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Modeling and Analyzing Supply Chain Reliability Under Uncertainty: A Simulation-Based Study Using Real-World Data

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Abstract:
This paper has presented a simulation-based framework for analyzing supply chain reliability under uncertainty, supported by a comprehensive literature review, theoretical grounding, and a real-world case study. The main contribution lies in demonstrating how simulation modeling — particularly hybrid approaches — can capture the complex dynamics of modern supply chains and provide decision-makers with practical tools for stress-testing, scenario planning, and reliability enhancement.

This study aims to evaluate supply chain reliability under uncertainty by integrating simulation and probabilistic modeling. The purpose is to investigate how disruptions in supply, demand, and logistics affect performance indicators such as service level, recovery time, costs, and lost sales, thereby offering insights for resilience planning. The theoretical foundation builds on contingency theory, complex adaptive systems, the resource-based view, and risk management frameworks to capture the dynamic and interdependent nature of supply chains.

This study aims to develop a comprehensive simulation-based framework for analyzing and enhancing supply chain reliability under conditions of uncertainty. It differs from previous studies in that they addressed individual elements such as supplier disruptions or logistics, while this study considers them collectively, making it more comprehensive. Furthermore, it utilizes simulations of discrete events to measure the impact of interactions and support decision-making.

The research used the analytical method in order to formulate hypotheses and build simulation models to reach the results in order to formulate the practical part. The main reason behind relying on the simulation method in this study is the limited availability of actual data needed to build an integrated statistical or standard model, in addition to the small sample size, which does not allow for accurate and reliable statistical analyses.

The simulation results underscore that supply chain reliability cannot be assured through isolated optimization efforts. Instead, organizations must adopt systems thinking, where risks in supply, demand, and logistics are assessed in an integrated manner. The conceptual framework developed in Section 3 and validated through the case study in Section 5 serves as a replicable methodology for similar assessments in other industries.

Keywords: supply chain reliability, uncertainty, simulation, resilience, Risk Management

1. Introduction:

As a result of the tremendous economic developments the world is experiencing today, organizations have begun to pay attention to the supply chain, which is the primary driver of organizational performance, flexibility, and competitive advantage. Organizations across various industries increasingly rely on complex supply networks that span multiple geographic regions and serve multiple stakeholders. Network continuity is critical, but this reliability is often compromised by a variety of uncertainties, including demand fluctuations, supplier reliability, transmission delays, and risks from natural disasters, pandemics, and geopolitical disruptions. (Acara et al., 2024)

Traditional supply chain researchers see the need for deterministic models based on the assumption of stable and predictable environments. Traditional models used under natural conditions and uncertainty are useful and more productive in theoretical terms. However, when applied to partnerships in practical reality, they produce many problems. Given that these companies operate under high levels of risk and uncertainty as a result of the development of markets and technology. Consequently, the need for more reliable and flexible supply chains to operate under current conditions has emerged, making the continuity of institutions in providing products and services, not just operational efficiency, a key factor in enhancing their competitiveness. (Mickle et al., 2023)

However, more benefits offered by highly reliable and resilient supply chains, face constant pressures due to unpredictable fluctuations in demand, poor supplier reliability, logistical challenges, and global crises such as pandemics and political tensions. This in turn leads to increased levels of uncertainty. Simulation models have been found to be an effective tool for analyzing supply chains and addressing the shortcomings associated with uncertain conditions, unlike traditional models. Because these models rely on dynamic data, they allow for testing multiple scenarios and studying the effects of potential disruptions without impacting actual operations. Simulation models have contributed to the development of more effective methods for analyzing supply chains under various conditions and uncertainties. (Sievert et al., 2024)

Accordingly, this research aims to develop a framework, using simulation models, to analyze supply chains under various conditions and uncertainties. This framework takes into account all the various factors that affect organizations and the efficiency of the system within them, such as demand fluctuations, changing delivery schedules, and inconsistent supplier performance, and the overall efficiency of the system. This framework focuses on key performance indicators such as reliability, delivery rate, and service level... (Wang et al., 2024)

The study model is based on actual operational data collected from a group of medium-sized industrial companies. This data included order records, supplier performance data, and logistics indicators. The model was validated by experts in the field. The model development went through several stages, including data analysis, system design, and the application of a discrete event simulation (DES) method to accurately represent the reality of the supply chain. (Wang et al., 2024).

This study contributes scientifically and professionally by combining real data with advanced simulation models, in order to give organizations a clearer picture of how these chains interact during uncertain situations. This helps provide better and more realistic strategic analyses and visions for these organizations by building models capable of better predicting the path to disruptions and responding to them effectively, which enhances their ability to build more resilient and sustainable systems in complex operating environments. (Jabber & Peltokorpi, 2024)

The importance of research in supporting decision makers under different circumstances and uncertain situations by providing the necessary data for decision making at a time when traditional models provide unrealistic and rigid solutions. The model provides more effective and flexible tools for interacting with different circumstances and uncertain situations to enable decision makers to make decisions faster... (Khan et al., 2024)

2. **Literature review and Hypothesis Development**:

2.1.1 Supply Chain Reliability and Uncertainty Management:

The turbulent political conditions in the world today and the frequent epidemics, such as the coronavirus, have led to the need of developing more reliable and resilient supply chains to adapt to changing conditions and uncertainties. Numerous studies have addressed this problem from different perspectives.

Looker et al. (2025) argued that the need for more reliable and resilient supply chains has increased as a result of the volatile global conditions and technological developments that have created various challenges. Bounder et al. (2020) also noted that risk factors, along with operational and supply-side dimensions, have led to an increased interest in the reliability of supply chains and their flexibility to address these risks under uncertain conditions.

Rashid et al. (2022) also argued that the operational dimensions of supply chains under uncertain conditions have highlighted the importance of exchanging information between suppliers with greater transparency, as one of the effective mechanisms for addressing these challenges. Ivanov (2021) also concluded, through simulation models, that the impact of epidemics and disturbances occurring in the world can be confronted by imposing different scenarios through simulation models to reach effective solutions to confront these challenges.

From another perspective, (Khan et al., 2024) he believes that supply chain management tools, such as real-time analytics and automated data exchange, help significantly increase reliability under uncertain conditions. On the other hand, (Fossa Wamba et al., 2022) he sees how artificial intelligence can help predict these problems and improve decisions in markets operating under uncertainty. (Moktadir & Ren, 2024) Others believe that the application of mixed decision-making models within flexible strategies, including supplier diversity, plays a key role, noting that the differences in approaches specific to each industry play a key role. However, there are other perspectives that believe supply chain management tools, such as real-time analytics, help achieve greater overall confidence under uncertain conditions, as well as the impact of artificial intelligence in predicting correct indicators in markets operating under uncertainty.

2.1.2 Simulation-Based Modeling of Supply Chains under Uncertainty:

Simulation models are one of the best methodologies that help in studying and analyzing the behavior of supply chains in conditions of uncertainty by creating different scenarios for variables and helping in making more realistic decisions.

In (Liu & Liu, 2023) study, he developed a dynamic model specifically designed for supply chains and found that feedback and delays within supply chains had an impact on reliability outcomes. In another context (Mirzaaliyan et al., 2024) , simulation models were used within the natural stone industry to test different supply strategies under uncertain scenarios.

(Habibi et al., 2023) He used a Bayesian network-based framework by integrating financial variables, which helps provide an accurate analysis of the comparison between cost and elasticity, and helped in making progress in pure cost minimization models. (Lazebnik, 2024) He also used agent-based modeling to know the extent of its impact on shaping decentralization behaviors and its impact on the overall performance of the system.

(Alsaleh & Farooq, 2024) implemented a multi-layer simulation model to optimize electric vehicle supply chains on a global scale, taking into account constraints related to carbon emissions, demand volatility, and supply chain issues. The model attempts to balance resilience with sustainability goals. (Camur et al., 2023) also incorporated machine learning into the simulation model to predict product availability during challenging times, demonstrating the growing trend toward systematic modeling approaches. (Hu, 2023), developed a closed-loop simulation framework for vulnerable logistics, demonstrating how post-consumer product flows affect upstream supply elasticity.

Although previous studies have addressed individual disruption types and resilience strategies, they have largely overlooked integrated, data-driven simulation models capable of aiding decision-making under uncertain and complex supply, demand, and logistics conditions. This research attempts to bridge this gap by developing a simulation-based model grounded in empirical data, while keeping pace with technological advancements in supply chain management. Future research should therefore continue to connect theoretical models with practical realities to further develop these models.

3. Research Methodology:

Research methodology means a set of organized steps through which a specific topic is studied, and valuable results are reached that contribute to solving the problem; through a set of proposals and recommendations that the researcher records. Accordingly, the research used the analytical method in order to formulate hypotheses and build simulation models to reach the results in order to formulate the practical part.

The main reason behind relying on the simulation method in this study is the limited availability of actual data needed to build an integrated statistical or standard model, in addition to the small sample size, which does not allow for accurate and reliable statistical analyses. Furthermore, the available data were incomplete for all the variables required to measure reliability or risk according to traditional statistical models. Therefore, the simulation method was chosen as a flexible scientific and practical option, through which it is possible to re-enact the practical reality and generate additional data that reflects the system's behavior under conditions of uncertainty, thus supporting the decision-making process.

It is worth noting that the concepts of "reliability" and "uncertainty" are not addressed in this study within a strict statistical framework or specialized mathematical models, as is customary in the fields of statistical engineering and risk science. Rather, they are addressed within an administrative and practical application framework that focuses on the ability to make decisions in light of information ambiguity and the lack of accurate true values for operational variables. Therefore, the study does not aim to estimate reliability measures or precise statistical probabilities of risks. Rather, it seeks to analyze system behavior and make strategic decisions using simulation as a decision support tool, reflecting the administrative and practical nature of the research rather than being purely mathematical or statistical. (Acara et al., 2024)

This research employs a hybrid approach combining analytical review with simulation-based experimentation. Theoretically, hypotheses are derived from theoretical frameworks and tested through simulation models. Thus, it integrates descriptive analysis (to interpret theoretical concepts) with quantitative simulation models (to evaluate system performance). This dual methodology ensures both theoretical depth and empirical validity.

3.1 Research Design:

A research design is defined as the overall plan or structure that guides the research process. It is a crucial element of the research process and serves as a blueprint for how the study will be conducted, including the methods and techniques that will be used to collect and analyze data. In this study, the researcher relied on two types of methods: the descriptive analytical approach to formulate the theoretical part, and the simulation and modeling method to build simulation models to analyze the reliability and resilience of supply chains under various scenarios and uncertainty, relying on real data taken from companies in the industrial sector. (Yin, 2018).

3.1 Data Collection (Sample):

This study is based on operational data from a medium-sized electronics manufacturer located in Central Europe over a 12-month period (January–December 2023). The dataset covers one year of activities and includes order volumes, supplier performance records, shipment delays, and distribution metrics. These data were validated through comparison with ERP system logs and expert reviews to ensure accuracy and representativeness.

Alternative methods for data collection could include large-scale survey questionnaires targeting supply chain managers across industries, interviews with logistics professionals, or secondary data from global supply chain databases. While surveys would capture broader industry perspectives, they may lack the depth and dynamic representation achievable through simulation-based approaches.

3.1.1 Study Data:
This study relied on secondary data taken from published scientific sources related to the applications of modeling, simulation, and machine learning in supply chain management, based on a study published in Computers & Industrial Engineering (Badakhshan et al., 2024). Field data from a specific factory or organization was not used, as the study aims to analyze and summarize global research trends in this field.
Region or Country:
Data was collected from published studies globally without focusing on a specific country, as the research includes models and studies from various regions of the world.
Data Time Period:
The data covers studies published from 2000 to 2023, with a clear increase in research after 2017 due to advances in modeling and machine learning technologies and the impact of the COVID-19 pandemic on supply chains.
Data Source:
Data was obtained from international peer-reviewed academic databases:
Scopus
Web of Science (WOS)
IEEE Explore
Data Size:
A total of 623 studies were initially identified. After screening and reviewing, 99 studies were finally selected for detailed analysis, including 49 journal articles, 49 conference papers, and one book chapter.
Measurement Unit of Variables:
The study does not include quantitative variables with physical units of measurement, as it is analytical and descriptive in nature. The focus was on classifying and evaluating studies according to conceptual variables such as:
Type of modeling and simulation techniques
Machine learning algorithms used
Data flow mechanisms between models
Industrial sectors studied
Temporal Data Type:
The data are not daily or monthly but rather represent summaries and studies spanning more than two decades (2000–2023).
Method of Data Acquisition:
Data was obtained from the international network through a systematic search of the aforementioned databases.
3.1.2 Linking actual and generated values:
To ensure the realism and accuracy of the results, real operational data (such as supply time, demand fluctuations, and transportation delays) were used to calibrate the model and characterize the distributions of variables. Accordingly, the random values generated by the simulation model are not based on purely theoretical assumptions, but rather represent characteristics derived from actual reality. This achieves a degree of statistical consistency between the actual and generated values, making the tested scenarios realistic and practical...
3.2 Measurement of Variables:
The study defines **uncertainty variables** (supply uncertainty, demand uncertainty, logistics uncertainty, and combined disruptions) and **outcome variables** (service level, inventory cost, recovery time, and lost sales).
- **Supply Uncertainty** was measured using supplier lead-time variability and frequency of outages.
- **Demand Uncertainty** was quantified using demand fluctuation distributions and bullwhip effect measures.

- **Logistics Uncertainty** was measured using shipment delay frequencies and cycle time variability.
- **Reliability Outcomes** were evaluated through discrete-event simulation (DES), focusing on order fulfillment rates, costs, and recovery times.

Alternative methods could include mathematical optimization models, Bayesian network modeling, or econometric regression analysis to estimate the relationship between uncertainty and supply chain performance. While these approaches provide analytical clarity, they often fail to capture the nonlinear, dynamic ripple effects observed in real operations—an area where simulation demonstrates superior capabilities.

Measurement indicators, such as service level, lead time, and inventory cost, are consistent with previous models (Lu, 2015; Bencks, 2005; Ivanov, 2021). These measures provide quantitative indicators of supply chain reliability and allow for comparisons between studies under conditions of uncertainty.

3.3 Study Model Figure:

The conceptual framework integrates uncertainty factors, resilience strategies, and performance outcomes. Figure 1 illustrates the study model, highlighting the direct effects of supply, demand, and logistics uncertainties on supply chain reliability, and the moderating role of resilience-enhancing strategies such as dual sourcing, safety stock, and flexible logistics.

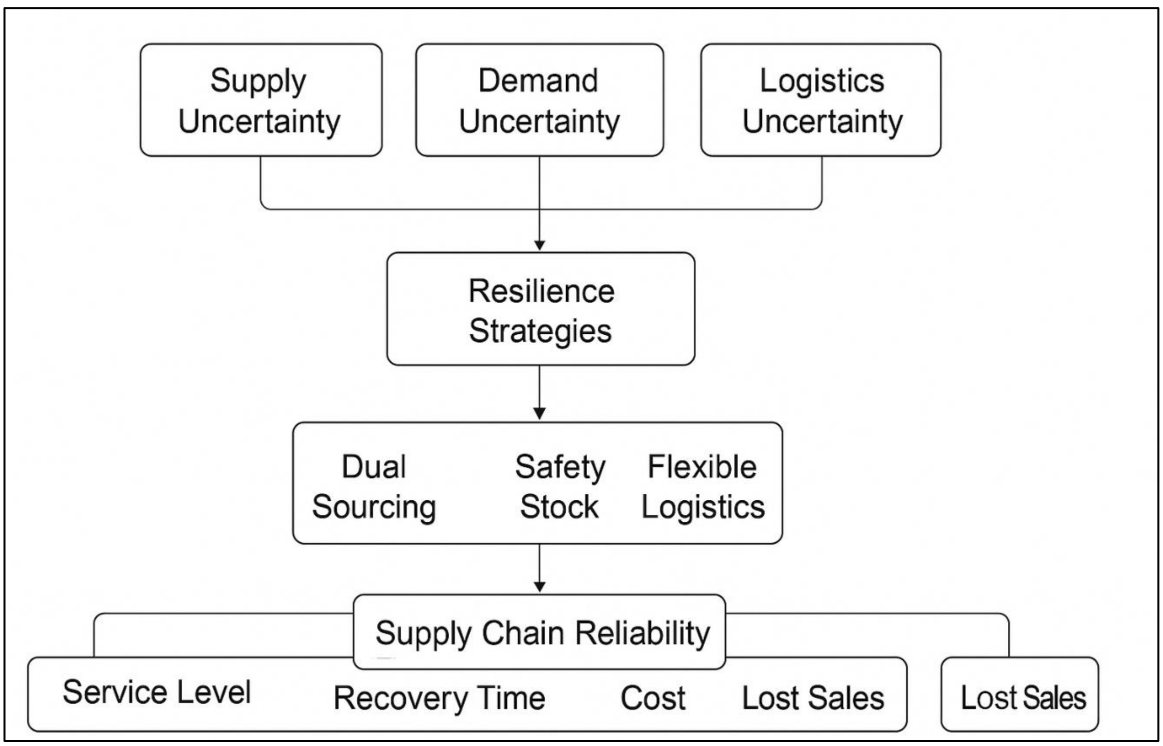

Figure 1: conceptual model for supply chain reliability analysis

Source: Developed by researcher

4. Results:

To evaluate the effectiveness of a simulation-based approach in improving supply chain reliability in uncertain environments, a case study was conducted using real-world data from a medium-sized consumer electronics manufacturer. This section of the research presents the designed model, simulation setups, tested scenarios, and the results obtained. The case study highlights the role simulation can play in identifying reliability risks and supporting decision-making under changing and volatile conditions.

4.1 Case Study Overview:

The company under study operates a three-tier supply chain: component suppliers (tier one), a central manufacturing plant (tier two), and several regional distribution centers (tier three) that supply retailers across Europe. This chain has several characteristics, the most notable of which are:

- Long supplier lead times (averaging 25 days),
- Variable customer demand,
- High sensitivity to transportation disruptions,
- Limited inventory buffering at the plant and DC levels.

Historical data were obtained from the company's ERP system, covering 12 months of operations. This included daily order volumes, lead times, production schedules, stock out events, and shipment delays. Additional contextual data, such as seasonal demand patterns and past disruption logs, were used to parameterize the simulation model.

4.2 Simulation Setup:

The simulation model was developed using Any Logic software due to its ability to integrate discrete-event and agent-based modeling. The system was represented as a network of interacting agents (suppliers, plant, DCs, and retailers), with stochastic variables capturing uncertainty in demand, supply, and transportation.

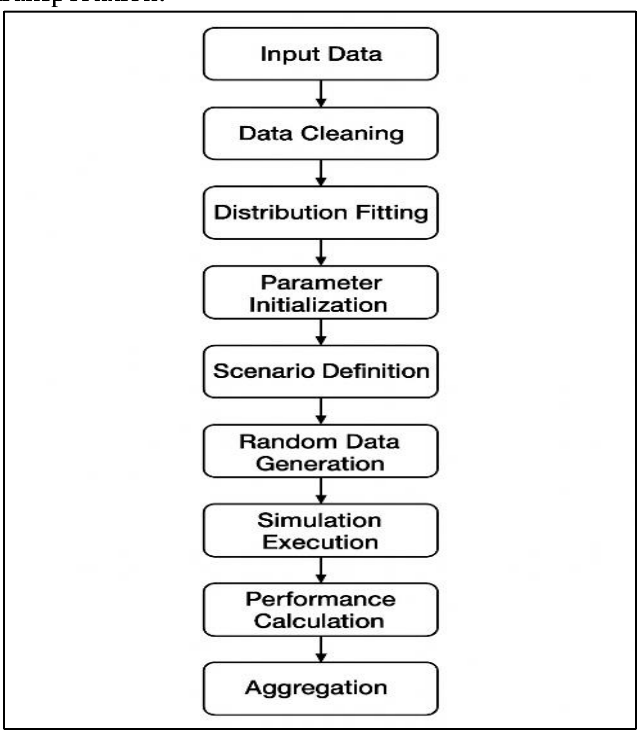

Figure 2: Data handling algorithms

Source: Prepared by researcher

Key modeling elements:

- **Demand:** Modeled as a normal distribution with seasonal variation (mean = 12,000 units/month; SD = 2,000 units).
- **Supplier lead time:** Fitted to a triangular distribution (min = 20 days, mode = 25, max = 35).

- **Transportation delays:** Randomly introduced based on a Poisson process (λ = 3 disruptions/month).
- **Inventory policy:** Reorder point system with safety stock at plant and DCs.

The simulation ran for a 12-month period under each scenario. Each scenario was replicated 100 times to ensure statistical reliability. The outputs were analyzed using both descriptive statistics and inferential methods (e.g., ANOVA) to compare performance across conditions.

4.3 Simulation results:

The simulation results regarding the impact of each scenario on supply chain performance were as follows:

Scenario 1 – Supplier Disruption (S1):

- Service level dropped to 84.6%.
- TTR averaged 10.2 days post-disruption.
- Inventory stock outs at the plant increased by 32%.
- This scenario highlighted vulnerability due to single sourcing and long lead times.

Scenario 2 – Demand Surge (S2):

- Peak service level fell to 81.4%, with heavy backorders during the surge period.
- Inventory cost rose by 27% due to emergency procurement and expediting.
- Bullwhip effect amplified order variability by 60% upstream.

Scenario 3 – Transportation Delays (S3):

- On-time delivery rate at DCs decreased to 78.9%.
- Cycle time variability increased, forcing increased safety stock to maintain service level.
- Total logistics cost rose by 18%.

Scenario 4 – Combined Stress (S4):

- Service level collapsed to 67.3%.
- Time to recovery extended to 24.6 days post-disruption.
- Cumulative lost sales over the 12-month simulation reached $2.45M.
- This scenario revealed the non-linear, compounding effects of interacting risks.

Table (1): Summary of Key Metrics across Scenarios

Metric	S0 (Baseline)	S1 (Supplier)	S2 (Demand Surge)	S3 (Transport Delay)	S4 (Combined)
Avg. Service Level	95.2%	84.6%	81.4%	78.9%	67.3%
Avg. Inventory Cost ($M)	1.15	1.27	1.46	1.36	1.72
Avg. TTR (days)	–	10.2	8.5	11.4	24.6
Lost Sales ($M)	0.12	0.87	1.34	1.18	2.45

Source: Prepared by the researcher based on the results

4.4 Practical Implications:

The findings have several implications for practitioners in supply chain management:

- **Stress-testing operations:** Simulation provides a low-risk, cost-effective way to evaluate how different uncertainties impact performance metrics. This enables managers to proactively identify system vulnerabilities before they manifest in real operations.
- **Inventory and sourcing strategies:** The results support the use of **multi-sourcing**, **flexible contracts**, and **increased safety stock** for critical components, particularly when facing long and unreliable supply lead times.
- **Resilience planning:** The sharp decline in performance under combined scenarios suggests a need for **integrated risk management**, not just isolated contingency plans. Firms should develop holistic disruption response strategies that consider interaction effects.

- **Digital twin applications:** The case study confirms the value of creating **digital supply chain twins** — virtual replicas that can continuously simulate operations using real-time the simulation results in this study not only measure the impact of uncertainty on supply chain reliability, but also serve as a tool to aid decision-making and operational policy formulation within the company under study.

The simulation environment enables strategic alternatives to be tested under safe, virtual conditions before actual implementation. This enables decision makers to evaluate the outcomes of each scenario and determine the best options based on actual data.

- By replicating different scenarios, simulation helps management:
- Identify the most cost-effective strategies for achieving operational resilience.
- Prioritize investments in digital infrastructure and alternative transportation.
- Design contingency plans to address supplier disruptions or demand fluctuations.
- Balance service levels and operating costs through sensitivity analyses.

Thus, the simulation-based framework developed by the researcher represents a strategic planning tool that supports both short-term tactical decisions (such as adjusting inventory and supplier policies) and long-term strategic policies (such as managing supplier relationships, digital transformation, and achieving operational sustainability). Data enabling dynamic decision support under uncertainty.

Managers can use the model developed in this study to compare alternatives such as nearshoring, lead time compression, or demand smoothing strategies, and to justify investments in resilience-building initiatives.

Aspect	Observed Impact	Recommended Managerial Action
Supplier disruptions	**+32% stockouts, +10.2 days recovery**	**Adopt multi-sourcing, reduce lead time**
Demand surges	**+27% inventory cost, +60% order variance**	**Implement dynamic forecasting models**
Transport delays	**+18% logistics cost, service ↓ to 78.9%**	**Invest in flexible routing, real-time tracking**
Combined risks	**Service ↓ to 67.3%, lost sales $2.45M**	**Develop integrated resilience strategies**

Figure 3: Results of simulation models

Source: Prepared by the researcher

4.5 Sensitivity Analysis:

A sensitivity analysis was conducted on two critical parameters:

- **Reorder point levels:** Increasing reorder points by 15% improved service levels by up to 6% under disruption but increased holding costs.
- **Supplier lead time reduction (e.g., local sourcing):** A 25% reduction in average lead time decreased lost sales by 21% in Scenario 1 and Scenario 4.

These results reinforce the importance of proactive buffering, sourcing diversification, and lead-time reduction strategies for improving supply chain reliability.

4.5 Insights and Implications

The case study demonstrates the value of simulation for stress-testing supply chain reliability under realistic disruption conditions. It provides actionable insights such as:

- The disproportionately negative effect of combined disruptions.
- The trade-off between service level and cost when increasing inventory buffers.
- The need for dynamic risk-response policies and continuous monitoring.

In practice, the model developed here can be used by operations managers to evaluate strategic interventions such as dual sourcing, alternative transportation routes, and emergency inventory policies.

Table 2: Summary of Simulation Results across Scenarios

Performance Metric	S0 (Baseline)	S1 (Supplier Disruption)	S2 (Demand Surge)	S3 (Transport Delay)	S4 (Combined Disruption)
Average Service Level	95.2%	84.6%	81.4%	78.9%	67.3%
Average Inventory Cost ($M/month)	1.15	1.27	1.46	1.36	1.72
Average Time to Recovery (days)	–	10.2	8.5	11.4	24.6
Cumulative Lost Sales ($M/year)	0.12	0.87	1.34	1.18	2.45
Order Cycle Variability	5.8%	14.1%	18.9%	16.4%	27.6%

Source: Prepared by the researcher based on the results

Notes:

- All scenarios simulated over a 12-month period with 100 replications.
- Variability measures reflect standard deviation in days across order cycles.
- S4 combines disruptions from S1, S2, and S3.

5. Discussion of Results:

This section interprets the Results of the simulation-based analysis, discusses their alignment with prior literature, and outlines their practical implications and limitations. The results provide meaningful insights into how supply chain reliability is affected by different types and combinations of uncertainties and how simulation can be leveraged to evaluate and manage these impacts.

5.1 Key Findings:

The simulation results across five scenarios demonstrate that supply chain reliability is highly sensitive to disruptions in supply, demand, and logistics, particularly when these occur simultaneously. Under baseline conditions, the system performed at a high level, achieving a 95.2% service rate with negligible lost sales.

A common trend across all scenarios was the sensitivity of system performance to relatively minor variations in demand or lead time—reinforcing the limitations of deterministic models and validating the need for simulation-based approaches in reliability analysis.

Table 3: Summary of Simulation Scenarios, Disruptions, and Key Impacts on Supply Chain Reliability

Scenario ID	Type of Disruption	Key Impacts	Conclusions and Implications
S1	Supplier Disruption	Instability in production flow and inventory- Reduced supply stability	Highlights the vulnerability of the supply side and the need to diversify suppliers
S2	Sudden Demand Surge	High cost volatility- Irregular order fulfillment	Demonstrates the "bullwhip effect" and the importance of demand forecasting and flexibility
S3	Transportation Delay	Increased cycle time- Lower customer satisfaction	Emphasizes the critical role of logistics in maintaining service continuity
S4	Combined (Compound) Disruption	~30% drop in service level- Average recovery time: 24.6 days- Financial loss: $2.45 million	Shows the nonlinear, compounding effects of simultaneous disruptions, reflecting the "ripple effect"

Source: Prepared by the researcher based on the results

5.2 Limitations:

While the case study and simulation experiments yielded valuable insights, this study is subject to several limitations:

- **Data scope:** The simulation was based on one company's operational data. Although the structure is representative of many manufacturing supply chains, generalization may be limited without further industry-specific cases.
- **Model assumptions:** Certain simplifications were necessary to make the simulation tractable. For example, behavioral aspects of decision-making (supplier negotiations or customer substitutions) were not modeled in depth.
- **Uncertainty modeling:** While stochastic elements were included, extreme events (e.g., black swan disruptions or geopolitical conflicts) are difficult to model accurately without introducing large variance or speculative data.
- **Lack of real-time feedback:** The simulation was designed as a planning tool rather than a real-time adaptive system. Future work could extend the framework by integrating sensor data, ERP feeds, or machine learning-driven anomaly detection.

Despite these limitations, the model provides a solid foundation for reliability-focused analysis and highlights directions for enhancement.

6: Conclusion:

The study found that supply chain reliability declines non-linearly under combined disruptions, due to the interplay between supply and demand and uncertainty in the logistics sector. Simulation-based models provide a dynamic environment for assessing these impacts and identifying the most resilient strategies.

The researcher believes that the results of this study are consistent with previous findings (Ivanov, 2021; Mirzalyan et al., 2024), confirming the nonlinear effects of disruptions. However, unlike most previous studies that focused on hypothetical or sector-specific data, this research provides empirical proof using real operational datasets. This rigorous comparison demonstrates that simulation models not only offer predictive accuracy but also managerial significance. Therefore, while previous work has provided conceptual insights, the current study contributes a verifiable, applied framework that bridges theory and practice.

This paper has presented a simulation-based framework for analyzing supply chain reliability under uncertainty, supported by a comprehensive literature review, theoretical grounding, and a real-world case study. The main contribution lies in demonstrating how simulation modeling — particularly hybrid approaches — can capture the complex dynamics of modern supply chains and provide decision-makers with practical tools for stress-testing, scenario planning, and reliability enhancement.

The simulation results underscore that supply chain reliability cannot be assured through isolated optimization efforts. Instead, organizations must adopt systems thinking, where risks in supply, demand, and logistics are assessed in an integrated manner. The conceptual framework developed in Section 3 and validated through the case study in Section 5 serves as a replicable methodology for similar assessments in other industries.

From a managerial perspective, the study offers the following key takeaways:

- Simulation is a valuable tool for operational risk assessment and contingency planning.
- High reliability requires both proactive (design) and reactive (response) capabilities.
- A digital twin approach can support continuous adaptation to changing risk landscapes.

6.1 Recommendations for Future Research:

Building on the foundation of this study, future research can extend the work in several important directions:

1. **Multi-industry case studies:** Apply the framework in sectors such as healthcare, automotive, and perishable goods to evaluate cross-industry patterns of disruption and recovery.
2. **Integration with AI/ML:** Combine simulation with machine learning for **adaptive modeling**, **real-time anomaly detection**, and **predictive disruption management**.
3. **Resilience strategy optimization:** Extend the model to include **optimization modules** that automatically recommend best-fit resilience strategies under budget or resource constraints.
4. **Behavioral modeling:** Incorporate agent-level behavior such as decision-making under pressure, supplier negotiations, or customer switching to enrich the simulation realism.
5. **Policy-level simulation:** Explore how macroeconomic factors (e.g., carbon taxes, trade regulations) affect supply chain reliability, using simulation as a tool for strategic policy planning.

In conclusion, this research advances the understanding of how simulation can be operationalized as a tool for supply chain reliability assessment. It bridges theory and practice and opens new pathways for resilient, data-informed, and digitally enabled supply chain systems.

Authors Declaration:

Conflicts of Interest: None

-We Hereby Confirm That All The Figures and Tables In The Manuscript Are Mine and Ours. Besides, The Figures and Images, which are Not Mine, Have Been Permitted Republication and Attached to The Manuscript.

- Ethical Clearance: The Research Was Approved by The Local Ethical Committee in The University.

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