Dynamic supply chain risk management plans for mitigating the impacts of the COVID-19 pandemic

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Abstract

COVID-19 pandemic prompted supply chain (SC) disruptions and heightened demand for crucial items like facemasks and ventilators. Lockdowns and border closures hindered raw material supply and manufacturing capacity expansion. Consequently, manufacturers faced challenges in inventory, transport, and delivery, resulting in higher shortage costs, elevated SC expenses, and reduced SC efficacy. Using an integrated agent-based model (ABM) and optimization, this paper examines COVID-19's multifaceted impacts on facemask SCs. It assesses four primary resilience strategies: enhancing manufacturing capacity, improving raw material supply, increasing transportation and distribution facilities, and maintaining dynamic inventory policy. Moreover, the model tested the proposed strategies under different scenarios by optimizing the inventory policy and transportation strategies, leading to improved facemask production and delivery during extreme events. Our study found that increased production capacity through an optimal inventory and transportation strategy for a long period reduced the multiple impacts of the pandemic on facemask SCs, resulting in diminished total SC costs and increased consumer access to finished products. Based on demand forecasts, maintaining dynamically optimal reordering points and order up to levels can help maximize raw material supply and inventory levels, thereby minimizing risks. Using these findings, future risks related to outbreaks and pandemics can be more effectively planned.

Keywords: Risk management; supply chain; large-scale disruption; resilience; agent-based model.

1. Introduction

Global supply chains (SCs) have faced significant risks and uncertainties due to random and unpredictable disruptions during the last decade (Paul & Chowdhury, 2020a; Paul & Chowdhury, 2020b; Furstenau et al., 2022). SC disruptions largely depend on the type of industry and the impacted geographical locations (Rahman et al., 2020). The recent COVID-19 pandemic has drastically imposed "unknown-unknown" risks and uncertainties in global SCs, the long-term impacts of which in post disruptive stage are yet to be ascertained (Ivanov, 2021b; Rahman et al., 2021). In contrast to the known-known, known-unknown, and unknown-known risks, the unknown—unknown risks cannot be planned for similarly to the other three risk categories (Chowdhury et al., 2021). Currently, very little is known about the risks that might emerge post-COVID-19 pandemic because of other uncertainties, such as the Russia-Ukraine war, and previous studies focused only on those three groups (Njomane & Telukdarie, 2022). The COVID-19 pandemic can be considered a super disruption that has raised the importance of restructuring global SCs and business models to survive and sustain during and after such long-lasting disruptions (Ivanov, 2021c). Long-established efficient SCs cannot manage the simultaneous, dynamic, and multiple impacts of the disruptions (Cheramin et al., 2021). A paradigm shift is needed to transform the current efficient SC models into resilient SCs to make them viable and sustainable (Queiroz et al., 2020). This paradigm shift may raise the current level of SC costs to avoid bigger losses (Ivanov, 2021b).

During the COVID-19 pandemic, multiple region-based lockdowns and shutdowns hampered the operational process of SCs and businesses, hindering their revenue and goodwill (Ivanov & Dolgui, 2021). Most manufacturing companies, particularly those that manufacture essential items, faced extreme supply-demand fluctuation during the pandemic (Paul & Chowdhury, 2020a; Rahman et al., 2021). For example, the demand for essential healthcare items, such as facemasks and ventilators, increased when the rate of COVID-19-related infected cases increased (Coustasse et al., 2020). The manufacturers of facemasks and ventilators faced a stockout of raw materials and struggled to immediately ramp up their production capacity during the pandemic due to supply failure and shortage of production capacity (Mehrotra et al., 2020). Hence, significant attention should be paid to considering the underlying risks and vulnerabilities to adopt dynamic adaptation strategies to increase raw material supply and production rate. To date, most SC risk-related studies have focused on risk identification, assessment, and mitigation, with limited research focusing on risk recovery from the simultaneous, dynamic and multiple long-term impacts of disruptions (Chowdhury et al., 2021; Rahman et al., 2021). Most manufacturers of essential healthcare items struggled to predict the multiple impacts on SCs, and find the appropriate dynamic adaptation strategies to recover from the effects of the COVID-19 pandemic (Ivanov, 2021c). Hence, a dynamic SC model combined with adaptation strategies and a long-term plan that will ensure agility, resilience, and sustainability is needed to increase the viability of SCs (Govindan et al., 2020; Bender et al., 2022).

Due to the lack of research on the potential simultaneous, dynamic and multiple impacts of the COVID-19 pandemic on SCs, and dynamic and long-term plans to handle both the impacts, the present research investigates the following research questions:

1. What are the likely simultaneous, dynamic, and multiple impacts of the COVID-19 pandemic on the SC networks of manufacturers?
2. What optimal combination of dynamic adaptive strategies and long-term plans can be used to manage the simultaneous, dynamic, and multiple impacts and make the SCs viable during and post the disruption era?
3. What methods and techniques can be used as analytics tools to predict the impact of super disruptions and measure the effectiveness of the proposed adaptation strategies to manage multiple and long-term impacts in SC networks?

The long-established and conventional capabilities of SCs—agility, efficiency, and effectiveness—are not sufficient for essential healthcare manufacturers to craft adaptive strategies to recover from the long-term effects of SCs due to the super disruptions (Chowdhury et al., 2021; Bag et al., 2022; Hsu et al., 2022). Shifting toward adaptive, reconfigurable, resilient, and viable SCs could alleviate the impacts of the COVID-19 pandemic (Ivanov, 2021c; Sonar et al., 2022).

The present study's contribution is three-fold. First, we identify several dynamic adaptation strategies focusing on the essential healthcare product industry. The second contribution we make to the literature is an SC simulation model using an ABM to understand the simultaneous and dynamic impacts of the COVID-19 pandemic on facemask SCs, including multiple disruptions in supply, demand, manufacturing capacity, inventory management, transportation, and distribution. Rahman et al. (2021) used an ABM model to study a short-term disruption, i.e., a demand fluctuation; however, they did not optimize any parameters to maximize SC performance. The last contribution is to conduct an optimization experiment within an agent-based simulation model by optimizing inventory policies and transportation planning to justify dynamic strategies and plans to manage disruption impacts in the SCs, production, and delivery to sustain them during and after a disruption. This data-driven model can be used to predict and reconfigure SCs when super disruptions, such as the COVID-19 pandemic, occur.

The rest of the paper is organized as follows. Section 2 reviews the literature on large-scale SC disruptions, such as COVID-19, adaptation strategies, mitigation methods, and research gaps. Section 3 presents the problem statement, while Section 4 describes the proposed adaptation strategies, recovery plans, and model formulation. The results, scenario analysis, and discussions are elaborated in Section 5. Section 6 describes the managerial implications and theoretical contributions, while Section 7 concludes the research by providing future research directions.

2. Literature Review

This section conducts a literature review on the simultaneous and dynamic impacts of large-scale SC disruptions. It also explores dynamic adaptation strategies to manage disruptions, in addition to stating the potential research gaps.

2.1. Large-scale SC disruptions

SC risks and disruptions have been studied extensively (Ivanov, 2021a). The recent COVID-19 pandemic, classified as a super disruption, has drastically disrupted global SCs, imposing a series of unknown risks and uncertainties in global SC networks (Ivanov, 2021c). The adaptation strategies to manage disruptions in SCs depend on the merit of the disruptions (Bianco et al., 2023). Ivanov (2020a) recently opined that manufacturers need to shift their long-established efficient model of SCs to more resilient models, if SC networks are to become more viable and sustainable. The COVID-19 pandemic has shown that survivability and adaptability are the main concerns in sustaining the current level of SCs in the future (Ivanov, 2021c). A complex combination of agility, resilience, and sustainability-based SC model is needed to survive future pandemics or climate change-related disruptions (Chowdhury et al., 2021).

SC disruptions can be caused by micro-events, such as fire, natural disasters, and cyber-attacks. Such SC disruptions can be short-term and sometimes lead to large-scale disruptions (Dolgui et al., 2020). The tsunami in Japan in 2011 was a short-term micro disruption, but it impacted global SCs on a large scale (Pettit et al., 2013). Increasing a firm's recovery and resilience can help alleviate such micro-level SC disruptions (Kumar & Anbanandam, 2020). Major large-scale SC disruptions can be caused by either meso-events, such as the COVID-19 pandemic, which can be medium-term or long-term; or by macro-events, such as climate change, which are long-term disruptions (Adobor & McMullen, 2018). The global semiconductor shortage is one example of the many impacts of the COVID-19 pandemic (Ivanov, 2019; Ivanov & Dolgui, 2021). Similarly, the Spanish flu in 1918 was the reason behind a worldwide coal shortage (Rahman et al., 2021). The impact of macro events, such as climate change, on global SCs is futuristic. However, global SCs need to be ready to adopt multi-structural transformation in their current SC structure to improve their viability to sustain in such future catastrophic events (de Vargas Mores et al., 2018; Ivanov & Keskin, 2023).

Our study focuses on the impacts of large-scale disruptions, such as the COVID-19 pandemic. During the COVID-19 pandemic, most countries initiated several regional lockdowns to stop the spread of the COVID-19 virus, causing simultaneous and multiple impacts on SC networks (Raj et al., 2022). Multiple disruptions, such as supplier failure for a long-term, manufacturing unit shutdown, restrictions in movement (fewer transportations), increased demand for certain essential products, decreased demand of low-demand products (i.e., apparel and automotive products), and inventory shortage, have caused long-term effects on SCs (Ivanov & Dolgui, 2021; Choi, 2021). The impacts of the pandemic on SCs are unpredictable and relatively long-term. The unknown-unknown risks and uncertainties that global SCs face due to the recent pandemic have raised the importance of studying the types of impacts in various SC echelons and designing adaptive, reconfigurable, and dynamic strategies to manage those impacts to survive (Chowdhury et al., 2021; Ivanov & Keskin, 2023).

2.2. Simultaneous and dynamic impacts of the COVID-19 pandemic in SCs

Global SCs have faced various simultaneous and dynamic impacts of mild, moderate, and extreme SC disruptions occurring in parallel and/or sequentially during the COVID-19 pandemic (Dolgui et al., 2018; Ivanov, 2020b; Ivanov & Sokolov, 2019). For example, when a manufacturing facility in one region was partially shut down due to the emergence of COVID-19 cases, the production capacity decreased, and the situation continued for three weeks. The suppliers of the manufacturing unit located in other regions provided full support due to the normal situation in those regions. During the second week of the manufacturing facility's partial shutdown, one of the suppliers in another region was required to stop its operations due to a full emergency shutdown. At that point, the manufacturing facility faced a parallel disruption that triggered significantly heavier ongoing disruptions. If this situation continued for a further five weeks and then improved, the manufacturing facility could have reopened fully, and the suppliers would have started to operate fully. As such, the SC network of the manufacturing unit would have recovered gradually. However, another wave of virus emergence after a few weeks meant that the manufacturing facility faced a surge in demand for the product. At the same time, another lockdown stopped its regular operations for two consecutive weeks. This type of disruption can be termed sequential disruption. Both parallel and/or sequential dynamic disruptions have severely impacted SC networks (Paul et al., 2017; Rahman et al., 2021; Rozhkov et al., 2022).

The COVID-19 pandemic has disrupted the SCs of various industries (Rahman et al., 2021). Both high-demand essential and low-demand luxury products industries faced demand disruptions (Chowdhury et al., 2021; Paul & Chowdhury, 2020b). Due to continuous lockdowns and border closures in many countries, suppliers could not provide raw materials to manufacturers in other countries (Hall et al., 2020). As a result, manufacturers of essential products (i.e., food and healthcare) could not increase their production and failed to meet the demand surge (Fernandes, 2020; Nayeri et al., 2022). Manufacturers lacked transportation capabilities to deliver large quantities of products to retailers (Ivanov, 2020b). Further, the low inventory capacity to accommodate huge amounts of products in manufacturing warehouses was evident (Dolgui et al., 2018). Thus, simultaneous supply failure, production capacity degradation, transportation shortage, inventory shortage, and demand surge of essential products caused heavy and long-term impacts on the SC networks of manufacturers of essential products (Aldrighetti et al., 2021).

Conversely, the manufacturers of low-demand products (i.e., apparel, automotive, etc.) faced a demand decrease during the pandemic (Chowdhury et al., 2021; Ivanov, 2020a). It was also very challenging for manufacturers to shift their production to other relevant essential items to sustain their revenue (Wang & Yao, 2021). After the emergence of the COVID-19 pandemic and due to the series of lockdowns and border closures, the continuous/scheduled delivery of raw materials to manufacturers was lacking (Ivanov, 2021c). The global shortage of electronic devices and automobile parts due to the shortage of semiconductors is an example of such a supply-side disruption during the pandemic (Dolgui et al., 2018; Ivanov, 2021c). Emergency healthcare products such as ventilators were essential for COVID-19-affected patients (Ivanov, 2021b). Due to the scarcity of ventilators, some suppliers in the automotive sector began producing respirator valves to meet the growing healthcare demand, which is a good example of repurposing business capabilities (Ivanov, 2021a; Mehrotra et al., 2020). Essential product manufacturers continue to struggle to find adaptive strategies to ramp up their production capacities amid this global pandemic due to a series of simultaneous and dynamic disruptions (Chowdhury et al., 2021; Ivanov, 2021a). Hence, this study proposes dynamic adaptation strategies and long-term plans to manage such large-scale SC disruptions.

2.3. Adaptation strategies and methods to manage simultaneous disruptions in SCs

To address the issues of simultaneous and dynamic impacts of the COVID-19 pandemic, the "viable supply chain" (VSC) model was proposed by Ivanov (2021b). The objectives of VSC models are to: (i) react agilely to positive changes, (ii) be resilient to absorb negative events and recover after the disruptions, and (iii) survive during long-term and global disruptions by capacity utilizations and their allocations to demands in response to internal and external changes in line with the sustainable developments to secure the provision of society and markets with goods and services in long-term perspective (Ivanov, 2021b).

Adaptation and survivability are the main themes that drove the creation of this model (Ivanov, 2020a; Ivanov & Dolgui, 2021; Li et al., 2021). The VSC model's layers comprise three concerns: SC ecosystems, reconfigurable SC network systems, and firm's resources capabilities. Across these three concerns, the VSC is based on three cycles: lean and agile (i.e., “leagility”), resilience, and survivability (Ivanov, 2021c). Furthermore, four types of related adaptation strategies aid the SC’s cycles: intertwining, substitution, scalability, and re-purposing (Ivanov, 2021c). SC risk levels vary across different areas, such as manufacturing, supply of raw materials, transportation, uncertain demand, and inadequate inventory management, all of which pose potential risks (Wang & Yao, 2021). Manufacturing disruptions can significantly impact production processes, while the supply of raw materials may experience shortages or delays. Transportation disruptions can have a significant impact on logistics networks. Uncertain demand and inadequate inventory management further compound these risks (Chowdhury et al., 2021; Paul & Chowdhury, 2020b). To effectively manage these risks, adaptation strategies such as diversifying suppliers, maintaining alternative sources, optimizing logistics routes, enhancing forecasting capabilities, and implementing agile inventory systems are crucial in ensuring the resilience and stability of supply chains (Rahman et al., 2021). Adaptation strategies (detailed in Table 2) aim to create some system preparedness (i.e., redundancy of resources), system flexibility related to operations, and resources to improve new network reconfiguration under changing characteristics of disruptions (Ivanov, 2019, 2020b, 2021b; Li et al., 2021).

During the COVID-19 pandemic, the automotive and electronic industries faced a severe shortage of semiconductors due to consumers’ initial low demand (Ivanov, 2021c; Wang & Yao, 2021). Electronic companies collaborated with related industries and intertwined their supply chains when the disruptions subsided and semiconductor supplies improved gradually in order to obtain enough semiconductors to increase production (Ivanov, 2021b; Li et al., 2021). AGCO Corporation, an agricultural equipment manufacturer, searched for alternative suppliers in China for substitution and assessed the vulnerabilities promptly (Ivanov, 2021c, 2021b). Raw materials were strategically moved to European markets where businesses ran smoothly (Ivanov, 2021b), and shipments were sent via rail rather than through conventional means. For these substitutions, lockdown in suppliers’ countries did not hamper AGCO’s business (Ivanov, 2021c). Healthcare company Johnson and Johnson faced a 100% increase in demand for essential healthcare products during the COVID-19 pandemic (Ivanov, 2021c). To respond to the increasing demand, the company scaled up production using its backup facilities as a part of its scalability adaptation strategy (Chowdhury et al., 2021; Dolgui & Ivanov, 2020; Ivanov, 2019). Ford Motor Company faced a severely low demand for automotive parts and strategically repurposed its production line to manufacture personal protective equipment, such as face shields, to meet the demand surge during the pandemic (Aldrighetti et al., 2021; Bals & Tate, 2018; Ivanov, 2021b).

Based on the above literature review, Table 1 summarizes studies on SC risk management, Table 2 presents adaptation strategies, and Table 3 shows modeling methods to manage SC disruptions.

Table 1: Studies on risk management in SCs

References	Contributions/findings
(Wang & Yao, 2021)	This study reveals that collaborating (intertwining adaptation strategy) with other industries' transportation facilities will help fulfill delivery demands in an emergency and reduce transportation related risks.
(Papadopoulos et al., 2017)	Aid from the government can support the manufacturers in scaling up and repurposing production capabilities and reduce financial risks.
(Ivanov, 2020)	As an intertwining adaptation strategy, resource sharing can be easily done by horizontal and vertical collaboration to enhance sourcing and production to meet consumers' demands during a pandemic and reduce manufacturing related risks.
(Ivanov, 2019)	This research finds that sub-contracting (substitution adaptation) helps to continue production in the time of primary manufacturing facility disruption to reduce manufacturing facilities related risks.
(Ivanov, 2021b)	Robot-enabled manufacturing can be adopted in collaboration with human skills and intelligence to enhance production capacity even in times of super disruptions. Further, to make the delivery smooth during disruption, multimodal and multi-route shipments allow changes to transportation plans with alternative routes or modes of transport.
(Durach et al., 2021)	Major findings of this study reveal that blockchain and advanced tracking technology help to create SC visibility, disruption identification, and recovery support. This reduces information related risks in SCs.
(Paul et al., 2017)	More collaborative distribution centers close to customer zones help to increase resilience in logistics and ensure smooth delivery during a disruptive situation.
(Dolgui & Ivanov, 2021)	By having multiple suppliers as part of a substitution strategy, manufacturers can replace their suppliers in case of extraordinary disruptions and recover from supply related risks.
(Dolgui et al., 2018)	Backup sourcing as a substitution adaptation strategy helps to continue supply in case of a primary supplier failure.
(Ivanov, 2021c)	Local sourcing helps to enhance higher supply flexibility at lower transportation costs which may create robust redundancy in the case of the COVID-19 pandemic.
(Dolgui & Ivanov, 2020)	As part of the repurposing adaptation strategy, reshoring and back-shoring are used to reduce vulnerabilities and increase robustness, which helps when a super disruption such as the COVID-19 pandemic exists.
(Chowdhury et al., 2021)	Nearshoring and domestic production help to reduce production vulnerability and increase robustness during disruptions. Strategic stock/risk inventory may aid in meeting fluctuating demand and eliminate stockout.
(Paul & Chowdhury, 2020a)	Producing adequate alternative items may aid to fulfill the extra demand during any disruption. This is a good example of a substitution adaptation strategy to reduce production related risks.

(Aldrighetti et al., 2021)	Backup facilities (substitution adaptation strategy) help the distribution process even after the primary warehouse disruption recovery from distribution related risks.
(Tarafdar & Qrunfleh, 2017)	The findings reveal that postponement helps manufacturers to respond quickly to unpredictable customer demand and improve inventory efficiency.
(Manuj et al., 2014)	Product line flexibility and modularization help respond to the fluctuation of consumers' demand during disruptions.
(Ivanov & Sokolov, 2019)	Keeping reserve liquidity allows the business to continue chain activities even during a pandemic and reduces financial risks.
(Pavlov et al., 2019)	This study suggests that decentralized manufacturing facilities increase robustness during super disruptions and reduce manufacturing related risks.
(Ivanov, 2021a)	Increasing and decreasing inventory policy during and post-disruptions will help maintain a sustainable inventory level to meet the demand that surges or decreases.
(Furstenau et al., 2022)	This study examines the impact of digital technologies on the resilience of healthcare supply chains and offers guidance for decision-makers.
(Bender et al., 2022)	This research examines how households have adapted to the COVID-19 pandemic by increasing food prepared at home and identifying strategies that align with practices that enhance resilience in the food supply chain.
(Bag et al., 2022)	It examines how big data and predictive analytics can improve supply chain visibility and resilience in the South African mining industry under extreme weather conditions.
(Ivanov & Keskin, 2023)	The study contributes by presenting new research on efficient, resilient supply chains in long-term crises, such as the COVID-19 pandemic.
(Bastas & Garza-Reyes, 2022)	This paper investigates the impact of COVID-19 on manufacturing organizations in Northern Cyprus and presents strategies used to respond to the pandemic, contributing to knowledge on manufacturing management and resilience.
(Longo et al., 2022)	This article presents a simulation-based framework for manufacturing design and resilience assessment, which is demonstrated through a case study in the wood sector, showing that preparedness can limit damage and increase productivity in the face of disruptions.

Table 2: Adaptation strategies for supply chain risk management

SC risk level	Sub-strategies	Purposes	References
Manufacturing	Ramp-up emergency production	To meet the demand surge to avoid high shortage costs.	(Ivanov, 2021a; Pavlov et al., 2019; Rahman et al., 2021; Choi et al., 2021; Bastas & Garza-Reyes, 2022)
	Decentralizing manufacturing facilities	To increase the production capacity during an emergency.	
	Sub-contracting facilities and backup factory	To continue production in the time of failure of the primary manufacturing facility due to uncertain disruption.	

	Human-robot collaboration	To maintain social distancing to stop the spread of the virus and to continue production during a pandemic.	
	Reshoring and nearshoring	To reduce the dependencies on manufacturing facilities in other countries	
	Product diversification and substitution	A large number of alternative items may aid to fulfill the extra demand of essential items.	
	Re-purposing production capability	To unlock opportunities to increase production of other/similar items to meet the extra demand.	
Supply of raw material	Alternative supplier or backup sourcing	To manage sudden supply-side disruptions in existing suppliers to sustain production during disruptions	(Chowdhury et al., 2021; Ivanov & Sokolov, 2019; Rahman et al., 2021; Wang & Yao, 2021; Choi, 2019; Bender et al., 2022)
	Multiple suppliers	If there is any disruption in one or some of the suppliers, other active suppliers can help supply raw materials.	
	Local sourcing	To enhance supply flexibility at lower transportation costs, which may create robust redundancy during a pandemic.	
	Emergency sourcing from other relevant industry	To increase raw material supply to meet the demand surge. In an emergency like COVID-19, facemask manufacturers can get raw materials from the garment industry.	
Transportation	Collaboration with other transporters	Collaborating with other industries' transportation facilities will help fulfill the emergency delivery demand.	(Aldrighetti et al., 2021; Li et al., 2021; Xiaoyan Xu et al., 2021; Raj et al., 2022)
	Multimodal and multi-route shipment	To reduce the risks and uncertainties in fulfilling deliveries to the retailers and consumers during the lockdowns in a pandemic.	
	Establishing more collaborative distribution centers	More collaborative distribution centers close to customer zones help increase logistics resilience and ensure smooth delivery in times of disruptive situations.	
	Omni-channel	It provides a seamless customer experience to get their deliveries by using online platforms during a strict lockdown.	

Demand and inventory	Strategic stock, risk inventory, and redundancy	Manufacturers with a large inventory can withstand a long period of scarcity caused by a natural disaster or strike action.	(Liu et al., 2016; Wang & Yao, 2021; Furstenau et al., 2022)
	Maintaining minimum inventory policy	To have optimal inventory by increasing the frequency of orders to the suppliers.	
	Virtual stockpile pooling (VSP) system	To improve delivery in times of emergency.	

Researchers have used various modeling techniques to justify strategies for making SC networks more robust, resilient, and viable. According to Ivanov & Dolgui (2021), modeling methodologies are used in literature to make network-wise assessments, plan choices, manage processes, and justify measures that make supply chains more resilient (please refer to Table 3). Bayesian networks, Complexity theory, Reliability theory, Petri nets, and Markov chains can be used to identify bottlenecks in supply chain networks. Mathematical optimization is a superior modeling tool for planning choices (Chowdhury et al., 2021). Meanwhile, several simulation methodologies are used for process control analysis (Longo et al., 2022). By combining mathematical optimization with simulation methods, models and strategies can be developed to evaluate process decision-making strategies to better understand the consequences of large-scale disruptions in supply chains (Paul & Chowdhury, 2020b). The ABM is a data analytics tool for understanding the behavioral elements of SC digital manufacturing (Rahman et al., 2021). Using a system dynamics simulation, Chen *et al.* (2020) studied the resiliency of oil imports under shock. An agent-based simulation model without capability optimization was developed by Rahman et al. (2021) to predict and manage the impacts of COVID-19 based on short-term and single disruption. On the other hand, Tan, Cai, and Zhang (2020) used a discrete event model and ABM to analyze the strategies for SC resilience in an SC network. Nevertheless, there is a gap in the literature regarding establishing an ABM-based simulation-optimization data analytics model that can accurately predict the effects of long-term and large-scale SC disruptions and provide a better recovery strategy.

Table 3: Modelling methods to manage SC disruptions (Ivanov & Dolgui, 2021)

Network and complexity theories	Mathematical optimization	Simulation
Bayesian networks		Agent-based simulation

Complexity theory Reliability theory Petri Nets Markov Chains	Mixed-integer linear programming Robust optimization Stochastic optimization	Discrete-event simulation System dynamics
Network-wise analysis	***Planning decisions***	***Process control***

2.4. Research gaps

There is a lack of research in addressing the simultaneous and dynamic impacts of the COVID-19 pandemic on the SC networks of essential product manufacturers (i.e., facemasks, ventilators, etc.) and dynamic adaptative strategies and plans to manage these. Therefore, studying the impacts of simultaneous and dynamic disruptions in SC performances and evaluating the dynamic adaptive strategies to manage such long-term disruptions is crucial (Mitręga & Choi, 2021; Rahman et al., 2022). This evaluation framework would help essential product manufacturers adopt timely strategies to survive disruptions. A smooth flow of raw materials from suppliers, smooth operations in the manufacturing facility, available transportation and delivery systems, and a dynamic inventory policy are all needed to ensure essential product manufacturers' survivability during any pandemic or climate change-related meso- and micro-level disruption (Paul, Moktadir, et al., 2021; Ambrogio et al., 2022). These adaptation strategies may not aid all disruptions for all types of products, but they can be adopted by other manufacturers to survive any future disruptions. The previous literature indicates significant research on evaluating SC disruptions and mitigation strategies using mathematical modeling and optimization methods, multicriteria decision-making methods, structural equation models, and other structural network analysis and optimization methods (Chowdhury et al., 2021; Rahman et al., 2022). Nevertheless, few studies have attempted to predict the simultaneous and dynamic impacts of the COVID-19 pandemic in SC networks, evaluate dynamic adaptation strategies, and plan to manage such long-term disruptions using agent-based simulation and optimization modeling approach (Rahman et al., 2021). Rahman et al. (2021) developed an ABM model in their research into a single short-term disruption, such as demand fluctuation, which did not optimize any parameters to maximize SC performance. No significant research has been conducted on the simultaneous and dynamic long-term impacts of the COVID-19 pandemic in SC networks of essential healthcare product manufacturers (i.e., facemasks, ventilators, etc.), and none has evaluated the dynamic adaptation strategies to improve the conditions for survivability. This study observes the impacts of long-term simultaneous disruptions in SCs and evaluates dynamic adaptation strategies to manage them over a period by developing an integrated ABM and optimization method.

3. Problem Statement

The current SC disruptions caused by the COVID-19 pandemic can be classified under unidentified risks, known as unknown-unknown types of risks (Chowdhury et al., 2021; Ivanov & Dolgui, 2021; Bastas & Garza-Reyes, 2022). These types of risks are unpredictable in terms of their complexity, timing, and location of occurrence. They simultaneously occur as businesses are challenged to operate in a volatile, uncertain, complex, and ambiguous environment (Pettit et al., 2019; Vegter et al., 2020). The COVID-19 outbreak is an example of a large-scale unknown-unknown risk that has significantly affected national and international SC operations (Cai & Luo, 2020). During the outbreak, most manufacturers' production capacity reduced significantly due to restrictions to maintain social distancing and lockdowns, disruption of transportation and distribution systems, and disruption of the supply of essential products, which affected social and environmental sustainability practices and significantly reduced financial performance (Chowdhury et al., 2021; Ivanov, 2021c; Rahman et al., 2021). Most decision-makers design cost-efficient SCs and compromise resiliency, sustainability, and other risk management practices (Dolgui et al., 2018; Ivanov, 2021b; Wang & Yao, 2021). A cost-efficient SC is considered a lucrative option in the short term; however, such an SC may not survive in the longer term if decision-makers mostly focus on saving money and maximizing profit (Dolgui & Ivanov, 2020; Ivanov & Dolgui, 2021; Wang & Yao, 2021; Xiaoping Xu & Choi, 2021).

Exploring the facemask SCs provides an example in evaluating the simultaneously occurring supply failure, production capacity degradation, restrictions in transportation, and demand spikes of essential healthcare items during the COVID-19 pandemic in Australia. The demand for facemasks increased daily as the coronavirus infection rate increased (Rahman et al., 2021; Wu et al., 2020). Since the beginning of the pandemic, several states in Australia have faced several lockdowns (Chowdhury et al., 2021; Rahman et al., 2021; Zhou, 2020). Melbourne, Victoria's capital, has had more than eight lockdowns to stop the spread of the virus (Chowdhury et al., 2021). In addition, Australia closed its borders for about two years to most countries during the pandemic and subsequently faced severe supply-side disruptions (Paul et al., 2021). Due to lockdowns and border closures, most facilities' manufacturing capacities decreased to stop the virus from spreading among workers. Transporters could not deliver items to the retailers promptly. Thus, Australian manufacturers of essential products faced simultaneous and dynamic disruptions across their SCs. When the situation improved slightly, other disruptions, such as demand spikes or supply failure, hit the recovery progress (Rahman et al., 2021). Since July 2021, the COVID-19 Delta strain has halted the SC recovery progress in Australia (Chowdhury et al., 2021). Health researchers and policymakers were unsure when this COVID-19 pandemic would end (Chowdhury et al., 2021; Sharma et al., 2020). In 2023, COVID-19 has emerged severely in China that can increase the demand of facemask usage to stop the spread of the virus (Ivanov & Keskin, 2023). The Disease Control and Prevention (CDC) recommends wearing masks in public places and practicing other preventive measures such as frequent hand washing, social distancing, and staying home when unwell (Fernandes, 2020; Nayeri et al., 2022). The emergence of new variants of the coronavirus has the potential to increase the need for the use of facemask, which could lead to an increase in demand for them in the market in future. Hence, it is crucial to identify possible dynamic adaptation strategies and ensure long-term planning to manage the simultaneous and dynamic impacts of the COVID-19 pandemic on SCs and to regulate the flow of products in the market. This paper aims to develop an integrated ABM and optimization model to predict the impacts of the COVID-19 pandemic on essential product SCs. This paper also proposes adaptation strategies to manage the extreme impacts on SCs. These adaptation strategies are tested in different scenarios via the proposed model to observe the effectiveness of improving SC performance.

4. Proposed Dynamic Adaptation Strategies and Model Formulation

This section discusses the proposed dynamic adaptation strategies and model formulation for solving the stated problem using an integrated ABM and optimization model.

4.1. Proposed dynamic adaptation strategies

This present research proposes the following four main dynamic adaptation strategies to manage the simultaneous and dynamic impacts of the COVID-19 pandemic in SCs.

Strategy 1: Enhancing manufacturing capacity

The first strategy aims to streamline and ramp up manufacturing capacity to meet the demand surge for essential healthcare items during the COVID-19 pandemic.

Strategy 2: Improving raw material supply

This strategy aims to improve the supply flow of raw materials to manufacturers to scale up the production rate to meet the increasing demand for highly sought-after essential healthcare items during the COVID-19 pandemic.

Strategy 3: Increasing transportation and distribution facilities

This strategy aims to smoothen and improve the timely delivery of items to retailers and consumers during emergencies.

Strategy 4: Maintaining dynamic inventory policy

This strategy aims to maintain optimal inventory by means of "*s*, *S*" inventory policy in manufacturing facilities to continue extended production during extreme disruptions. These main strategies are all part of the scalability-adaptation strategy.

4.2. Proposed recovery plans

Based on the adaptation strategies, we have considered six scenarios, including long-, medium-, and short-term recovery plans for low, medium, and high levels of production capacity increases for adopting strategy 1 – "enhancing manufacturing capacity". Each scenario is optimized with decision variables—re-order point, order up to level, number of transports (trucks), raw material supply, production quantity, inventory level, and delivery quantity—to function dynamically to mitigate the simultaneous and dynamic impacts. Optimal re-order point and order up to level increase raw material supply and inventory level, as the *"s*, *S*" inventory policy is considered in the model for adopting strategies 2 and 4 – "improving raw material supply" and "maintaining dynamic inventory policy". The optimal number of trucks at manufacturing facilities is also obtained to maximize the delivery capacity and minimize total supply chain costs for adopting strategy 3 – "increasing transportation and distribution facilities". Table 4 and Figures 1-3 summarize the scenarios considered for analysis in this study.

Table 4: Scenarios considered for analysis in this study

Scenarios	Recovery period	Increase in production capacity	Decision variables for single objective optimization (Min-Max)		
			ROP (s_j)	Order up to level (S_j)	Trucks (l)
Scenario 1	Long	High (+100%)	Min (+50%): 1500 – Max (+100%): 2000	Min (+50%): 4500 – Max (+100%): 6000	Min (+50%): 15 – Max (+100%): 20
Scenario 2	Long	Low (+50%)	Min (+25%): 1250 – Max (+50%): 1500	Min (+25%): 3750 – Max (+50%): 4500	Min (+25): 13 – Max (+50%): 15
Scenario 3	Medium	High (+100%)	Min (+40%): 1400 – Max (+80%): 1800	Min (+40%): 4200 – Max (+80%): 5400	Min (+40%): 14 – Max (+80%): 18
Scenario 4	Medium	Low (+50%)	Min (+20%): 1200 – Max (+40%): 1400	Min (+20%): 3600 – Max (+40%): 4200	Min (+20%): 12 – Max (+40%): 14
Scenario 5	Short	High (+100%)	Min (+30%): 1300 – Max (+60%): 1600	Min (+30%): 3900 – Max (+60%): 4800	Min (+30%): 13 – Max (+60%): 16
Scenario 6	Short	Low (+50%)	Min (+15%): 1150 – Max (+30%): 1300	Min (+15%): 3450 – Max (+30%): 3900	Min (+15%): 11 – Max (+30%): 13

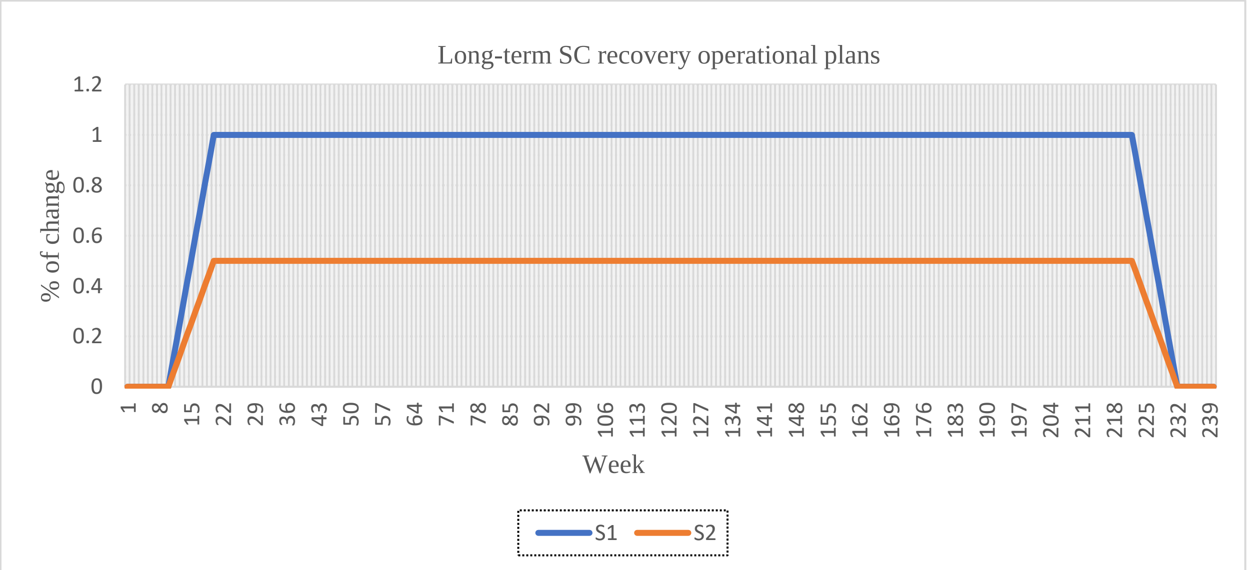

Figure 1: Long-term recovery plans for scenarios 1 (S1) and 2 (S2) for manufacturing capacity increase

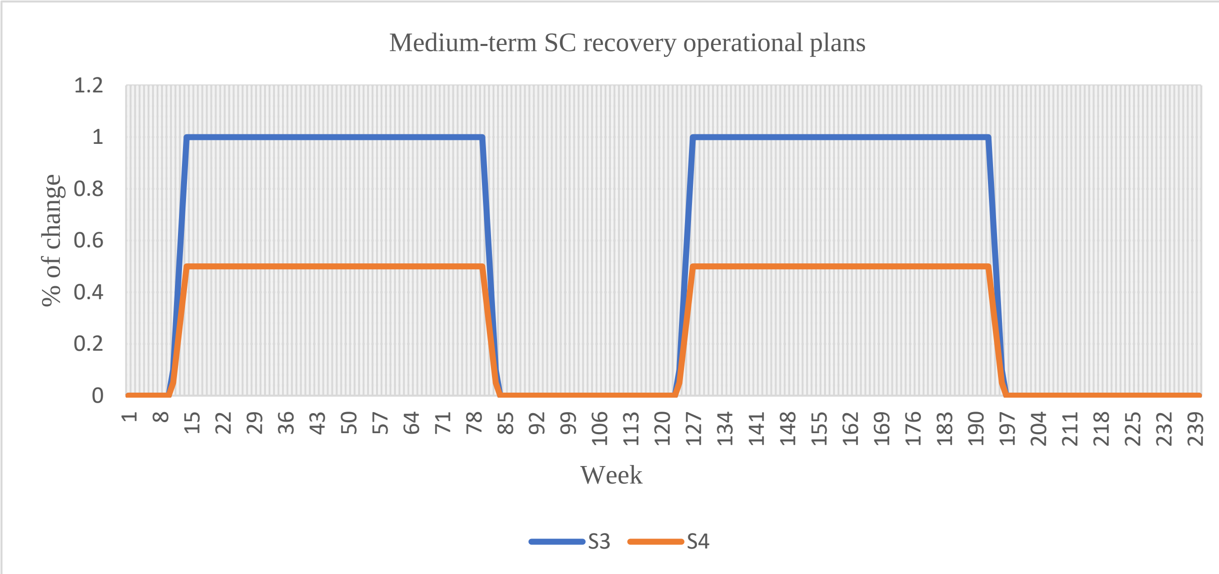

Figure 2: Medium-term recovery plans for scenarios 3 (S3) and 4 (S4) for manufacturing capacity increase

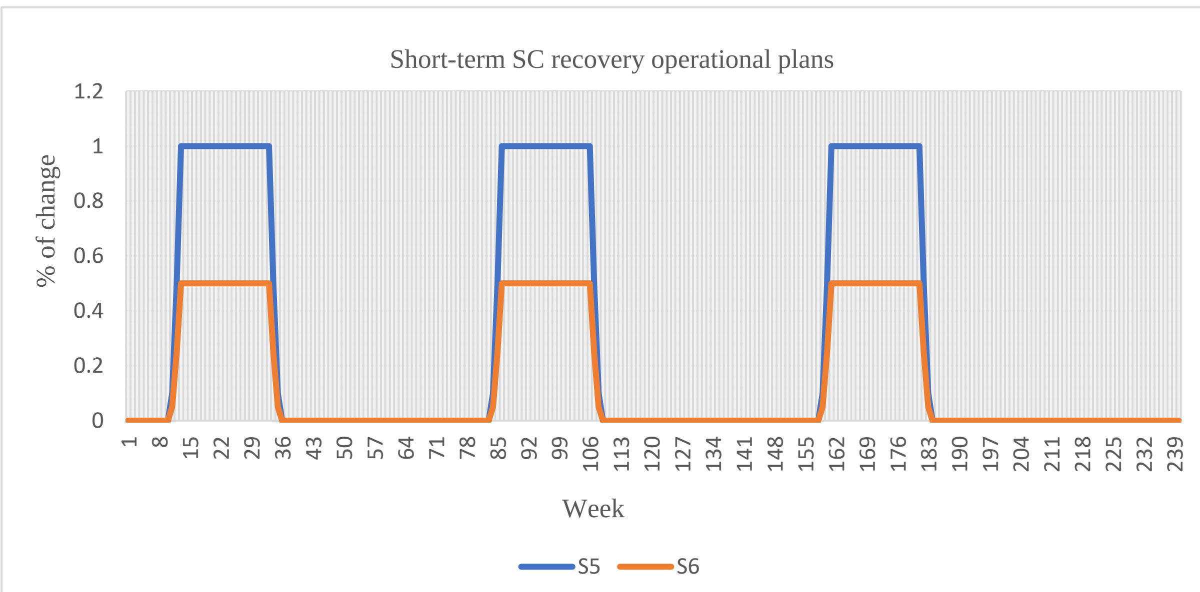

Figure 3: Short-term recovery plans for scenarios 5 (S5) and 6 (S6) for manufacturing capacity increase

4.3. An integrated ABM and optimization model formulation

In this section, we propose an ABM for simulating and optimizing a typical SC for facemasks to compare and mitigate risks. Please refer to Figure 4 for proposed research methodology.

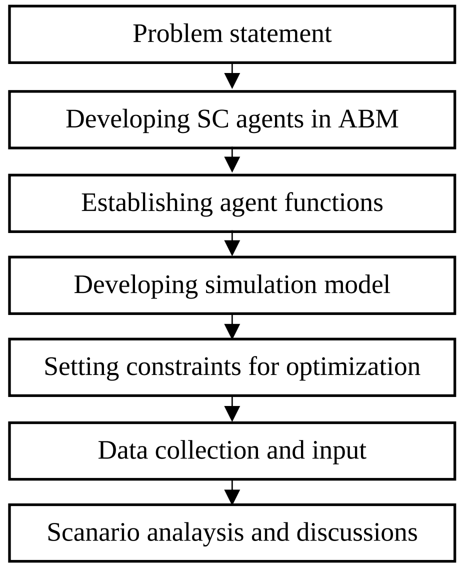

Figure 4: Proposed research methodology

In the proposed model, a set of agents represents SC entities in the real world. By coordinating SC entities and determining the decision variables' optimized values for the best outcome, they simulate specific functions to fulfill retail orders (Ivanov, 2017). To fulfill incoming orders for the finished products and raw materials, we considered the typical SC network of a facemask manufacturing company, which would involve a set of suppliers, manufacturers, and retailers, and a set of transport trucks for suppliers and manufacturers (Mizgier et al., 2012; Zhang et al., 2017). Our model used hypothetical data derived from secondary data. Please refer to Tables 5 and 6 for agent descriptions, model parameters, and Table A1 in Appendix for manufacturing agents' parameters, respectively, in Appendix A in the supplementary material. We evaluate the SC performance using the following measures:

Backorder level: Undelivered products to the retailer within a week by the manufacturer in time window t = d_j^t

Financial performances: The costs considered to evaluate financial performances in the analysis framework include,

a. total supply chain costs (TSCCs)
b. manufacturing costs (MCs, including the raw material costs from suppliers)
c. inventory costs (ICs) for manufacturers and retailers
d. transportation costs (TCs) for suppliers and manufacturers
e. shortage costs (ShCs) at the manufacturing stage

f. discount costs (DisCs) at the manufacturing stage. Table 7 lists the cost metric equations used by the agents.

Manufacturing performance: Based on the number of products manufactured by the j^{th} manufacturer in time window t = p_j^t

Table 5: Description of agents of the proposed model (Rahman et al., 2021)

Agent Name	Functions
Retailer agents	Orders (represented as order agents) are created continuously by retail agents to meet customer demand. When an order is created at a given time, it is assigned to the most preferred manufacturer.
Manufacturer agents	Once a manufacturing agent receives an order from a retailer agent, the agent tries to meet the order using its make-to-stock inventory of finished products (Q_j^t) and a set of available trucks. A request is sent to the suppliers if the inventory level drops below the reordering level (s_j), requesting a fixed amount of raw material and/or components (S_j) to replenish the stock of finished goods.
Supplier agents	This agent's role is to produce the components (in a make-to-order setting) and transport them to the respective manufacturer through trucks.
Order agents	Order agents are created stochastically by retail agents with predefined order size distributions and at predefined arrival times. They represent retail demand in the simulation model. For order fulfillment, order agents pass orders to relevant manufacturers.
Truck agent at manufacturers	Manufacturer trucks transport finished goods to retail agents through these agents.
Order supplier agent	These agents are part of the simulation model as an entity that represents the orders from manufacturers to suppliers for components and raw materials needed to manufacture finished products.
Truck agents at suppliers	Suppliers use these agents to ship components or raw materials to the manufacturers.
Evaluation agent	This agent communicates with all the other agents in the system to maintain track of the current SC's key performance indicators. They look at MCs, sourcing costs, TCs at the manufacturing and supplier stages, ICs at the supplier, manufacturer, and retail stages, ShCs, DisCs, and products/components produced/shipped/received at the various SC stages.

Table 6: Model parameters (Rahman et al., 2021)

Notations	Descriptions
$\boldsymbol{i}$	Retailers
$\boldsymbol{j}$	Manufacturers
$\boldsymbol{k}$	Suppliers
$\boldsymbol{l}$	Manufacturer trucks

$\boldsymbol{m}$	Supplier trucks
$\boldsymbol{D}$	Demand
$\boldsymbol{C_i}$	i^{th} Supplier's capacity
$\boldsymbol{IR_i}$	Holding costs for inventories for i^{th} retailer (each item, per day)
$\boldsymbol{\varphi_j}$	Fixed operating cost for j^{th} manufacturer
$\boldsymbol{\vartheta_j}$	Manufacturing cost per unit of j^{th} manufacturer
$\boldsymbol{IM_j}$	Inventory holding cost for j^{th} manufacturer (each item, per day)
$\boldsymbol{\psi_j}$	Fixed cost associated with managing transport services at j^{th} manufacturer
$\boldsymbol{\omega_j}$	Variable transportation cost at j^{th} manufacturer (per unit item per unit time)
$\boldsymbol{\eta_j}$	Shortage cost for j^{th} manufacturer (per unit item)
λ_j	Discount cost for j^{th} manufacturer (per unit item)
$\boldsymbol{\rho_k}$	Cost of manufacturing raw materials supplied by k^{th} supplier
$\boldsymbol{\theta_k}$	Fixed cost associated with managing transport services at k^{th} supplier
$\boldsymbol{\upsilon_k}$	Variable transportation cost k^{th} supplier (per unit item per unit time)
$\boldsymbol{s_j}$	ROP at j^{th} manufacturer
$\boldsymbol{S_j}$	Order up to level at j^{th} manufacturer
$\boldsymbol{a_j}$	Per unit manufacturing time at j^{th} manufacturer
$\boldsymbol{b_k}$	Per unit manufacturing time at k^{th} supplier
$\boldsymbol{p_j^t}$	Manufactured item by the j^{th} manufacturer
$\boldsymbol{\alpha_{ijl}^t}$	Transport time by truck l to carry items x_{jk}^t from j^{th} manufacturer to i^{th} retailer in time window t
$\boldsymbol{\beta_{jkm}^t}$	Transport time for supplier truck m to carry items y_{jk}^t from k^{th} supplier to j^{th} manufacturer in time window t
$\boldsymbol{x_{ij}^t}$	Items transported from j^{th} manufacturer to i^{th} retailer in time window t
$\boldsymbol{y_{jk}^t}$	Items transported from k^{th} supplier to j^{th} manufacturer in time window t
$\boldsymbol{\tau}$	Time window
$\boldsymbol{Q_j^t}$	Inventory level on average at j^{th} manufacturer in time window t
$\boldsymbol{R_i^t}$	Inventory level on average at i^{th} retailer in time window t
$\boldsymbol{d_j^t}$	Undelivered items to retailer within a week at j^{th} manufacturer in time window t
$\boldsymbol{w_j^t}$	Undelivered items to retailer within a specified time at j^{th} manufacturer in time window t (for the consideration of discount cost)
$\boldsymbol{\sum_j x_{jk}^t}$	Items supplied to the i^{th} retailer
$\boldsymbol{\sum_j y_{jk}^t}$	Raw materials supplied by the k^{th} supplier

4.4. Optimization within the simulation model

The optimal value of the following decision variables by optimization experiments is obtained using AnyLogic's (simulation software) in-built optimization algorithm within the simulation model: 1. *Reordering point* (s_j), 2. *Order up to level* (S_j), and 3. *Number of trucks* (l) used in manufacturing units using the upper bound and lower bound of the decision variables mentioned in Table 4 for each of the six scenarios considered in this study. The objective function is to minimize the TSCCs, as presented in Equation (1).

Min (TSCCs in time window t) $= \sum_j \varphi_j . \tau + \sum_j \vartheta_j . p_j^t + \sum_j \sum_k \rho_k . y_{jk}^t + \sum_j IM_j . Q_j^t + \sum_i IR_i . R_i^t + \sum_j \psi_j . \tau + \sum_l \sum_i \sum_j \omega_j . x_{ij}^t . \alpha_{ijl}^t + \sum_k \theta_k . \tau + \sum_m \sum_j \sum_k \upsilon_k . y_{jk}^t . \beta_{jkm}^t + \sum_j d_j^t . \eta_j + \sum_j w_j^t . \lambda_j$ (1)

Subject to: $\sum_j y_{jk}^t = S_j$ (2)

$\sum_j y_{jk}^t \leq Q_j^t$ (3)

$\sum_j x_{jk}^t \leq D$ (4)

$y_{jk}^t \leq C_i \, ; \forall_i$ (5)

$y_{jk}^t \geq s_j ; \forall_i$ (6)

Equation (1) is derived from the summation of manufacturing costs (MCs), inventory costs (ICs), transportation costs (TCs), shortage costs (ShCs), and discount costs (DisCs) mentioned in Table 7. Order constraint is mentioned in Equation (2), where total raw material supply ($\sum_j y_{jk}^t$) is equal to the order up to level (S_j) and must be less than the inventory capacity (Q_j^t) of the facility (inventory capacity constraint in Equation [3]). Demand constraint is mentioned in Equation 4, where the number of products ($\sum_j x_{jk}^t$) supplied to the retailers by the manufacturers must be less than or equal to the demand (D). Supplier's capacity constraint is mentioned in Equation (5), where raw material supply (y_{jk}^t) by the supplier must be less than the supplier's capacity (C_i). The constraint for the reordering point is mentioned in Equation (6).

Our model minimizes the backorder along with TSCCs by optimizing s_j and S_j over time as this model has used '*s*, *S*' inventory policy to increase raw material supply and inventory level. Optimizing s_j and S_j dynamically optimizes raw material supply *(* $\sum_j y_{jk}^t$ *)*, production quantities *(*p_j^t*)*, inventory level *(*Q_j^t *)*, and delivery quantities *(*$\sum_j x_{jk}^t$*)* over time t to meet consumers' demand to reduce the simultaneous and dynamic impacts of the disruptions. The model assumes that one-unit raw material is required for one-unit finished good for formulation simplicity. The optimized number of trucks (l) carry the goods to the retailer. Therefore, the proposed optimization model within the simulation maximizes production capacity by increasing the optimal level of the following decision variables to meet the unmet demand and demand surge over time dynamically:

1. Raw material from the suppliers ($\sum_j y_{jk}^t$)
2. Amount to produce in the manufacturing units (p_j^t)

3. Amount available in the inventory (Q_j^t)
4. Number of products to deliver to the retailers ($\sum_j x_{jk}^t$).

Please see the optimal values obtained for s_j, S_j, and l from the optimization experiments for the six considered scenarios in Table 9.

According to the current model, seven suppliers, three manufacturers, and 18 retailers are included in the study. To satisfy incoming orders from retailers, the agents collaborate to meet various performance objectives (such as lead times and total SC costs). Table A1 in Appendix A provides manufacturer details. Rahman et al. (2021) developed an ABM to simulate the SC of an essential product manufacturer. They included temporary, short-term fluctuations in demand and only used simulation capability. The significance of the present study lies in the fact that it extends the model and utilizes optimization experiments within the simulation in extended scenarios to find the optimal values of decision variables for managing the simultaneous and dynamic impacts of the COVID-19 pandemic over an extended period. We have built the ABM model and run the simulation and optimization in AnyLogic (version 8.3.2) simulation software for this study.

Table 7: Cost metrics assessed by agents in each of the periods (Rahman et al., 2021)

SC costs	Equation
Manufacturing cost in time window t	$\sum_j \varphi_j.\tau + \sum_j \vartheta_j.p_j^t + \sum_j \sum_k \rho_k.y_{jk}^t$
Manufacturing inventory cost in time window t	$\sum_j IM_j.Q_j^t$
Retailer inventory cost in time window t	$\sum_i IR_i.R_i^t$
Transport cost at the manufacturing stage in time window t	$\sum_j \psi_j.\tau + \sum_l \sum_i \sum_j \omega_j.x_{ij}^t.\alpha_{ijl}^t$
Transport cost at the supplier stage in time window t	$\sum_k \theta_k.\tau + \sum_m \sum_j \sum_k \upsilon_k.y_{jk}^t.\beta_{jkm}^t$
Shortage cost at the manufacturing stage in time window t	$\sum_j d_j^t.\eta_j$
Discount cost at the manufacturing stage in time window t	$\sum_j w_j^t.ƛ_j$
Total supply chain cost in time window t	$\sum_j \varphi_j.\tau + \sum_j \vartheta_j.p_j^t + \sum_j \sum_k \rho_k.y_{jk}^t + \sum_j IM_j.Q_j^t +$ $\sum_i IR_i.R_i^t + \sum_j \psi_j.\tau + \sum_l \sum_i \sum_j \omega_j.x_{ij}^t.\alpha_{ijl}^t + \sum_k \theta_k.\tau +$ $\sum_m \sum_j \sum_k \upsilon_k.y_{jk}^t.\beta_{jkm}^t + \sum_j d_j^t.\eta_j + \sum_j w_j^t.ƛ_j$

5. Results, Scenario Analysis, and Discussions

5.1. Baseline scenario analysis

In the proposed ABM model, we evaluated the performances of facemask manufacturers' SC under the business-as-usual situation and disrupted situation caused by the COVID-19 pandemic. We ran the simulation and optimization for a maximum of five years for better anticipation.

Business-as-usual situation (normal baseline situation): The SC of facemask manufacturers had no disruption. We simulated the ABM with all normal parameters in a business-as-usual or normal baseline situation. The simulated results (see Figure 6) indicate that the facemask manufacturer's SC was normal. There were no significant backorder-related (unmet demand) shortages and discount costs. The manufacturing units produced adequate finished goods with their capacity, maintained an optimal inventory, and arranged transportation for smooth delivery to retailers. The TSCCs were normal in the business-as-usual situation. Hence, the existing SCs for facemask manufacturers ran their production effectively and fulfilled demand smoothly.

***COVID-19 pandemic-related disruptive situation (disrupted baseline situation)*:** In the disruptive situation caused by the COVID-19 pandemic, the facemask SCs faced mild (single disruption, such as a demand spike), moderate (parallel disruptions due to several lockdowns), and extreme (parallel and/or sequential disruptions due to lockdowns and border closure) simultaneous disruptions. Our model assumed that the demand, manufacturing capacity disruptions, and supply delay due to lockdown and shutdown began after a couple of weeks (i.e., ten weeks) of the simulation run, as presented in Figure 5.

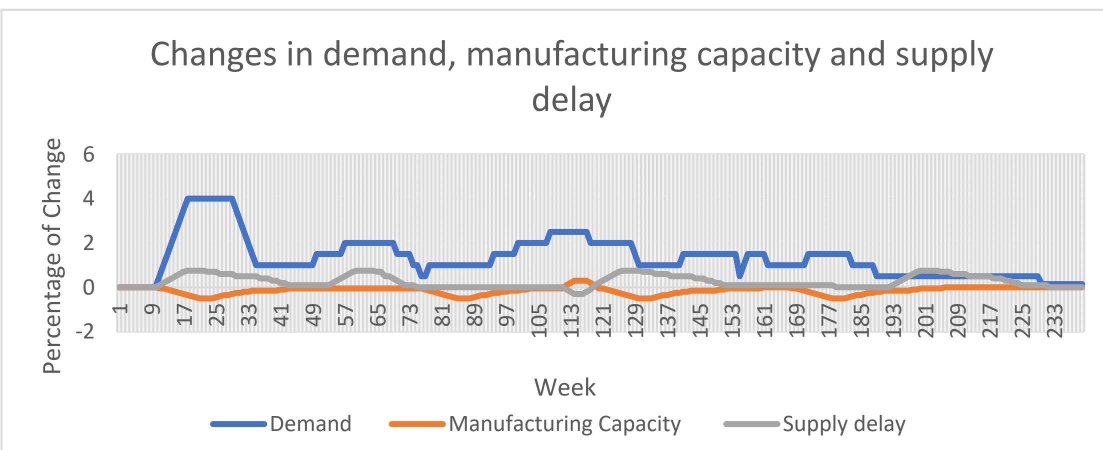

Figure 5: Changes in demand, manufacturing capacity, and supply delay

Demand initially peaked for several months and stayed very high, increasing by 15% to 400% during the five years in the simulation run. It is assumed that the increased demand for facemasks is 150% on average during the disruption in the simulation model. Essentially, one of the major issues of a sudden increase in demand, such as 400% in a certain period, was irrational consumption of products during the pandemic due to panic-purchasing. Our model considered irrational consumption as a demand spike that gradually becomes rational over time. Similarly, manufacturing capacity disruption occurs in parallel and/or one after another, along with demand disruption. From Week 10, the manufacturing capacity is disrupted to varying extents due to location-based lockdowns. The manufacturing capacity decreased in the 5% to 100% range, with an average decrease of 15% at different times, mimicking the shutdown of manufacturing units during the pandemic. Similarly, the supply delay is assumed to be in a range of 10% to 75%, and an average delay of 25% at different times, mimicking the delay of raw material supply due to the temporary shutdown of local suppliers and borders being closed to overseas suppliers. Also, in the simulation, we assumed there was no strategy adopted in this disruptive circumstance. To assess how simultaneous disruptions affect the performance of facemask SCs, we assumed a disruption scenario (refer to Figure 5) into our ABM framework. This scenario closely resembles the demand, manufacturing, and supply disruptions observed during the COVID-19 pandemic and its aftermath. By simulating these disruptions, we obtained valuable insights into their impact on the overall performance of the facemask supply chain.

5.2. Analyzing impacts of simultaneous disruptions in SC performances

The simultaneous and dynamic impact of the pandemic on SCs when no strategy is adopted to manage ethe situation is presented in Figure 6 and Table 8, and described in the following texts:

Impact on backorder level: In the baseline disrupted scenario, facemask demand increased up to 400%, with an average increase of 150% during the five years in simulation. The manufacturing capacity decreased up to 100%, with an average decrease of 15% at different times. Similarly, the delayed supply was up to 75%, with an average delay of 25%. Manufacturers had to shut down their facilities temporarily and could not receive raw materials from suppliers due to strict lockdowns and the emergence of infected cases. As such, the manufacturing capacity decreased over time in the baseline scenario, and facemask SCs could not meet demand in time as a result. Due to the high unmet demand in this situation for over five years, the backorder level increased significantly compared to the normal situation, as seen in Table 8. In the disrupted simulation, the absence of an adaptation strategy, specifically increasing production capacity, has led to a high backorder level. The manufacturers, therefore, need to implement proposed strategies to boost production, penetrate the market, and reduce the impacts.

Table 8: SC performances in disruption compared to the normal situation

	SC performances in disruptions compared to the normal situation							
	Backorder level (Avg units/Week)	**Financial performances (Avg A$/Week)**						**Manufacturing performance (Avg units/Week)**
	Demand unmet	**TSCC**	**MC**	**IC**	**TC**	**ShC**	**DisC**	**Products manufactured**
Normal situation	921.16	1978582.28	1754319.50	120291.73	93139.61	3684.65	7146.78	12560.17
Disrupted situation	11109043.64	51793633.86	2396618.26	232554.43	69527.48	44436174.56	4658759.13	17589.21

Impact on SC's financial performances: As demand surged, production capacity decreased, and raw materials supply decreased, facemask SCs faced a high number of backorders due to unmet demand, resulting in high ShCs (A$ 44.43M approximately). This high shortage cost due to high backorder level happened because no adaptation strategy was adopted in the simulation in disrupted situation. The estimated discount cost increased to A$ 4.66M approximately for delivery delay-related discounts. The TSCCs increased to A$ 51.79M approximately compared to the normal situation. The MCs increased only 37%, so the SC could barely ramp up its manufacturing capacity due to lockdowns in several locations during the simulation run. The manufacturing units could not receive raw materials from suppliers smoothly. When raw materials arrived, sudden shutdowns prevented production capacity from increasing, leading to a higher inventory level. This led facemask manufacturers' ICs to increase to 93%. Another important observation is that TCs decreased to 25%, compared to the normal situation. Due to lockdown and transportation restrictions, suppliers and manufacturers could not utilize their transports to send raw materials and finished goods to manufacturers and retailers, respectively. Thus, the facemask SC could not fulfill the huge demand that increased TSCCs and degraded overall SC performance (see Figures 6 and Table 8).

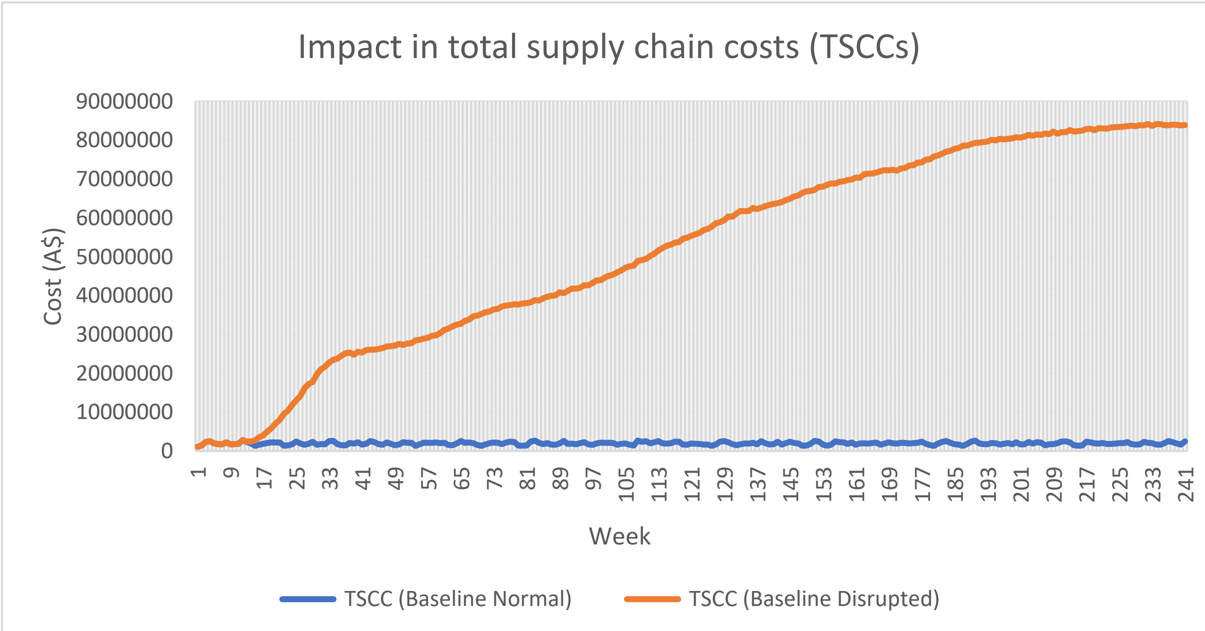

Figure 6: Multiple impacts of disruption in TSCCs

Impact on manufacturing performances: Table 8 shows that the number of products manufactured increased to only 40% in the disrupted situation, which is below the required number to meet the huge market demand during the pandemic. The manufacturing facilities could not ramp up production capacity due to raw material shortages, several shutdowns, and transportation restrictions during the pandemic. This resulted in a huge increase in unmet demand. Thus, ShCs, DisCs, and, eventually, TSCCs increased, and the SC performance degraded significantly. The disruption has had a huge impact on SCs because no strategy was adopted in the simulation of disrupted situation.

Therefore, this study found that high demand, decreased production capacity, and limited raw materials supply led to a significant number of backorders and high shortage costs for facemask SCs, resulting in increased total supply chain costs and degraded overall SC performance.

5.3. Recovery plan implementation, scenario analysis, and evaluation of SC performance

We implemented the proposed recovery plans based on adaptation strategies in six scenarios (see Section 4.2 for details) to improve the performance of the facemask SC. The recovery plans in the six scenarios are summarized as follows:

Scenario 1 (S1) increased the production capacity up to 100% for a long period of 50 months.
Scenario 2 (S2) increased the production capacity up to 50% for a long period of 50 months.

Scenario 3 (S3) increased the production capacity up to 100% for medium periods of 18 months.
Scenario 4 (S4) increased the production capacity up to 50% for medium periods of 18 months.
Scenario 5 (S5) increased the production capacity up to 100% for short periods of 6 months.
Scenario 6 (S6) increased the production capacity up to 50% for short-term periods of 6 months.

In each scenario, we ran the optimization experiment with the parameters listed in Table 4 to optimize ROP (s_j), order up to level (S_j), and truck (l) to maximize manufacturing capacity in order to meet the maximum level of demand and minimize TSCCs. With an optimal ROP and order up to level, raw materials will be delivered to manufacturers from suppliers, which in turn will maintain an optimal inventory. Meanwhile, optimal trucks will improve transportation and distribution. Table 9 shows the scenarios' optimal values of the decision variables.

Table: 9: Optimal value for decision variables by optimization experiment

Scenarios	**Optimal value for decision variables**		
	ROP *(s_j)* (Units)	**Order up to level *(S_j)*** (Units)	**Trucks *(l)*** (Numbers)
Normal situation	1000	3000	10
Scenario 1	1567	6000	15
Scenario 2	1441	4457	14
Scenario 3	1457	4628	14
Scenario 4	1243	3757	13
Scenario 5	1314	4634	14
Scenario 6	1206	3484	11

Evaluation of backorder level: In the disrupted situation, backorder levels started to increase from Week 17 (refer to Fig. 7 of the evaluation of TSCCs) and remained at very high levels. We increased the manufacturing capacity (Strategy 1) by 100% for a long time with optimal s_j (1567), S_j (6000), and l (15) in S1. In S1, the backorder level decreased to 95% compared to the disrupted situation. S1 revealed the best result compared to the other scenarios. Notably, optimal ROP and order up to level to suppliers improved raw material supply from the supplier (Strategy 2) and maintained an optimal inventory (Strategy 4). The second-best scenario was S3. In S3, we increased the production capacity up to 100% for medium-term periods with an optimal value of s_j (1457), S_j (4628) and l (14). S3 decreased the backorder level to 84% compared to the disrupted situation. In S2, we increased production capacity up to 50% for a long time with optimal s_j (1441), S_j (4457), and l (14), while increasing production capacity up to 100% for short-term periods with optimal s_j (1314), S_j (4634), and l (14) in S5. In S2 and S5, the backorder level is decreased to 82% and 81%, respectively. In fifth and sixth place are S4 and S6, respectively. Production capacity increased to 50% for medium-term periods in S4 with optimal s_j (1243), S_j (3757), and l (13); and for short-term periods in S6 with optimal s_j (1206), S_j (3484), and l (11). S1, S3, S2, and S5 showed better results as production capacities were increased and steps were taken to increase raw material supply (Strategy 2) and inventory level (Strategy 4) by increasing ROP and order up to level dynamically, and the optimal increased level of transportation (Strategy 3) was used for smooth delivery.

Evaluation of financial performances

Total supply chain costs (TSCCs): TSCCs started to increase from Week 17 in the disrupted situation (see Figure 7). When we increased production capacity, optimized raw material supply, inventory capacity, and transportation capacity in S1, the TSCCs decreased to 86%, which is lower than all other scenarios. In S1, SC manufacturers could meet huge demand due to adaptation strategies, which reduced the backorder level and associated ShCs and DisCs. Inventory holding costs were lowest in S1, as an optimal level of inventory could be maintained due to optimal ROP and order up to level. MCs and TCs were not too high. The second, third, and fourth positions are S3, S2, and S5, respectively, where TSCCs decreased to 74%, 71%, and 70%, respectively. Like S1, 100% production with optimal raw materials, inventory, and transportation for medium-term periods also showed good results. Suppose raw materials are scarce and there are obstacles in manufacturing units due to lockdowns and shutdowns. In that case, production can be increased 50% for a very long time, or production can be increased 100% for short-term periods to reduce TSCCs and maximize production capabilities to meet the huge demand. S4 and S6 are in the fifth and sixth positions, respectively, where TSCCs are reduced to 53% and 31%, respectively. When there is a huge scarcity of resources (i.e., raw materials), 50% production capacity with optimal ROP and order up to level can be increased for medium-term periods rather than short-term periods for better SC performances.

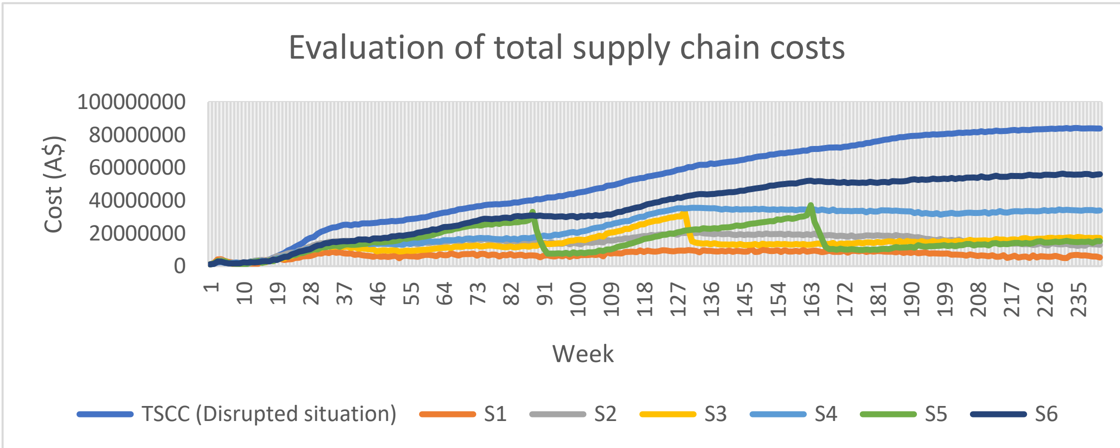

Figure 7: Evaluation of TSCCs from the scenarios

Manufacturing costs (MCs): It is noted from the previous section that S1, S3, S2, and S5 improved the SC better than the other strategies in other scenarios. S1, S3, S2, and S5 increased MCs to 12%, 13%, 12%, and 17%, respectively, compared to the disrupted situation. After implementing the adaptation strategies and recovery plans, the manufacturing capabilities increased in all four scenarios, which helped reduce backorder levels and TSCCs. Compared to long-term recovery plans, a 100% increase in production for a medium-term period in S3 and a short-term period in S5 spiked the production costs very quickly in weeks 89 (S5), 130 (S3), and 168 (S5). The MCs in S4 and S6 increased to 8% and 5%, respectively. These findings highlight that the lack of increased manufacturing capacity to meet higher demand and insufficient efforts to enhance raw material supply for optimal inventory levels were the factors behind the limited manufacturing capabilities observed in S4 and S6, as depicted in Figure 8.

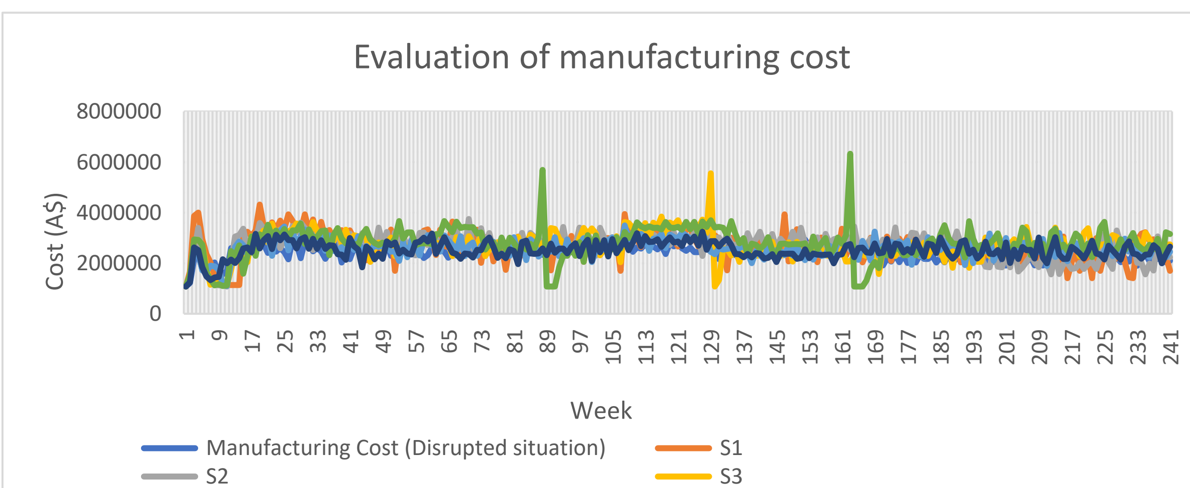

Figure 8: Evaluation of MCs from the scenarios

Inventory costs (ICs): In S1, the ICs only increased to 3% compared to the disrupted situation—the lowest among other scenarios. Although the order up to level was increased to 100% and ROP also increased to 57%, the manufacturing units in S1 could increase their production capacity to meet the extra demand, and there were fewer backorders (see Table 9 for optimal values of ROP and order up to level, and Table 10 for improvement of SC performance). Companies could utilize their inventory properly, reducing ICs both for manufacturers and retailers. In S3, S2, and S5, the ICs increased to 32%, 12%, and 53%, respectively. Similar to S1 and S2, the production capacity is increased for a long time to properly use inventory to meet the extra demand, reducing their IC compared to other scenarios. The TSCCs indeed decreased in other scenarios, such as S3 and S5, but it is also true that production capacity did not increase for a long time, leading to an increased inventory level and thus an increase in inventory costs (ICs) in weeks 90 (S5), 130 (S3), and 165 (S5). In cases of recovery plans in medium- and short-term periods, there should be a more dynamic inventory policy to avoid increased inventory holding costs. As production capacity was not increased significantly in S4 and S6, ICs slightly decreased (3% and 22%, respectively) compared to the other scenarios. Consequently, backorder levels and TSCCs increased in S4 and S6, as depicted in Figure 9.

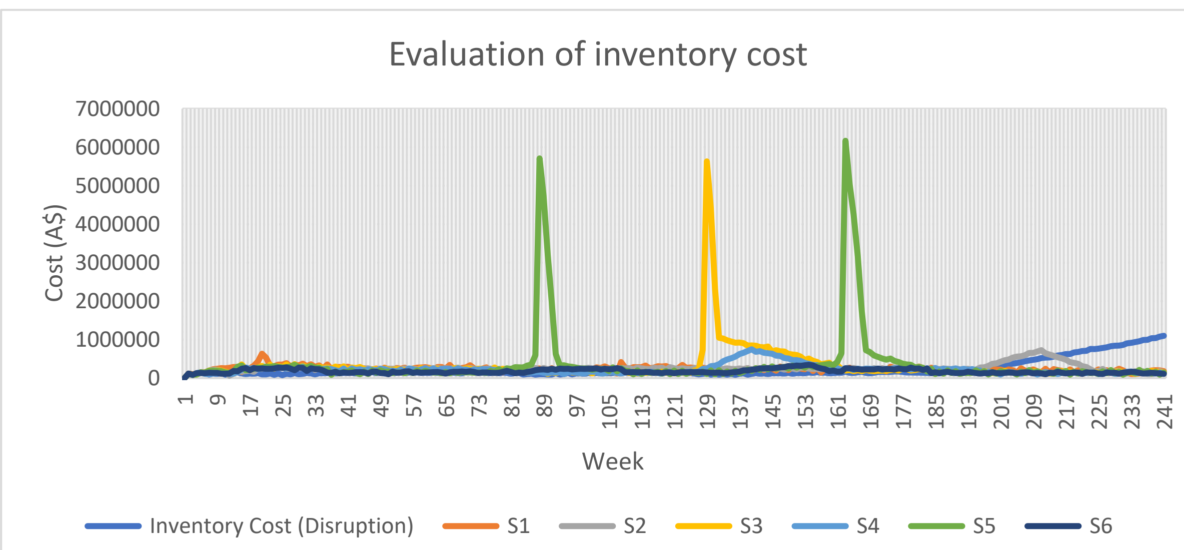

Figure 9: Evaluation of ICs from the scenarios

Transportation costs (TCs): Compared to the disrupted situation, the TCs for S1, S3, S2, and S5 increased to 35%, 30%, 36%, and 34%, respectively, (see Figure 10). The main reason for this increase is that 50%, 40%, 40%, and 40% transportation capacities increased (Strategy 3) in S1, S3, S2, and S5, respectively (see Table 9 for the optimal value of transports), as the production capacities were boosted to manufacture and deliver more products to retailers to meet consumers' extra demand. Though there were small increases in the TCs in those scenarios, the extra transportation and delivery capacity helped manufacturers deliver the extra items produced to meet high demand, eventually helping them reduce TSCCs and increase SC performances. In weeks 89 (S5), 130 (S3), and 168 (S5), the TCs spiked extremely fast due to the 100% increase in production for the medium-term in S3 and for the short-term in S5. In these weeks, TCs spiked sharply, probably due to manufacturers acting quickly to increase trucks to meet increased retailer delivery. Conversely, TCs in S4 and S6 increased at a slower rate (22% and 12%, respectively) than in the other scenarios. The limited ability to increase raw material supply and production capacity had a detrimental impact on TSCCs, leading to decreased supply chain performance. Specifically, in S4 and S6, the number of trucks only saw marginal increases of 30% and 10% respectively, further exacerbating the challenges faced.

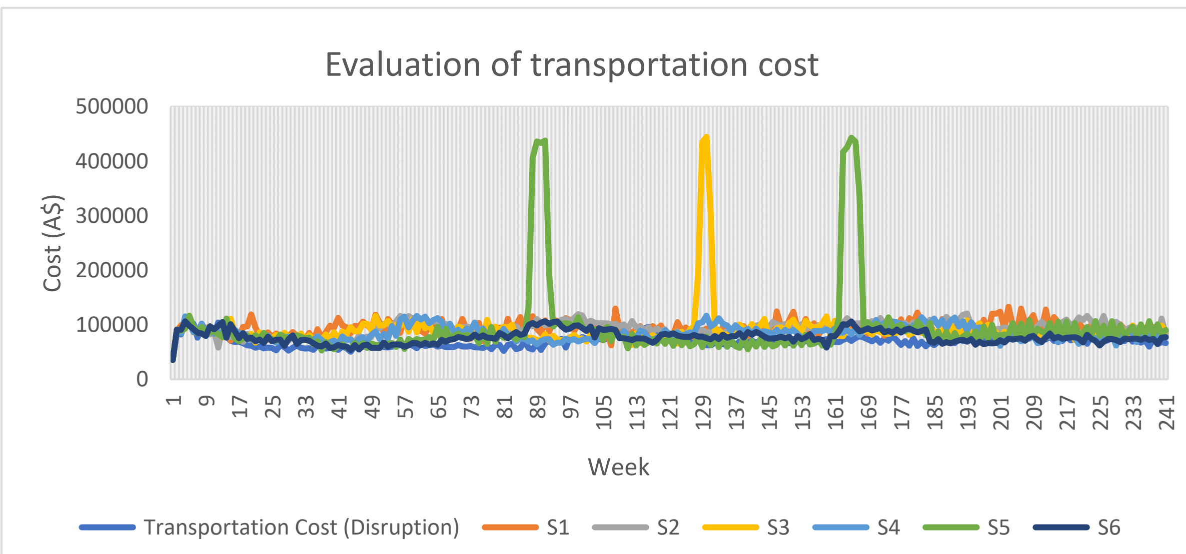

Figure 10: Evaluation of TCs from the scenarios

Shortage costs (ShCs): In the disrupted situation, ShCs started to increase from Week 17 and remained at very high levels (see Figure 11). In S1, ShCs decreased to 95% compared to the disrupted situation. This is because there were significantly fewer backorders due to increases in raw materials, production capacity, and delivery facilities. S1 reduced the backorders and TSCCs better than all the other scenarios (see Figure 7). S3 was second in improving SC; it decreased the ShCs to 84% compared to the disrupted situation. S2 and S5 follow, with ShCs decreasing to 82%

and 81%, respectively. S4 and S6 are in fifth and sixth place, respectively. S1, S3, S2, and S5 improved the SC as production capacities were increased, and steps were taken to increase the raw material supply and inventory level by increasing ROP and order up to level and the optimal level of transport used for smooth delivery. A 100% production with optimal raw materials, inventory, and transports could reduce ShCs in all terms of recovery periods. However, a 50% production increase could reduce backorders if continued for a very long period. Conversely, a 50% production capacity increase with optimal ROP, order up to level, and delivery system in medium- and short-term periods cannot comparatively and significantly reduce ShCs.

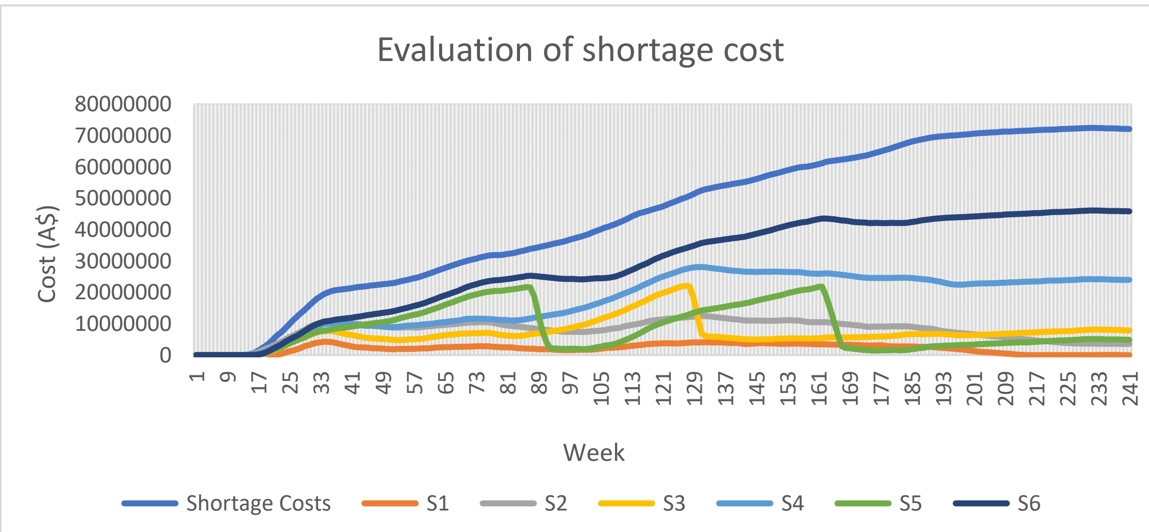

Figure 11: Evaluation of ShCs from the scenarios

Discount costs (DisCs): In the disrupted situation, DisCs for late delivery to retailers started to increase from Week 15 and remained at very high levels (see Figure 12). Unmet demand is included in the backorder level, delivered later with discounts to retailers to sustain goodwill and avoid lost sales. In S1, the DisCs decreased to 58% compared to the disrupted situation, as there was less unmet demand due to increased raw materials, production capacity, and delivery facilities. S1 reduced the DisCs and TSCCs better than all the other scenarios, as shown in Figures 7 and 12. S3 and S5 are in the second and third positions, respectively. This decreased the DisCs to 24% and 21%, respectively, compared to the disrupted situation. Next, S2, S4, and S6 decreased DisCs to 16%, 17% and 17%, respectively. S1, S3, and S5 decreased DisCs, as production capacity increased to 100% with optimal ROP, order up to level, and the number of transports in long-, medium- and short-term periods. However, 50% production, raw materials, and transportation increases across periods but barely reduced DisCs comparatively. An important observation across all scenarios is the presence of high DisCs, highlighting the significant occurrence of unmet demands or backorders and emphasizing the initiative to restore customer goodwill.

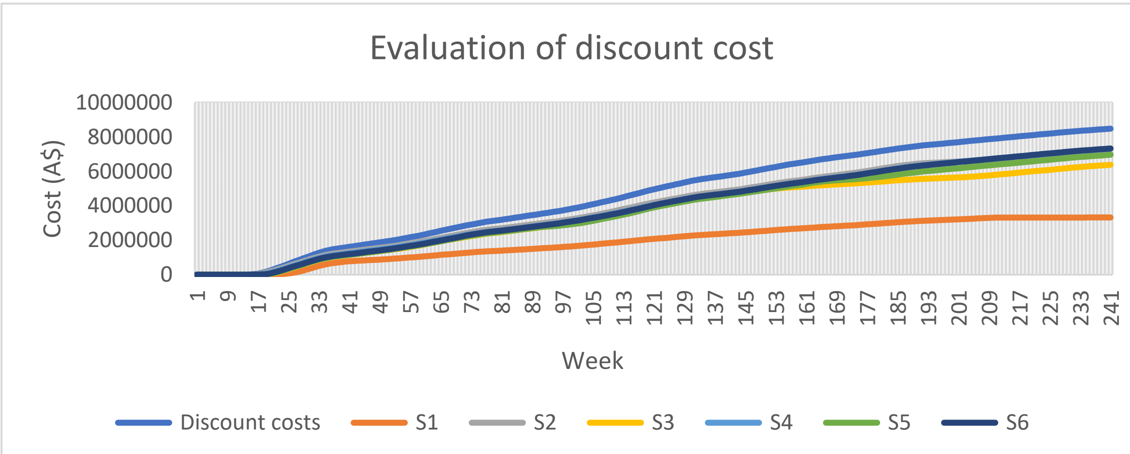

Figure 12: Evaluation of DisCs from the scenarios

Evaluation of manufacturing performances: The products manufactured in the manufacturing units significantly improved after adopting the strategies in the scenarios in Table 10. Specifically, the production rate increased to 66%, 64%, 59%, and 62% in S1, S2, S3, and S5, respectively. Notably, a 100% production increase (Strategy 1) with optimal raw materials (Strategy 2), inventory policy (Strategy 4), and transports (Strategy 3) for the long term, increases the production performances compared to other strategies. It is also imperative to increase the production capacity with optimal inventory policy up to 100% for medium-terms and short-terms for better manufacturing performances. Conversely, manufacturing performances did not improve in S4 and S6. They only increased the number of products manufactured by 43% and 22%, respectively. Finally, a 50% production increase with fewer raw materials in medium-term and short-term periods could not improve manufacturing and overall SC performances.

Table 10: SC performances' improvement analysis compared to the disrupted situation

Variation in scenarios	**SC performances' improvement analysis compared to the disrupted situation**							
	Backorder level	**Financial performances**						**Manufacturing performance**
	Demand unmet	**TSCCs**	**MCs**	**ICs**	**TCs**	**ShCs**	**DisCs**	**Products manufactured**
S1	-95%	-86%	+12%	+3%	+35%	-95%	-58%	+66%
S2	-82%	-71%	+12%	+12%	+36%	-82%	-16%	+64%
S3	-84%	-74%	+13%	+32%	+30%	-84%	-24%	+59%

S4	-61%	-53%	+8%	-3%	+22%	-61%	-17%	+43%
S5	-81%	-70%	+17%	+53%	+34%	-81%	-21%	+62%
S6	-35%	-31%	+5%	-22%	+12%	-35%	-17%	+22%

5.4. Sensitivity analysis

We used a one-variable-at-a-time method. This is the variation (±20%) of several parameters of the base case values of demand, *ROP* (s_j), *order up to level* (S_j), and *trucks (l)* at a time to evaluate the validity and sensitivity of the model.

Variation in backorder level: Backorder levels are more sensitive to demand changes than other parameters, such as s_j, S_j, and l. A 20% decrease in demand decreased the backorder level to 23% and a 20% increase in demand increased it to 24%. Manufacturers of essential products need to increase raw material from suppliers and production capacity during disruptions to avoid huge backorders. The other changes in the backorder level are reported in Table 11.

Variation in financial performances: The analysis highlighted that the model is most sensitive to demand changes, as it significantly varies TSCCs, ShCs, and DisCs. TSCCs, ShCs, and DisCs decrease to 22%, 23%, and 21% for a 20% demand decrease and increased to 22%, 24%, and 15% for a 20% demand increase. When demand increases and manufacturing units cannot ramp up production capacity due to supply shortage and COVID-19 lockdown, the TSCCs, ShCs, and DisCs increase. Considering the same capacity, the manufacturing units could fulfill more demand when the demand decreased, decreasing their TSCCs, ShCs, and DisCs. Without ramping up production capacity or raw material supply, changes in ROP, order up to level, or number of transports cannot significantly alter costs or performance. MCs and TCs were not significantly altered for changes in parameters. Conversely, ICs changed significantly with changes in each parameter. As such, manufacturers need to minimize TSCCs, ShCs, DisCs, and ICs by optimizing ROP, order up to level, and transports to increase SC performances to meet consumers' demands. This will help manufacturers increase production capacity, maintain an optimal inventory, and avoid backorders.

Variation in manufacturing performances: Manufacturing performances were not significantly affected by changes in parameters such as demand, ROP, order up to level, and number of transports, as manufacturing performance (number of products produced weekly) is more related to production capacity. During disruptions, manufacturing performance significantly decreases. Adopting strategies such as increasing raw material supply and the inventory level to increase production capacity can significantly enhance manufacturing performances. Table 11 summarizes the changes in manufacturing performances. The sensitivity analysis reveals that the model outputs are robust, and can provide insights into the dynamics of SC performances. By varying the parameters, it is evident that the model is validated and robust.

Table 11: Synopsys of sensitivity analysis

Parameters	**Rate of change**	**Variation in backorder level**	**Variation in financial performances**						**Variation in the number of products produced**
		Unmet demand	**TSCCs**	**MCs**	**ICs**	**TCs**	**ShCs**	**DiCs**	**Number of products manufactured**
Demand	**-20%**	-23%	-22%	-3%	-30%	+4%	-23%	-21%	-8%
	+20%	+24%	+22%	+2%	-36%	-3%	+24%	+15%	0%
ROP *(s_j)*	**-20%**	+1%	0%	-6%	-35%	-1%	+1%	-4%	-6%
	+20%	+1%	+1%	+1%	+24%	0%	+1%	-2%	0%
Order up to level *(S_j)*	**-20%**	+1%	0%	-11%	-19%	0%	+1%	0%	-5%
	+20%	+2%	+2%	+7%	+24%	0%	+2%	-3%	0%
Trucks *(l)*	**-20%**	+1%	+1%	-2%	+26%	-1%	+1%	-2%	-1%
	+20%	+1%	+1%	-2%	+18%	0%	+1%	-1%	0%

6. Managerial Implications

Our findings show that dynamic adaptation strategies and long-term plans to increase optimal raw material supply and production capacity, arrange optimal transports, and maintain an optimal inventory increase the resilience of essential products' SC and significantly reduce the simultaneous impacts of long-term disruptions. This study has several managerial implications, as discussed below.

Managerial insight 1: When we evaluated the recovery plans associated with production capacity increases (Strategy 1), the recovery plan in scenario 1 (S1) performed best. We increased 100% production capacity with optimal ROP, order up to level, and transports for a very long time in S1 during the disruption, which significantly improved the SCs and recovery from simultaneous and dynamic impacts. A 100% production increase with optimal ROP, order up to level, and transports for medium-term periods (Scenario 3) is similarly a beneficial recovery plan (see Table 10).

Thus, during large-scale disruptions, adopting dynamic strategies and plans for long-term or medium-term periods helps manage simultaneous and multiple SC disruptions and makes essential products such as facemasks available to the market. This works best if sufficient resources (i.e., raw materials, production capacity and transportation) are available through adaptation strategies during disruptions.

Managerial insight 2: When it comes to improving SCs, the recovery plans in scenario 2 (S2) and scenario 5 (S5) are ranked next. In S2, 50% production capacity is increased with optimal ROP and order up to level to increase raw materials from suppliers (Strategy 2), inventory level (Strategy 4), and the number of transports (Strategy 3) for a long-term period. Furthermore, 100% production capacity is increased in S5 with optimal ROP, order up to level, inventory level, and the number of transports for short-term periods. Both strategies improved the facemask SCs.

The recovery plans in S2 and S5 reveal that when there is less possibility of having sufficient resources or capacity, it is imperative that decision-makers either increase 50% of their raw material supply, production capacity, and delivery capacity by optimal ROP and order up to level for long-term periods or increase the capacities to 100% for short-term periods to reduce TSCCs and improve SC resilience. Decision-makers need to evaluate the situation and their capabilities to implement timely adaptive strategies to make their SCs resilient.

Managerial insight 3: Although 50% production capacity and raw material increases for a long-term period improved the SCs, a 50% increase in raw material supply, production capacity, and transports by optimal ROP and order up to level for medium- and short-term periods did not significantly improve the SCs. This can be seen in the recovery plans in S4 and S6 in Table 10.

When there is a very low possibility of increasing raw material and production capacity within limited resources, it is imperative to continue increasing production capacity (i.e., 50%) with optimal raw material order and transports for a long-term period rather than medium- and short-term periods.

In summary, by adopting strategy 1 – "enhancing manufacturing capacity", manufacturers can ramp-up emergency production capacity by decentralizing their manufacturing capacity (Rahman et al., 2022), sub-contracting facilities (Vecchi et al., 2020) and keeping backup factory (Nayeri et al., 2022). The decision-makers can adopt human-robot collaboration in their manufacturing facilities to boost production capacity during the COVID-19 pandemic (Choi et al., 2021). The decision-makers need to understand the importance of nearshoring their manufacturing facilities to nearby places or countries to avoid the impact of extreme situations like lockdowns caused by the COVID-19 pandemic (Fernández-Miguel et al., 2022). They even can repurpose their production to boost the production of emergency products such as facemasks and ventilators (Ivanov, 2021c). The decision-makers can also diversify their product ranges to boost production and penetrate the market (Rahman et al., 2022).

***Managerial insight 4*:** The production increase in manufacturing units needs a dynamic inventory policy (Strategy 4) for smooth raw material supply and cost-effective inventory levels. In S1, a production capacity increase of 100% for a very long-term provided the best result. This needed a 100% increase to get up to level and a 57% increase in ROP, which we obtained by running optimization experiments.

In summary, in the case of a significant increase in production capacity for a long-term period, increasing order up to a level more than ROP is crucial for better raw material supply and inventory. Similarly, optimization experiments obtained the optimal ROP and order up to level in all the scenarios (see Table 9). Decision-makers need to implement their optimization capability to determine the optimal level of ROP and order up to the level to maintain an optimal inventory that would not increase their inventory holding costs even after the disruption ends (Paul et al., 2017). Therefore, by adopting strategy 4 – “maintaining dynamic inventory policy”, decision-makers of the manufacturing facilities can keep strategic stock, risk inventory, and redundancy to maintain optimal inventory in their facilities. Virtual stockpile pooling system can be used among their retailers to maintain the inventory smoothly (Rahman et al., 2022).

Managerial insight 5: In all the scenarios reported in Table 9, the number of transports (trucks) for smooth delivery was obtained by optimization experiments. The experiment revealed that 50%, 40%, 40%, 30%, 40%, and 10% increases in the number of transports (Strategy 3) helped manufacturers in S1–S6 to deliver products to retailers smoothly, which reduced TSCCs and improved SCs.

When the raw material and production capacities are increased to improve SC resilience, it is imperative to identify the optimal level of transportation number for smooth delivery to consumers and retailers to reduce further TSCCs and improve SCs. Otherwise, prompt failure to deliver to the consumers would increase backorder levels (Mehrotra et al., 2020). Therefore, by adopting strategy 3 – " increasing transportation and distribution facilities", the decision-makers can collaborate with other transporters to improve delivery support during the COVID-19 pandemic, if more goods are needed to be delivered (Wang & Yao, 2021). They can also adopt multimodal and multi-route shipments for smooth delivery (Kumar et al., 2014). Decision-makers of manufacturers can establish more collaborative distribution centers for enhanced delivery of products to customers in times of emergency (Rahman et al., 2022). Utilizing omni-channel and e-commerce can be of great use during the pandemic for smooth ordering and delivery (Zhang et al., 2021).

Managerial insight 6: As "*s, S*" inventory is assumed in the current integrated ABM and optimization model, it is noted that increasing optimal ROP and order up to level in all the scenarios can significantly increase raw material supply (Strategy 2) to manufacturers so they can produce adequate finished goods (see Table 10). For 100% production increase in long-, medium-, and short-term periods in S1, S3, and S5, the ROP increased to 57%, 46%, and 31%, and order up to level increased to 100%, 54%, and 54%, respectively. However, 50% production increases in long-, medium-, and short-term periods in S2, S4, and S6 saw ROP increases of 44%, 24%, and 21%, and order up to level increases of 49%, 25%, and 16%, respectively (see Table 9 for optimal values of ROP, and order up to level). Dynamic ROP and order up to level in the scenario by optimization in our model significantly improved the SC's raw material supply.

Therefore, manufacturing facilities' managers need to be strategic and quickly determine the dynamically optimal ROP and order up to level increase to increase raw material supply to produce finished goods. Incorrect and static ROP and order up to level may decrease or increase raw material supply, which may hamper production or cause more inventory holding costs (Ivanov, 2017). Therefore, by adopting strategy 2 – "improving raw material supply", decision-makers of manufacturers can arrange alternative or backup sourcing for getting raw material smoothly. Having multiple suppliers can also help get raw materials in an emergency and reduce the risk of supply failure (Rehman & Ali, 2021). During pandemics like the COVID-19 outbreak, local sourcing of raw materials can be beneficial as it can help to ensure a seamless supply of raw materials even when global supply chains are disrupted (Remko, 2020). When extreme disruption occurs, such as during the COVID-19 pandemic, manufacturers can arrange emergency sourcing from other similar industries to get raw materials in time (Rahman et al., 2021).

Managerial insight 7: The current model is more sensitive to consumer demand (see Table 11). Essential product manufacturers' managers need to determine the demand fluctuation earlier and increase their production capacity using adaptation strategies as soon as possible to meet the demand. Based on the demand, managers must dynamically determine the frequency of ordering to suppliers to avoid further backorder-related ShCs. This can significantly improve the SCs.

Managerial insight 8: The findings of this study reveal that long-term adaptive recovery strategy and dynamic plans can significantly reduce the simultaneous impacts of the COVID-19 pandemic. Short-term recovery plans barely improve SC performances and can leave some after-disruption effects called disruption tails (Ivanov, 2019). Decision-makers must adopt long-term recovery plans to reduce the impacts of extreme disruptions.

However, the proposed strategies and recovery plans are well suited to manage extreme disruptions, such as the COVID-19 pandemic, and the model shows dynamism in formulating the strategy based on demand. It is imperative to revise the recovery plans when the disruption gradually ends; otherwise, SC may face further disruptions. Decision-makers of essential healthcare product manufacturers can consider this study's findings and adopt timely adaptation strategies to manage the impacts of large-scale disruptions to make their SCs much more resilient and viable.

7. Conclusions and Future Research Directions

Researchers and practitioners have recently focused on resilient and viable SC practices, particularly in light of the COVID-19 pandemic's impact. SCs across industries require survival and adaptation guidelines to maintain sustainability and robustness. Decision-makers must promptly choose adaptation strategies such as re-purposing, scaling up, substituting, and intertwining SCs to effectively face disruptions. Essential healthcare product manufacturers, like facemask producers, faced severe challenges during the pandemic, exemplified by Australia's prolonged lockdown and closed borders. Our study developed an integrated ABM and optimization SC model to evaluate proposed strategies such as “enhancing manufacturing capacity”, “improving raw material supply”, “increasing transportation and distribution facilities”, “maintaining dynamic inventory policy” for mitigating the pandemic's impact on essential product SCs. Results showed that without adaptable measures to increase production capacity, ensure raw material supply, and maintain optimal inventory, SC performance suffered from high shortage costs, highlighting the need for proactive measures during disruptions.

This study makes three significant contributions. Firstly, it proposes dynamic adaptive strategies to enhance the resilience of healthcare product SCs. Secondly, it extensively examines the COVID-19 pandemic's simultaneous and dynamic impacts on SCs, aiding in understanding vulnerabilities and developing adaptive strategies. Finally, it conducts an SC optimization using agent-based modeling method to justify proposed strategies and recovery plans, aiming to minimize total supply chain costs and improve performance and resilience. Overall, the study provides valuable insights for managing pandemic impacts on essential healthcare SCs.

Furthermore, this study proposes several recommendations for essential product manufacturers to enhance their production capacity during crises like the COVID-19 pandemic. These include increasing production through ramping up production, subcontracting facilities, utilizing backup facilities, and diversifying products in the long term. In preparation for future disruptions, decentralizing manufacturing capacity, leveraging human-robot collaboration, and considering reshoring and nearshoring can be effective strategies to scale up production capacity. Manufacturers can also adopt adaptation strategies such as alternative or switching to backup supplier, having multiple suppliers, and localizing sourcing to mitigate supply disruptions. Optimizing strategic stock management, implementing minimum inventory policies, and making dynamic adjustments in the inventory can improve inventory levels in the face of disruptions. To ensure swift delivery during lockdowns, decision-makers should identify optimal transportation options, foster collaboration with other transporters, and employ multimodal and multi-route shipment methods. Retailers can utilize omni-channels to facilitate smooth delivery during lockdown periods. Given the prolonged nature of the COVID-19 pandemic, long-term dynamic planning is essential for optimal outcomes. The study emphasizes the need for manufacturers to utilize data analytics tools to dynamically determine optimal raw material quantities, inventory levels, and number of transportations, as demonstrated by the ABM and optimization methodology employed in the research, in order to effectively mitigate the simultaneous impacts of the large-scale SC disruption caused by pandemic. The proposed adaptation strategies and recovery plans, facilitated through a simulation and optimization model, provide valuable insights for facemask manufacturers to effectively manage concurrent supply chain disruptions.

However, this study is not without limitations. Theoretically, a few adaptation strategies were considered for the simulation and parameters for optimization to understand the multiple impacts on SCs focusing on the healthcare product industry. In future studies, it would be beneficial to take into account other industry-specific (such as the semiconductor industry) strategies, as different industries may have distinct features and difficulties that necessitate tailored strategies. To predict impacts and improve SCs, the present study used hypothetical data based on secondary data. During the COVID-19 pandemic, primary data collection was challenging as industries had to spend time collecting it. A future empirical study can compare the results based on primary data. Future studies could explore strategies to minimize instability in SCs during disruptions caused by war and other global events. Another important avenue in making SCs more resilient could be evaluating SCs' sustainability performances after implementing the resilient strategies. Future research also needs to identify and manage capability types, such as people, skills, systems, and processes, alongside adaptation strategies to manage large-scale SC disruptions. The present study is the first of its kind to predict the simultaneous and dynamic impacts of the COVID-19 pandemic and assess adaptation strategies to manage them. This study sets a benchmark and provides practical implications for future research.

Disclosure statement

The authors confirm that they have no conflict of interest and there are no relevant financial or non-financial competing interests to report.

Data availability statement

The authors confirm that the data supporting the findings of this study are available within the article [and/or] its supplementary materials.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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Appendix

Table A1: Parameters for manufacturing agents (Rahman et al., 2021)

Manufacturer name	**Latitude**	**Longitude**	**Trucks**	**Manufacturing capacity (Units)**	**State**	**Manufacturing fixed cost (A$)**	**Manufacturing item cost (A$ per unit)**	**Holding cost (A$ per unit per day)**	**Shortage cost (A$ per unit per day)**	**Transportation cost to retailer (A$)**	**ROP (s)**	**Order up to level (S)**
Melbourne	-37.7459	144.77	10	90	VIC	50000	5	0.75	4	500	1000	3000
Sydney	-33.8688	151.209	10	80	NSW	51000	5	0.75	4	550	1000	3000
Brisbane	-27.4698	153.025	10	100	QLD	53000	5	0.75	4	520	1000	3000