Mathematical Model	Readiness
(Cuong et al. 2023)	Proactive	Deep Learning	Readiness
(Hosseini and Ivanov 2022)	Proactive	Mathematical Model+ Simulation	Readiness
(Hosseini et al. 2019)	Proactive+ Reactive	Mathematical Model	Readiness+ Response
(Ivanov 2023)	Proactive+ Reactive	Digital Twin, AI in general	Readiness+ Response
(Long et al. 2023)	Proactive	Echo state network Model (ESN), Artificial Neural Network	Readiness
(Lorenc and Kuźnar 2021)	Proactive	Artificial neural networks	Readiness
(Mohammed et al. 2021)	Proactive	Mathematical Model	Readiness
(Sani Mohammed et al. 2023)	Proactive	Simulation	Readiness
(Silva et al. 2023)	Proactive	Simulation	Readiness
(Singh et al. 2019)	Reactive	Multi	Recovery
(Tsiamas and Rahimifard 2021)	Proactive	Simulation	Readiness
Present study	Proactive+ Reactive	Intelligent Recommendation Systems+Simulation	Readiness+ Response

From the action aspect perspective, research focusing on developing resilience measures from the reactive aspect is limited. In the reactive SCRes frame, attempts to build SCRes at the response stage are insufficient. It can also be noted that leveraging a recommender system technique as an SC resilience tool, particularly for agile response, is neglected. Recommender systems can support resource-intensive processes such as supply chain management as they can increase item/service explorations and reduce the search costs for identifying relevant opportunities (van Capelleveen et al. 2021). Research interests in IRS from the supply chain management community have been raised recently. However, applying (intelligent) recommender in supply chain management is still in its infancy.

An intelligent recommender system (IRS) that employs artificial intelligence (AI) techniques has intelligent behavior with a set of capabilities such as information (knowledge) representation (clustering), learning, optimization, and reasoning mechanisms (Borràs et al. 2014; Aguilar et al. 2017). The combination of these capabilities can exploit extensive information (knowledge), update it, and infer it (Aguilar et al. 2017).

Current RSs poorly cover supply chain management, and research on the overlap between supply chain management and (intelligent) recommender systems is still limited (Dadouchi and Agard 2021). Although the agility capability of (I)RS makes it possible to become an effective SC disruption risk mitigation tool, research exploring the potential of (I)RS as a resilience measure of SC disruption risk mitigation remains unfulfilled. Moreover, previous research usually addressed the SCRes problem from a static perspective, but studies on generating real-time resilience strategies, where the response time is vital, are rare.

3 THE PROPOSED DATA-DRIVEN SC DISRUPTION RESPONSE INTELLIGENT RECOMMENDER SYSTEM FRAMEWORK AND IMPLEMENTATION

3.1 Framework Overview and Description

This section presents the details of the proposed IRS, which aims to increase SCRes at the response phase to mitigate supply chain disruption risk. Figure 2 illustrates the mechanism of the developed IRS as an SCRes tool for fast response after SC disruption. According to this process, Figure 3 explains the inner workflow of the proposed IRS. The related literature suggests that proper communication and structured information exchange are important components in establishing a long-term SC partnership and maintaining such a relationship (Ghadimi et al. 2018; Ghadimi et al. 2019; Perera et al. 2022). Information-sharing, collaborative communication, mutually created knowledge and joint relationship efforts increase SCRes via increased visibility, velocity and flexibility (Scholten and Schilder 2015). Toward this end, the proposed IRS will be more effective in a more cooperative SC partnership, where collaboration between different supply chain participants is solid and practical, especially in data exchange and information-sharing activities.

The steps of the developed IRS are described in the following:

Step 1. Identify and recommend available internal resources (redundancy) as the initial SC disruption mitigation reaction.

Step 2. Identify and recommend available external resources (redundancy) as the SC disruption mitigation reaction before the recovery stage.

The recommendation sequence is from step 1 to step 2. First, the IRS will recommend internal resources to the disrupted entity as an initial response to SC disruption. When the internal resources run out, the IRS will turn to available external resources to help mitigate SC disruption risk.

Step 1 represents the system's internal resources recommendation function in the initial response phase. In the initial response period, information on available internal resources, such as inventory/capacity buffer or human resources, will be searched to mitigate SC disruption risk, filtered in the company's internal database to identify the available internal resources and straightforwardly recommended to the disrupted entity.

After the initial response, with internal resources running out, the disrupted organization tends to acquire available resources within the supply network. This is a more efficient way to deal with the current shortage, as preparing new supplements will take a long time.

Step 2 illustrates the proposed system's external resources recommendation function in the response phase after the initial internal response action. In this period, information on available external resources such as inventory/capacity buffer or human resources will be searched and filtered in the central database shared by the disrupted entity and the external suppliers to identify the available external resources in the same network.

Unlike the internal straightforward recommendation, the external recommendation will consider constraints such as lead time, emergency cost, transportation channel, or other constraints/criteria before generating the final recommendation results to make the recommendation meet the practical operation environment and the actual user needs, as the priority of user to select external resource will vary based on different disruption scenario and the exact user needs. Sometimes, the user will consider lead time the most critical factor in mitigating a sudden disruption; in other scenarios, the user may consider the emergency cost as the most crucial criterion before getting recommendation results, as the shortage situation is not entirely urgent. This IRS will keep searching and filtering until all the requirements are met. After careful consideration, the recommendation results will finally be generated.

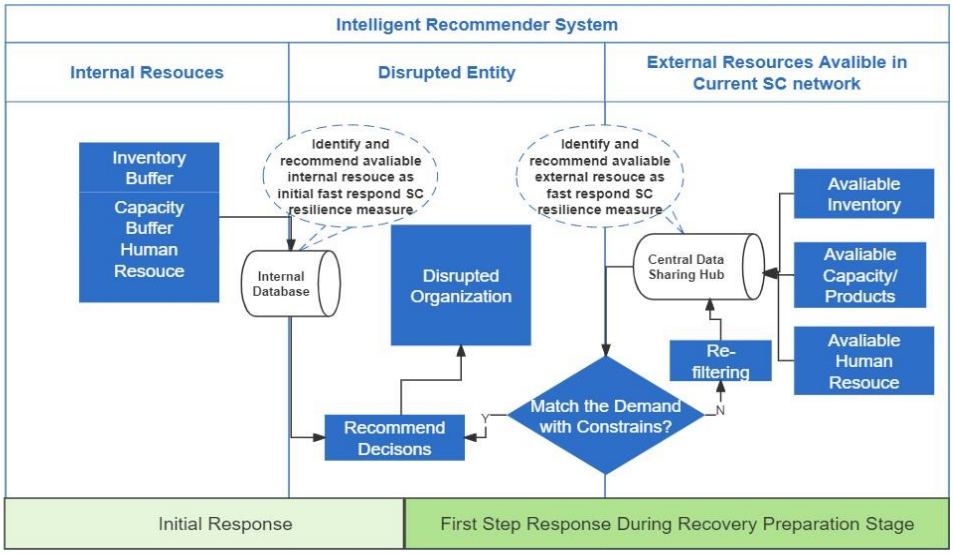

Figure 2: The proposed IRS mechanism.

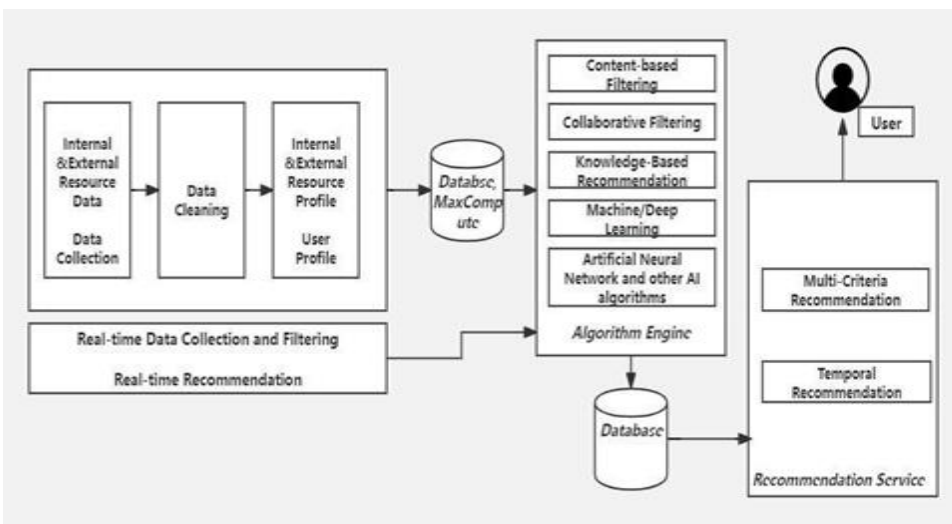

Figure 3: Inner workflow of the IRS.

The most distinctive part of this IRS is considering practical constraints in the current network, as this will help SC practitioners make more appropriate decisions based on internal and external reality. This feature transforms the proposed IRS into technologically sophisticated, grounded, smart, and contextually relevant SCRes measures. Moreover, dynamic and real-time recommendations can be conducted internally or externally to better match the complex and dynamic supply chain.

The inner workflow of the proposed intelligent recommender system is explained in Figure 3. This IRS can be used for both static and dynamic real-time data. The inner workflow was organized into three sections: (i) data processing, (ii) recommendation algorithm selection, and (iii) recommendation service conduction. The input data will be collected, cleaned, and used to generate a basic available resource profile in the first data processing step. Once the basic resource profile is generated, it will be used to match the existing user profile, as this is the primary mechanism of recommender systems, and the second algorithm selection step will be executed to make a suitable match between user and resource profiles. Proper recommender algorithms will be selected based on the characteristics of problems and data patterns to generate results. Content-based, collaborative and knowledge-based recommendation algorithms can be found in the IRS, i.e., the content-based filtering, the collaborative filtering, and the knowledge-based recommendation. AI-based recommender algorithms such as (unsupervised) machine learning, deep learning, and artificial neural network (ANN) are also embedded in the IRS algorithm engine. The final stage of this workflow is recommendation service conduction; once the algorithm is selected, the practical constraints and the potential real-time needs will be considered, and in this case, multi-criteria and temporal recommendations will be taken as the primary recommendation service.

3.2 Framework Implementation

The proposed IRS conceptual framework can be implemented as a private intelligent information system owned by supply chain participants aiming to develop reaction agility and flexibility. Through this intelligent information hub, users, usually the disrupted companies, can find the current redundancy inside the organization as the initial reaction to SC disruption. Afterwards, available redundancy from other participants in the current supply network can also be identified. The intelligent recommender system can promote results rapidly according to users' requirements on the resource in demand, considering practical constraints such as lead time, production capacity, costs, and inspection results. This research illustrated an example of the external resource recommendation, which is crucial in approaching SCRes with the IRS.
Firstly, the data used for generating resource profiles and user profiles was input based on the open supply chain data on Kaggle at https://www.kaggle.com/datasets/harshsingh2209/supply-chain-analysis. Profiles are listed in Table 2.

Table 2: User and resource profiles.

User Profile	External Resources Profile
Product Type	Supplier name
SKU	Location
Price	Lead time
Availability	Production volumes
Number of products sold	Manufacturing lead time
Revenue generated	Manufacturing costs
Customer demographics	Inspection results
Stock levels	Defect rates
Order quantities	Transportation modes
	Routes
	Costs

The IRS can detect user demand after the SC disruption according to features such as internal availability, stock levels, and order quantities. Supervised machine learning algorithms such as Decision Trees, Random Forest, Support Vector Machine, and K-Nearest Neighbors can be used for external resources classification based on the historical performance data based on features such as supplier name, location, lead time, cost (Cavalcante et al. 2019) and inspection results in this use case to gain the initial overview of the external resources. After the initial exploration, knowledge-based recommendation techniques can also be used in these different supplier groups before the multi-criteria recommendation service, as the weights of recommendation criteria or constraints such as lead time, cost, production volume, and inspection results should be defined by internal experts of this disrupted organization beforehand.

Supervised machine learning was deployed in this use case mainly because the data is historical, well-patterned, and has a good structure. This paper does not present the steps of such deployment due to space limitations. If the input data are un-patterned, the embedded unsupervised machine learning algorithm or deep learning can be first used to detect the data pattern. The unsupervised algorithms, such as Density-Based Spatial Clustering of Applications with Noise (DBSCAN), can first help users cluster the external suppliers and give users a quick sketch of available external resources; based on the rough results, knowledge-based recommendations can be used afterwards to assist disrupted organizations in finding available external resources from chaos. Real-time recommendation is also not used for this case, mainly because the dataset is static. The recommendations for this use case are listed in Table 3 based on the procedure discussed above.

Table 3: External available resource recommendation.

Demand	Recommended Resource	Overall score
SKU32	Supplier 3	1.043993169
SKU9	Supplier 2	1.037888232
SKU76	Supplier 2	0.98991082
SKU75	Supplier 1	0.984446383
SKU56	Supplier 1	0.980386609
SKU30	Supplier 4	0.940934473
SKU10	Supplier 5	0.931832375

The overall score indicates the performance marks of external resource suppliers, released by a multi-criteria recommendation based on the priority weights at 0.35 in 'Lead time', 0.25 in 'Production volumes', 0.2 in 'Inspection results', and 0.2 in 'Costs'. This means the user selected 'Leadtime' as the most significant criterion for selecting the proper external resources. The key capability to help companies mitigate the SC disruption before they finish the recovery preparation work is quickly identifying and leveraging available redundancy from other participants in the current supply network. The proposed IRS framework can perform as a new and crucial part of the SCRes strategy development from the reactive side.

4 FRAMEWORK VALIDATION WITH SYSTEM DYNAMICS SIMULATION

When a business entity is disrupted, the general process for responding to (SC) disruption involves identifying the most suitable external resource suppliers, communicating with them, and replenishing the physical product as quickly as possible after internal resources are exhausted. This communication process consists of two main steps: 1) inquiring about available external resources and 2) placing emergency orders to deploy the physical product replenishment. Step 1 prepares for Step 2, and the placement of emergency orders is the crucial action that transitions the entire supply chain from normal operation to emergency response operation. The basic flow of information and materials following SC disruption is illustrated in Figure 4.

We assume the communication process ends with an order placement action after the inquiry action. A lower inquiry time usually leads to a higher frequency of order placement actions in a fixed time frame. For example, with conventional information sharing schemes such as phone calls or manually checking fractional data exchange systems, users (the disrupted entity) may finish 3-5 order placements in a fixed time unit (60 minutes) as the inquiry process took a relatively long time. With the IRS, the available external resources' information can be instantaneously displayed to user, the inquiry process becomes shorter which means that more than 3-5 orders can be placed in the same time unit.

Based on the illustrations above, the validation of the mechanism and effectiveness of this proposed IRS framework can be simplified to observe the effects of altering the order rate (Borshchev and Grigorey 2020). The KPI is to observe the replenishment stock level of the disrupted entity in a fixed time with different order rates, for example, 50 days, in this study. The higher replenishment stock level in a fixed period indicates less lead time to fulfil the emergency demand of a fixed order quantity under the same conditions. Therefore, the higher replenishment stock level in a fixed period indicates a faster SC disruption response speed and better SC disruption response performance, which also means stronger resilience of SC.

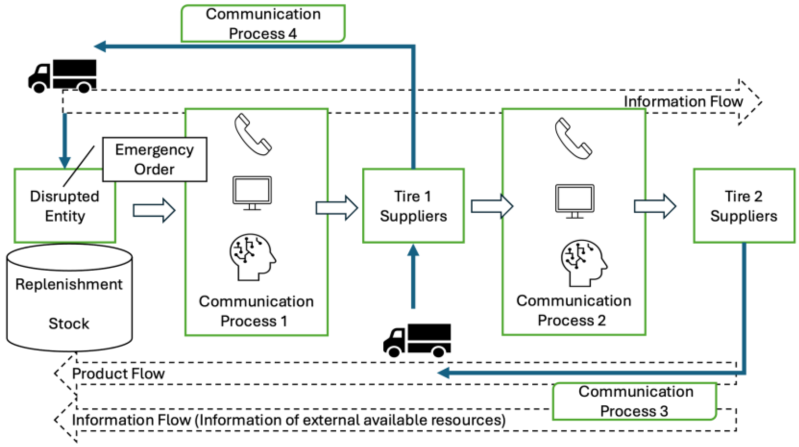

Figure 4: The information and materials flow after SC disruption.

A System Dynamics (SD) model was developed to represent a simple supply chain to validate the proposed IRS, given that the SD methodology is appropriate to detect the effectiveness of SCRes policy (Olivares-Aguila and ElMaraghy 2021), illustrated in Figure 5. The values and rules of all the parameters and variables were referred to in Borshchev and Grigoryev (2020).

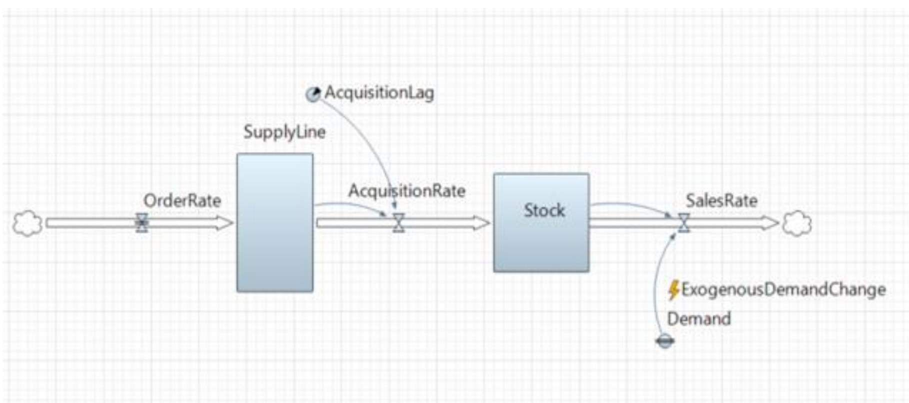

Figure 5: The system dynamics model to investigate the effects of the proposed IRS.

The ‘SupplyLine’ includes all the supply activities of external resources such as extra production of different tiers of suppliers and transportation of different third-party logistics forwarders in Figure 4. The ‘Stock’ is the replenishment stock of the user (disrupted entity). Both ‘OrderRate’ and ‘Demand’ are marked as constants, these two factors will be controlled from outside the System Dynamics model.

Demand will be changed by the ‘ExogenousDemandChange’ event is set up to occur at every time unit (day). The action rule of the ‘ExogenousDemandChange’ is set as Demand = max (0, Demand + uniform (-1, 1)); this code increases or decreases the value of the Demand variable by a random amount, uniformly distributed between -1 and 1. The max() function protects Demand from falling below zero. The ‘SalesRate’ uses the conditional operator Stock > 0? Demand: 0. While there is a product in stock, it sells at the Demand rate; Otherwise, nothing is sold. In this experiment, OrderRate is the only variable that can be controlled by the user to check the effectiveness of the proposed IRS. The experiment is about running the model with different OrderRate and investigating how the stock changes over time.

The model works in step-pause mode, allowing the user to change the order rate once every 50 days. Figure 6 shows that if the original OrderRate is set as 10, which is the order placement frequency under the conventional information sharing scheme, the replenishment stock will be 530.5 after 50 days. If the disrupted entity implemented the IRS as the new communication scheme, in this case, we set the OrderRate as 20; the replenishment stock will be 960.11 after 50 days.

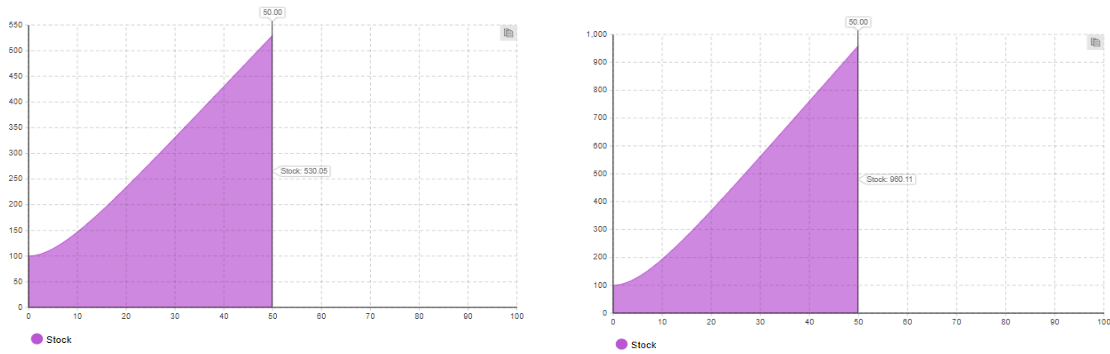

Figure 6: Comparison of response speed of IRS and other communication after SC disruption.

The results indicate that the proposed IRS can be implemented as an efficient information-sharing measure to proceed with the emergency order placement action, speed up the SC disruption response, and improve SC disruption response performance, which also means stronger SCRes.

5 CONCLUSION

This research proposed an intelligent recommender system framework to mitigate supply chain disruption risk. This IRS framework can be used for internal and external resource recommendations within a short time frame with constraints after supply chain disruption. Therefore, it can function as a resilience measure based on its fast response speed. The proposed IRS framework was implemented with a practical use case and validated as a new communication scheme after SC disruptions using a System Dynamics simulation model. The results showed that it could be implemented as an effective SC disruption mitigation measure in the SCRes response phase and help SC participants better react after the SC disruption.

This research study aimed to contribute to supply chain resilience and recommender system development literature. From the theoretical knowledge perspective, it enriched the SCRes literature by proposing a toolkit on the reactive side, which previous SCRes strategy development studies neglected. From the implementation perspective, it extended the application domain of the IRS to the SCRes research domain, which was also researched insufficiently in previously published literature. This study bridges these two gaps and sheds light on leveraging advanced digital tools as SCRes measures for supply chain risk management researchers and practitioners.

This study validated the proposed IRS framework as a highly efficient information-sharing scheme designed to enhance supply chain (SC) resilience with an SD simulation model. The simulation results demonstrated the positive effectiveness of the IRS framework as a reactive SC resilience strategy. The simulation results can also serve as the research foundation for developing high-efficiency recommendation algorithms in the future, as the response speed of the IRS framework may be constrained by increasing data volumes in certain practical scenarios. This study illustrated the basic function of this framework with static datasets. More concrete examples and use cases from different industrial domains can be proposed with dynamic and real-time recommendation experiments where different AI-based algorithms would be validated and tested. One important fundamental aspect of this work is that effective collaboration was conducted, especially the information sharing between different supply chain participants, which may also be a barrier in practical settings. Studies on enhancing information collaboration can be captured in the future. Besides AI, the integrated exploration on IRS and blockchain technology (Hu and Ghadimi 2022) can also be explored in the future to enhance the SCRes.

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