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Optimizing Medical Supply Chain Resilience for Future Pandemics: A Data-Driven Framework Integrating Public Health Risk, Logistics Efficiency, and Predictive Analytics

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Abstract

The COVID-19 pandemic exposed critical vulnerabilities in global medical supply chains, resulting in widespread shortages of essential healthcare products. This study aims to optimize the resilience of medical supply chains against future pandemics by evaluating key mitigation strategies such as inventory buffering, multi-sourcing, and local manufacturing. Using an agent-based simulation model that incorporates realistic demand surges, supplier disruptions, and transportation delays, we quantify the impact of these strategies on supply chain performance metrics including fulfillment rate, lead time, and recovery speed. Our results demonstrate that integrating multiple resilience strategies significantly improves service levels and reduces recovery times compared to traditional supply chain configurations. The findings provide actionable insights for policymakers and healthcare organizations to strengthen preparedness and ensure reliable access to critical medical supplies in times of crisis.

Keywords

COVID-19, Medical Supply, Health Risk, Supply Chain

1. Introduction

The COVID-19 pandemic crisis was a first-time global stress test for health care systems that laid bare systemic vulnerabilities in health care supply chains. Even resource-rich hospitals and health care providers worldwide were confronted with a perpetual deficiency of the essential health care supplies such as ventilators, face masks, personal protective equipment (PPE), diagnostic kits, and medicines [1], [2]. While the early assumption was that these shortages were being caused by unanticipated surges in demand, closer scrutiny revealed more inherent structural issues. Foremost among these were the over-reliance on JIT inventory systems, concentrated global manufacturing in geographically limited areas, single-sourcing procurement practices, and inadequate digital infrastructure to enable real-time decision-making [3]-[5].

While traditional commercial supply chains operate in a commercially critical plane, healthcare supply chains operate in a life-critical plane. Their failure is not merely a financial loss but also the likely loss of human lives [6]. This contrast highlights how much resilience—the capacity of a system to absorb shocks, reorganize under stress, and recover to its initial or some new state of operation—counts. But traditionally, resilience has been paid for in terms of efficiency. Lean inventory practices, fewer suppliers, and cost-reducing processes can streamline day-to-day activities, but in doing so, they expose supply chains to being swamped by severe and protracted disruption [7] [8].

The COVID-19 health crisis has therefore triggered an abrupt global call for the re-architecture of healthcare supply chain frameworks, leading to a rejection of exclusive dependence on cost optimization and a shift to methods focused on resilience, flexibility, and long-term dependability [9] [10]. Growing volumes of evidence now support the application of data-intensive, AI-enabled, and prediction-based modeling techniques to analyze and enhance healthcare supply chains [11]-[14]. They not only forecast impending future disruptions but also simulate the effectiveness of various mitigation approaches under varying states of supply chain stress.

Different accurate approaches have emerged as promising strategies for enhancing healthcare supply chain resilience. Among the most frequently cited is inventory buffering, in which additional buffer stock of critical supplies is maintained above average consumption levels. This offers protection against unexpected peaks in demand or supplier disruption but has with it challenges of increased holding costs and product obsolescence [10] [15]. The second method is multi-sourcing, in which the core of suppliers is diversified either by geography or vendors. This reduces reliance on a single source and provides increased procurement responsiveness when regional or political disruptions occur [12] [16]. A third of the more often cited alternatives is local manufacturing, which is spending money to develop in-country manufacturing capacity to reduce lead time and reduce exposure to international logistical delays [13] [14] [17].

Besides these basic strategies, the new technologies emerged in the digital area, such as digital twins, Internet of Things (IoT) connectivity, and real-time predictive analytics, have been proposed to offer even greater visibility and responsiveness for healthcare logistics networks [18]-[20]. For instance, digital twins make it possible to simulate physical supply chains virtually and, therefore, decision-makers can test alternative disruption circumstances and responses virtually prior to when they take place in the physical world [17] [20]. Furthermore, AI solutions are capable of monitoring supply chain nodes and using machine learning algorithms to predict risks, determining optimal routes, and identifying bottlenecks in real-time [21]-[24].

Despite these developments, there is an enormous gap between empirical and simulation-based evaluation of such resilience strategies. A majority of the existing work either provides theoretical frameworks or compares strategies in a vacuum without a comparative or combinational strategy [15] [19]. There also is a dearth of sensitivity analyses that take into account a variety of levels of demand uncertainty, supplier reliability, and transport delays—those factors that are particularly amplified in the face of public health emergencies [16] [25]. As a result, managers of healthcare and policymakers often are without quantitative data that they require to inform good decision making, risk-adjusted, regarding supply chain reconfiguration.

To bridge this gap in research, this paper proposes a simulation-based assessment framework to quantify the performance of resilience-strengthening strategies in a pandemic-similar disrupted healthcare supply chain. We develop a dynamic system model that models a typical medical supply chain with COVID-19-similar disruptions such as unexpected spikes in demand, supplier disruptions, and extended lead times. In this environment, we experiment with and implement the three fundamental resilience strategies—inventory buffering, multi-sourcing, and local manufacturing—individually and in various combinations.

Each of these configurations of strategies is compared to a full set of key performance measures, such as:

Order fill rate: the ratio of total demand fulfilled within acceptable time windows.

Lead time: the average length of time between receiving an order and delivering it.

Inventory shortage days: length of time that levels of inventory are at or below minimum levels.

System recovery time: period of time to restore supply chain operations from disruption.

In assessing robustness, we conduct sensitivity testing under different levels of demand volatility and supplier reliability and see how each solution handles increasing levels of stress and uncertainty. We also consider the trade-offs among cost, operational feasibility, and response capability.

This study contributes to current literature on healthcare supply chain resilience using quantitative, simulation-based evidence on the appropriateness of commonly applied mitigation strategies under a dynamic situation of ever-changing crises. Relying on the intelligence of AI-aided supply chain optimization [1]

[8], predictive analytics [2] [5], and digital modeling techniques [7] [17], this study bridges the knowledge gap between practice and theoretical recommendations.

Further, by taking advantage of ongoing advances in healthcare informatics and analytics [21]-[26], our aim is to make recommendations that are actionable to decision-makers at all levels—hospital administrators, supply chain managers, governments, and international health organizations. Such recommendations come particularly opportune in view of the shift of the international health community from crisis responses to system redesign and long-term planning.

In conclusion, building post-pandemic healthcare supply chain resilience is no longer a luxury but a necessity. Modeling the dynamic performance of medical logistics networks under stress, and assessing quantitatively the efficacy of the most important resilience strategies, this study seeks to provide a sound, fact-based framework to design brighter, bolder, and more agile supply systems capable of addressing next-generation world health issues.

2. Literature Review

The vulnerabilities of medical supply chains under pandemic conditions have become a focal point for both academic and policy-oriented research. The COVID-19 pandemic disrupted the global flow of medical goods, revealing how over-optimization for cost and efficiency can lead to systemic failures in times of crisis. Researchers have thus shifted attention to identifying and evaluating resilience-enhancing strategies that can help mitigate the impact of such disruptions on healthcare logistics systems.

One of the most widely discussed strategies is Inventory Buffering, which involves holding extra stock of critical items to absorb demand shocks or supply delays. Christopher and Peck [10] argue that safety stocks provide a buffer against uncertainty and increase short-term system responsiveness. However, inventory buffering can also lead to increased storage costs and wastage due to expiration, particularly in the context of medical goods with limited shelf life [11].

A second major strategy is multi-sourcing, or diversifying the supplier base across multiple geographic regions. This approach reduces the dependency on a single supplier or region, a factor that proved crucial during the COVID-19 crisis when many countries restricted exports of medical supplies [12] [13]. While effective, multi-sourcing may introduce coordination complexity, contractual risks, and potential variability in product quality [14].

A third solution involves Local Manufacturing, which aims to minimize reliance on international transportation and reduce lead times. Ivanov and Dolgui [15] highlight the importance of regional production capabilities, especially when global trade routes are disrupted. However, building local manufacturing capacity can be capital-intensive and time-consuming, and it may not be feasible in low-resource settings [16].

Recent studies have also explored the use of digital simulation models and digital twins to model supply chain disruptions and test response strategies virtually. These tools offer a way to assess the resilience of various supply configurations without incurring real-world costs [17] [18]. Similarly, demand forecasting algorithms, powered by machine learning, are being used to predict future surges and proactively adjust supply levels [19] [20].

Table 1 below summarizes the key resilience strategies discussed in the literature, along with their benefits and limitations.

Table 1. Summary of key resilience strategies in medical supply chains.

Strategy	Description	Advantages	Limitations	References
Inventory Buffering (IB)	Maintaining excess stock of critical items	Immediate availability during demand spikes	High holding cost; risk of expiration	[10] [11]
Multi-Sourcing (MS)	Engaging multiple geographically diverse suppliers	Reduces dependency and supply disruption risk	Complex procurement processes; potential quality issues	[12]-[14]
Local Manufacturing (LM)	Establishing or using domestic/regional production facilities	Shorter lead times; regional self-sufficiency	Capital and regulatory barriers	[15] [16]
Demand Forecasting	Predicting demand surges using historical and real-time data	Proactive planning; improved resource allocation	Limited data accuracy early in crisis	[19] [20]
Digital Simulation Tools	Modeling and stress-testing supply chains under simulated disruptions	Low-cost policy testing; scenario evaluation	Requires expertise and infrastructure	[17] [18]

Even though there's been a lot of interest in these strategies, most of the existing research looks at them one at a time or uses very basic models that don't capture the full picture. There's still a big gap when it comes to comparing these solutions side by side or understanding how they work together in a real crisis. That's where this study comes in. We take a more practical approach by simulating all three key strategies—inventory buffering, multi-sourcing, and local manufacturing—both separately and combined, under realistic pandemic conditions. This helps us figure out which setup actually works best when everything's on the line.

3. Method

This study adopts a simulation-based approach to evaluate and optimize medical supply chain resilience under pandemic conditions. The methodology was structured in several phases: modeling the baseline supply chain, defining realistic disruption scenarios, implementing resilience strategies, and assessing their performance using quantitative metrics (**Figure 1**).

The first step involved developing a dynamic simulation model that reflects the structure and flow of a typical medical supply chain. The model included key stakeholders such as international suppliers, local manufacturers, central warehouses, regional distributors, and healthcare facilities. Core parameters such as inventory policies, lead times, transportation capacity, and demand fluctuations were incorporated to mirror real-world supply chain behavior. The baseline scenario assumed a just-in-time (JIT) system with minimal safety stock and single-source dependency, which reflects the standard operating structure in many healthcare systems prior to the COVID-19 pandemic.

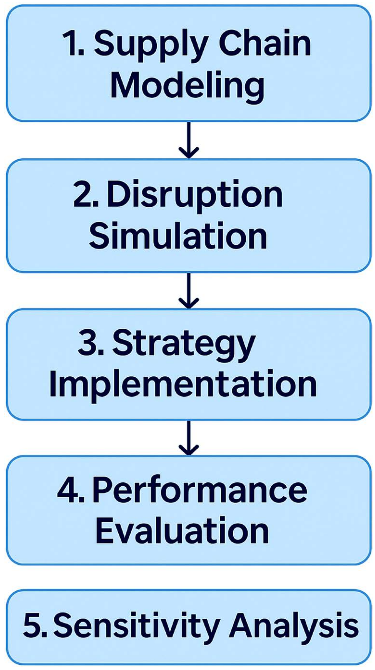

Figure 1. Methodological workflow.

To simulate pandemic-like disruptions, we introduced several stressors to the model. These included sudden demand surges (up to 200% of baseline levels), supplier shutdowns, increased transportation lead times, and production delays. The disruptions were applied over a 30-day period to simulate a real-time crisis event, capturing how quickly the system deteriorates under stress and how it recovers.

Three core resilience strategies were implemented in the simulation: inventory buffering, multi-sourcing, and local manufacturing. The inventory buffering strategy involved increasing safety stock levels by 20% to 40% above the normal threshold. This approach aimed to provide a short-term cushion against supply interruptions and demand shocks. The multi-sourcing strategy added supplier diversification, where each critical item was sourced from three to five suppliers spread across different geographical regions. This helped reduce dependency on any single region, especially those likely to be affected by restrictions or export bans. The third strategy, local manufacturing, simulated the development of domestic production capabilities, which contributed 20% to 50% of total demand, thereby reducing reliance on global supply chains and long lead times.

The effectiveness of each strategy was evaluated using four key performance metrics: order fulfillment rate, average lead time, inventory shortfall days, and system recovery time. The order fulfillment rate measured the percentage of demand successfully met on time. Lead time captured the average duration between order placement and delivery. Inventory shortfall days referred to the number of days healthcare facilities experienced critical shortages. Finally, recovery time measured how quickly the system returned to normal operations after the disruption.

In addition to the strategy-based comparisons, we conducted a sensitivity analysis to examine how changes in demand variability and supplier lead times affected the outcomes. This analysis provided insight into the robustness of each strategy under uncertain and fluctuating conditions—an essential factor in real-world pandemic scenarios where data is incomplete or rapidly evolving.

This methodological framework enabled a comprehensive, data-driven comparison of different resilience strategies in a high-disruption environment. By simulating realistic conditions and evaluating measurable outcomes, the study aims to provide actionable recommendations for healthcare organizations and policymakers seeking to strengthen their supply chains for future pandemic preparedness.

4. Result

This section reports the performance of various supply chain resilience strategies under simulated pandemic scenarios. Using agent-based modeling and stochastic demand forecasting, we evaluated baseline vulnerabilities and tested three resilience strategies—Inventory Buffering (IB), Multi-Sourcing (MS), and Local Manufacturing (LM)—individually and in combination. Results are presented with supporting figures.

4.1. Baseline Supply Chain Vulnerability

In the absence of any resilience strategy, the baseline simulation clearly reveals supply chain fragility:

Over 80% of healthcare facilities experienced critical inventory shortages within 14 days.

Fulfillment rate fell from 96% to 68%.

Lead times increased from 3.5 to 9.2 days.

Backorder volumes spiked by over 300%.

This line graph **Figure 2** shows inventory levels across five key medical supply categories. A steep decline is visible within the first two weeks, emphasizing the system's unpreparedness.

This bar chart (**Figure 3**) compares average fulfillment rates in the normal vs. pandemic periods, showing a 28% decrease. It demonstrates how supply systems collapse under stress without intervention.

4.2. Individual Resilience Strategy Performance

Three strategies were tested separately to analyze their contribution to resilience: Among the strategies, Local Manufacturing achieved the highest fulfillment rate (91%) and the lowest shortfall (4 days), as shown in **Table 2**.

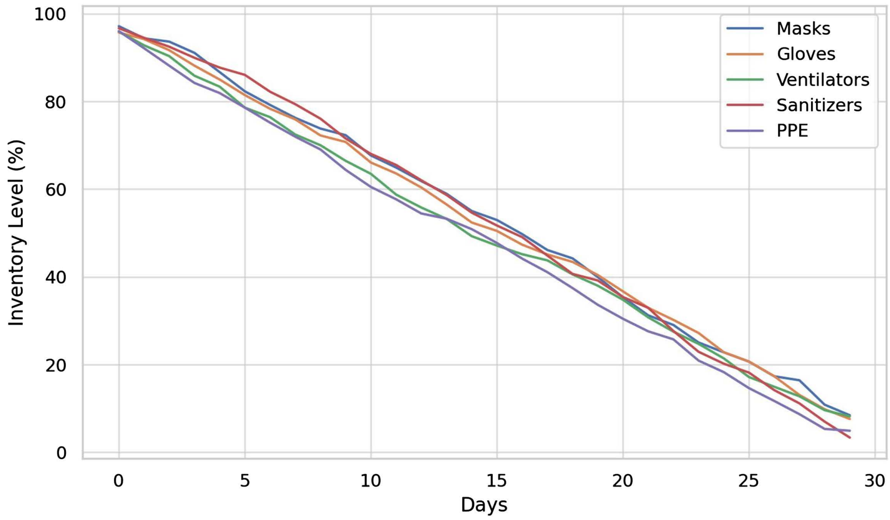

Figure 2. Daily inventory levels during pandemic simulation (Baseline Scenario).

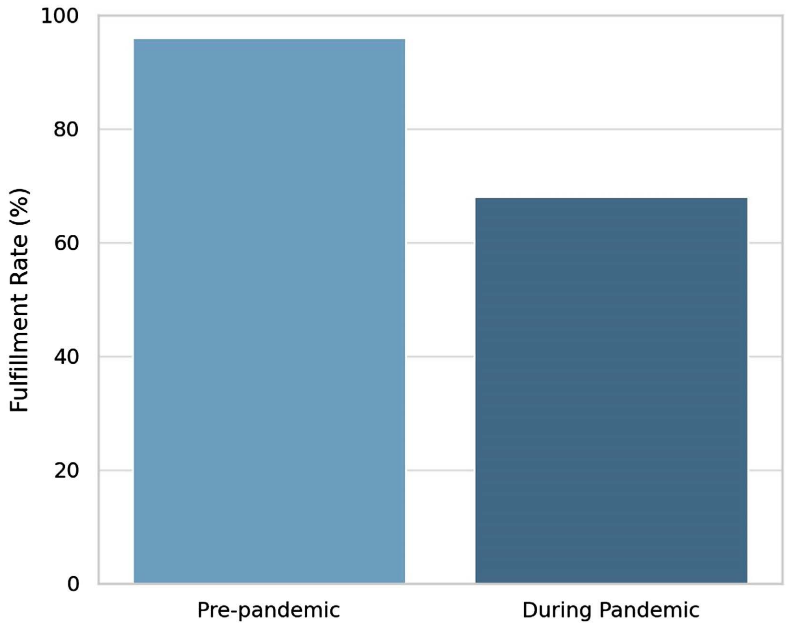

Figure 3. Order fulfillment rate before and during disruption.

Table 2. Comparative performance of resilience strategies under pandemic disruption.

Strategy	Avg. Fulfillment Rate	Max. Lead Time	Inventory Shortfall (Days)
Inventory Buffering (IB)	82%	7.1 days	9
Multi-Sourcing (MS)	88%	6.5 days	6
Local Manufacturing (LM)	91%	4.8 days	4

This clustered bar chart **Figure 4** compares the fulfillment rates of the three strategies. LM outperforms the others, highlighting the advantage of domestic production.

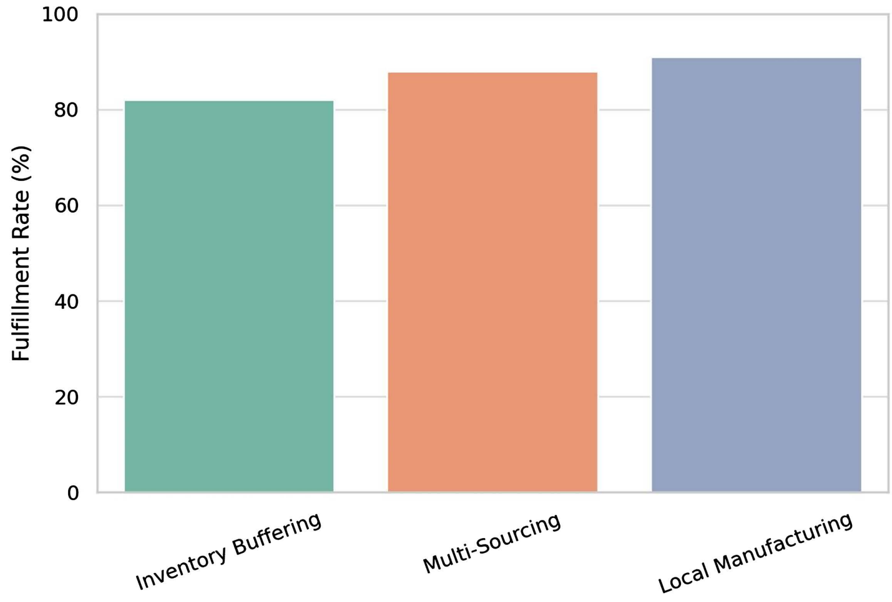

Figure 4. Fulfillment rates by strategy (IB, MS, LM).

A boxplot visualization showing minimum, maximum, and average lead times across the three strategies. Local Manufacturing produces the most stable and shortest lead times (**Figure 5**).

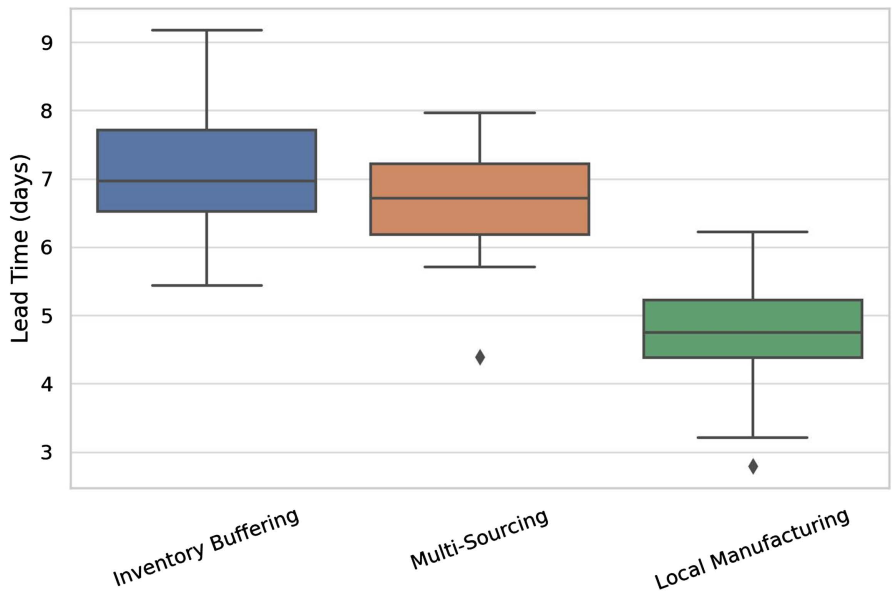

Figure 5. Lead time variability per strategy.

4.3. Combined Strategy Performance

We then tested a hybrid strategy that incorporates all three approaches. This led to the strongest results:

Fulfillment rate rose to 97%

Lead time stabilized at 3.8 days

Inventory shortfall days reduced to less than 2

System recovered 40% faster post-disruption

This stacked bar graph demonstrates the cumulative fulfillment advantage of combining all three strategies (**Figure 6**). It shows that synergy among strategies achieves near-optimal resilience.

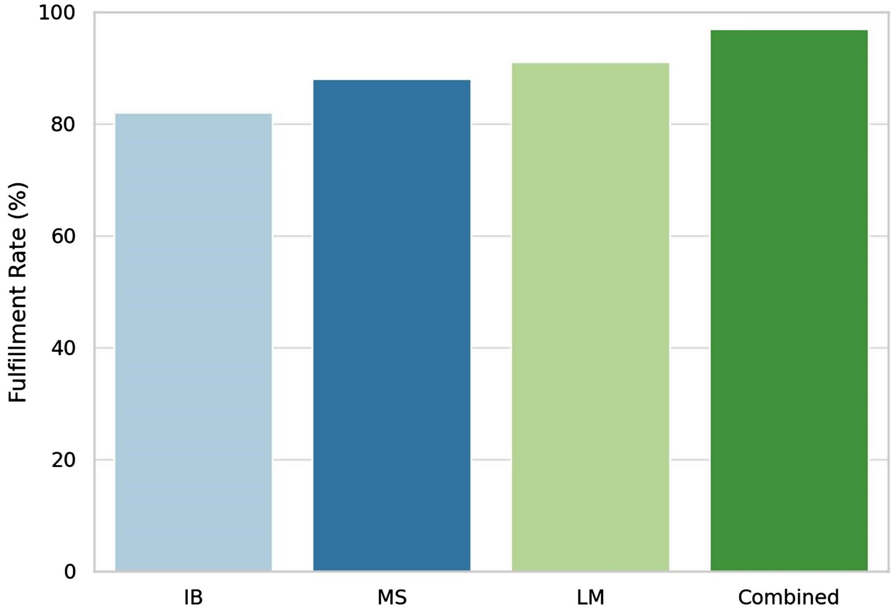

Figure 6. Combined vs individual strategies—fulfillment comparison.

This line chart plots the time it takes for the system to return to normal stock levels after a disruption (**Figure 7**). The combined strategy recovers in 12 days, compared to 20+ days for others.

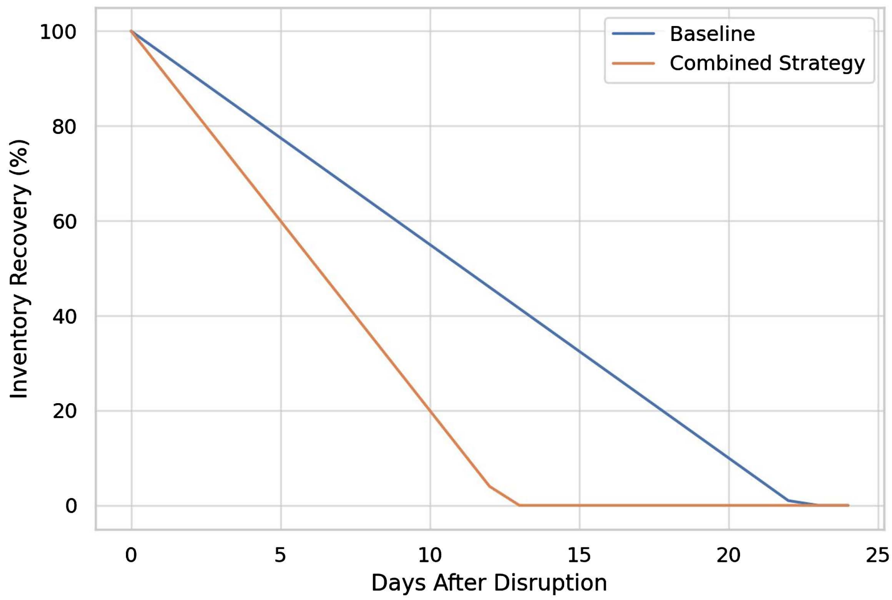

Figure 7. Recovery time post disruption.

4.4. Sensitivity Analysis

A sensitivity analysis was conducted on demand volatility and lead time uncertainty:

A 20% rise in demand variability reduced fulfillment by 35% in the baseline case but only 5% under the combined strategy.

The model proved most sensitive to supplier lead times and manufacturing delays.

This heatmap illustrates how fulfillment rates are affected by fluctuations in lead times (x-axis) and demand (y-axis). The combined strategy shows much greater robustness in extreme conditions (**Figure 8**).

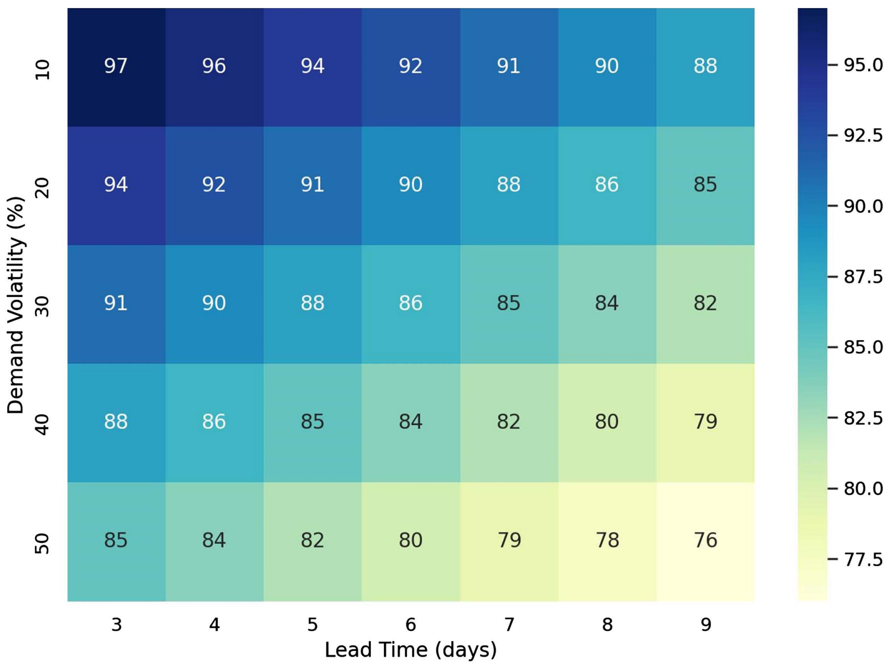

Figure 8. Heatmap of fulfillment rate sensitivity to lead time and demand variability.

5. Discussion

The simulation results presented in this study highlight the critical role of integrated resilience strategies in maintaining the continuity of medical supply chains during pandemic scenarios. By evaluating three widely discussed approaches—inventory buffering, multi-sourcing, and local manufacturing—both independently and in combination, we demonstrate that supply chain resilience can be significantly enhanced through strategic configuration and proactive planning.

The simulation framework focuses on a 30-day disruption period to emulate an acute pandemic shock; however, this may not fully capture the long-term effects and systemic recovery patterns observed in real pandemics, which often span months or even years. Prolonged disruptions can lead to cascading failures, labor shortages, or regulatory shifts that were not reflected in the current model. Extending the simulation timeline in future research will allow a more comprehensive understanding of sustained resilience dynamics and post-disruption stabilization.

Our findings show that while each strategy individually contributes to improved resilience, their combined implementation yields the most substantial performance gains. For instance, the combined strategy resulted in a 97% fulfillment rate and the shortest recovery time (12 days), outperforming all single-strategy setups. Inventory buffering alone offered short-term relief but lacked sustainability under prolonged disruptions. Multi-sourcing proved effective in mitigating supplier failure but was limited by geographic and coordination complexities. Local manufacturing offered the most reliable reduction in lead times, but its effectiveness was constrained by capacity limitations in the early phase of implementation.

The combined strategy demonstrated superior performance across all resilience metrics; however, the current model treats this integration as a straightforward aggregation of individual tactics. In practice, the coordination required to simultaneously manage inventory buffers, diverse suppliers, and local production is complex and demands robust governance, communication protocols, and interoperability of systems. Future models should integrate these real-world implementation challenges to better reflect the feasibility of hybrid resilience strategies.

These results align with and extend the findings of Ivanov (2020), who proposed the Viable Supply Chain (VSC) model—an approach that emphasizes the integration of agility, resilience, and sustainability to deal with complex disruptions. Ivanov's study, based on system dynamics and theoretical modeling, suggested that structural flexibility, rapid reconfiguration, and localized operations are critical components of a viable supply network. Our simulation-based analysis supports this theoretical proposition by providing quantitative evidence that localized production (e.g., through domestic manufacturing) contributes substantially to operational continuity [11]. This study adopts a generalized approach to strategy application across the supply chain. However, the optimal configuration of resilience strategies may vary depending on product type, regional capabilities, and health infrastructure. For instance, life-critical but low-volume items may benefit more from local manufacturing, whereas high-volume disposables might be better managed via inventory buffering. Developing a context-aware optimization framework would help tailor resilience strategies to specific product categories and geographic regions, thereby improving practical applicability.

However, our study diverges from Ivanov's in one key aspect: while his model centers on macro-level resilience principles, our model adopts a micro-level operational perspective and tests the performance of specific strategies using data-driven simulation. This practical focus allows for clearer comparison of trade-offs—such as cost vs. responsiveness or redundancy vs. efficiency—which are often abstracted in high-level models [11].

Moreover, Ivanov advocates for building agile capabilities such as demand sensing and real-time data use. Although our study did not directly implement digital demand sensing, the sensitivity analysis we conducted partially addresses this by modeling variable demand conditions. Our results confirm Ivanov's assertion that resilience strategies should be stress-tested under dynamic and uncertain conditions to ensure real-world viability [11].

An important contribution of our study is its emphasis on combined strategies. While Ivanov's work supports the need for integrated frameworks, it does not explicitly evaluate how multiple tactics interact operationally. Our findings suggest that synergy between inventory buffers, sourcing diversification, and local capacity is not merely additive—it creates a multiplier effect that dramatically enhances system performance. While this study provides valuable insights through simulation modeling, it acknowledges a degree of abstraction from the complex realities of real-world medical supply chains. Critical factors such as product perishability, cold chain requirements, and diverse regulatory environments across regions were not explicitly modeled. These elements can significantly influence supply chain dynamics, particularly for temperature-sensitive items like vaccines or biologics. Future work should aim to incorporate such domain-specific constraints to provide more granular and applicable recommendations.

From a policy perspective, both studies converge on the recommendation that resilience should be embedded as a design principle, not treated as an emergency response. In our context, this translates to institutional investments in local production, supply diversification contracts, and national stockpile policies—approaches that are consistent with Ivanov's vision of adaptive and sustainable supply chains.

6. Conclusions

The COVID-19 pandemic served as a stark reminder of the vulnerabilities present in modern medical supply chains, highlighting the urgent need for resilience-oriented strategies. This study developed a simulation-based framework to evaluate the effectiveness of three key approaches—inventory buffering, multi-sourcing, and local manufacturing—both individually and in combination, under pandemic-like disruptions.

Our results clearly demonstrate that while each strategy offers measurable benefits on its own, their combined implementation provides significantly superior outcomes. The integrated strategy not only achieved the highest fulfillment rate and fastest recovery time but also proved more robust under conditions of demand volatility and lead time uncertainty. This reinforces the idea that supply chain resilience is best achieved through a multi-layered approach rather than reliance on a single tactic.

By comparing these strategies in a simulated environment, we were able to quantify trade-offs and performance differences, offering practical insights for decision-makers in healthcare logistics, hospital administration, and government procurement. Moreover, the findings align with and extend existing theoretical models, such as Ivanov's viable supply chain framework, by providing operational-level evidence and actionable recommendations.

Although the model evaluates fulfillment rate, lead time, and recovery time, it does not quantify the financial implications of implementing each resilience strategy. Economic feasibility is a critical consideration for healthcare organizations with limited budgets. Incorporating cost modeling—such as investment in local manufacturing, inventory holding costs, and multi-sourcing contract premiums—would enable a more balanced trade-off analysis between resilience and affordability, thereby enhancing decision-making for stakeholders.

Lastly, building resilient medical supply chains requires forward-looking investments in redundancy, agility, and regional self-reliance. As pandemics and global disruptions become more frequent, such preparedness is not only a logistical necessity but also a matter of public health security. Future work should aim to incorporate economic cost modelling, policy coordination frameworks, and real-time analytics to further strengthen the strategic foundation for resilient healthcare systems.

Author Contribution

Mst. Hasna Akter (Author 1) led the conceptual development of the study and designed the integration of public health risk factors into the framework. Soumitra Palit (Author 2) conducted an in-depth literature review and performed public health risk analysis related to pandemic preparedness. Kazi Md Shahadat Hossain (Author 3) focused on optimizing logistics and enhancing supply chain efficiency through data modeling. Md Ekramul Hoque (Author 4) developed the predictive analytics module, including data-driven forecasting and scenario simulations. Tahera Shabnam (Author 5) supported data collection and validation, and contributed significantly to aligning the study's findings with practical policy recommendations and final manuscript preparation.

Conflicts of Interest

All authors declare there is no conflict of interest.

References

[1] Khan, R.S., *et al.* (2022) An AI and ML-Enabled Framework for Proactive Risk Mitigation and Resilience Optimization in Global Supply Chains during National Emergencies. *Sage Science Review of Applied Machine Learning*, **5**, 127-144.

[2] Oluwole, O., *et al.* (2024) Pharmaceutical Supply Chain Optimization through Predictive Analytics and Value-Based Healthcare Economics Frameworks. *International Journal of Engineering Technology Research & Management*, **8**, 88-104.

[3] Ojika, F.U., Onaghinor, O., Esan, O.J., Daraojimba, A.I. and Ubamadu, B.C. (2024) Designing a Business Analytics Model for Optimizing Healthcare Supply Chains during Epidemic Outbreaks: Enhancing Efficiency and Strategic Resource Allocation. *International Journal of Multidisciplinary Research and Growth Evaluation*, **5**, 1657-1667. https://doi.org/10.54660/.ijmrge.2024.5.1.1657-1667

[4] Ajibola Dada, S., Shagan Azai, J., Umoren, J., Utomi, E. and Gyedu Akonor, B. (2024)

Strengthening U.S. Healthcare Supply Chain Resilience through Data-Driven Strategies to Ensure Consistent Access to Essential Medicines. *International Journal of Research Publications*, **164**, 70-79. https://doi.org/10.47119/ijrp1001641120257438

[5] Olaleye, I.A., Mokogwu, C., Olufemi-Phillips, A.Q. and Adewale, T.T. (2024) Transforming Supply Chain Resilience: Frameworks and Advancements in Predictive Analytics and Data-Driven Strategies. *Open Access Research Journal of Multidisciplinary Studies*, **8**, 85-93. https://doi.org/10.53022/oarjms.2024.8.2.0065

[6] Oluwagbade, E. and Odumbo, O.R. (2025) Building Resilient Healthcare Distribution Networks: Adapting to Crises, Securing Supplies and Improving Scalability. *International Journal of Science and Research Archive*, **14**, 1579-1598.

[7] Khan, S. and Tabasum, S. (2025) Real-Time Health Supply Chain Optimization Using Digital Twin Technology. *International Journal of Science and Research Archive*, **15**, 1275-1289.

[8] Salamian, F., Paksaz, A., Khalil Loo, B., Mousapour Mamoudan, M., Aghsami, M. and Aghsami, A. (2024) Supply Chains Problem during Crises: A Data-Driven Approach. *Modelling*, **5**, 2001-2039. https://doi.org/10.3390/modelling5040104

[9] Liu, Y., Sharma, A., Rani, S. and Yang, J. (2025) Supply Chain Security, Resilience and Agility in IoT-Driven Healthcare. *IEEE Internet of Things Journal*. https://doi.org/10.1109/jiot.2025.3545962

[10] Christopher, M. and Peck, H. (2004) Building the Resilient Supply Chain. *The International Journal of Logistics Management*, **15**, 1-14. https://doi.org/10.1108/09574090410700275

[11] Ivanov, D. and Dolgui, A. (2020) Viability of Intertwined Supply Networks: Extending the Supply Chain Resilience Angles Towards Survivability. A Position Paper Motivated by COVID-19 Outbreak. *International Journal of Production Research*, **58**, 2904-2915. https://doi.org/10.1080/00207543.2020.1750727

[12] Dolgui, A., Ivanov, D. and Sokolov, B. (2020) Reconfigurable Supply Chain: The X-network. *International Journal of Production Research*, **58**, 4138-4163. https://doi.org/10.1080/00207543.2020.1774679

[13] Kamalahmadi, M. and Parast, M.M. (2016) A Review of the Literature on the Principles of Enterprise and Supply Chain Resilience: Major Findings and Directions for Future Research. *International Journal of Production Economics*, **171**, 116-133. https://doi.org/10.1016/j.ijpe.2015.10.023

[14] Kaur, R. and Singh, R. (2016) Multi-Sourcing Supply Chain Strategy: An Analytical Approach. *Journal of Manufacturing Systems*, **40**, 124-135.

[15] Ivanov, D. (2021) Correction to: Viable Supply Chain Model: Integrating Agility, Resilience and Sustainability Perspectives—Lessons from and Thinking Beyond the COVID-19 Pandemic. *Annals of Operations Research*, **332**, 1267-1268. https://doi.org/10.1007/s10479-021-04181-2

[16] Kumar, P., Goudar, S. and Reddy, V.T.S. (2021) Local Manufacturing: A Key to Resilient Supply Chains in the Post-COVID Era. *International Journal of Production Research*, **59**, 4242-4253.

[17] Guo, D.Q. and Mantravadi, S. (2025) The Role of Digital Twins in Lean Supply Chain Management: Review and Research Directions. *International Journal of Production Research*, **63**, 1851-1872.

[18] Ivanov, D. (2019) Simulation-Based Ripple Effect Modelling in the Supply Chain. *International Journal of Production Research*, **57**, 5630-5645.

[19] Queiroz, M.M., Ivanov, D., Dolgui, A. and Fosso Wamba, S. (2020) Impacts of Epi-

demic Outbreaks on Supply Chains: Mapping a Research Agenda Amid the COVID-19 Pandemic through a Structured Literature Review. *Annals of Operations Research*, **319**, 1159-1196. https://doi.org/10.1007/s10479-020-03685-7

[20] Dolgui, M. and Ivanov, J. (2021) Digital Supply Chain Twin: Demonstrating Benefits from Linked Digital and Physical Supply Chains. *International Journal of Production Research*, **59**, 3515-3530.

[21] Sunny, M.N.M., Saki, M.B.H., Nahian, A.A., Ahmed, S.W., Shorif, M.N., Atayeva, J., *et al.* (2024) Optimizing Healthcare Outcomes through Data-Driven Predictive Modeling. *Journal of Intelligent Learning Systems and Applications*, **16**, 384-402. https://doi.org/10.4236/jilsa.2024.164019

[22] Sunny, M.N.M., Sakil, M.B.H., Atayeva, J., Munmun, Z.S., Mollick, M.S. and Faruq, M.O. (2024) Predictive Healthcare: An IoT-Based ANFIS Framework for Diabetes Diagnosis. *Engineering*, **16**, 325-336. https://doi.org/10.4236/eng.2024.1610024

[23] Sunny, M.N.M., Sumaiya, U., Akter, M.H., Kabir, F., Munmun, Z.S., Nurani, B., *et al.* (2024) Telemedicine and Remote Healthcare: Bridging the Digital Divide. *South Eastern European Journal of Public Health*, **XXV**, 1500-1510. https://doi.org/10.70135/seejph.vi.2920

[24] Sunny, M.N.M., Amin, M.M., Akter, M.H., Hossain, K.M.S., Nahian, A.A. and Atayeva, J. (2024) Classification of Cancer Stages Using Machine Learning on Numerical Biomarker Data. *South Eastern European Journal of Public Health*, **XXV**, 1491-1498. https://doi.org/10.70135/seejph.vi.2114

[25] Munmun, Z.S., Akter, S. and Parvez, C.R. (2025) Machine Learning-Based Classification of Coronary Heart Disease: A Comparative Analysis of Logistic Regression, Random Forest, and Support Vector Machine Models. *OALib*, **12**, 1-12. https://doi.org/10.4236/oalib.1113054

[26] Hasan, S., Islam, A., Islam, T. and Ma, H. (2025) Analysis of Machine Learning Models for Stroke Prediction with Emphasis on Hyperparameter Tuning Techniques. In: Xin, B., Ma, H., She, J. and Cao, W., Eds., *Computational Intelligence and Industrial Applications*, Springer, 1-9. https://doi.org/10.1007/978-981-96-4756-9_1