

AI-Driven Causal Scenario Analysis for Healthcare Supply Chain Resilience

Manuscript Information

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Abstrak

Rantai pasok layanan kesehatan beroperasi dalam lingkungan yang sangat tidak pasti, di mana gangguan pemasok, fluktuasi permintaan, kekurangan persediaan, kegagalan transportasi, dan keterbatasan kapasitas dapat mengancam ketersediaan berkelanjutan sumber daya medis esensial. Kecerdasan buatan memberikan peluang baru untuk memantau kondisi tersebut, memprediksi risiko yang muncul, dan mendukung manajemen rantai pasok yang lebih responsif. Penelitian ini mengembangkan kerangka kerja analisis skenario kausal berbasis kecerdasan buatan untuk meningkatkan ketahanan rantai pasok layanan kesehatan. Kerangka kerja ini menggabungkan prediksi pembelajaran mesin, penalaran kausal, pemodelan skenario Bayesian, dan analisis kontrafaktual untuk mengkaji perubahan kondisi rantai pasok dalam berbagai skenario gangguan dan intervensi. Variabel utama yang digunakan meliputi permintaan, keandalan pemasok, tingkat persediaan, kapasitas transportasi, kebutuhan fasilitas, kondisi pengadaan, dan ketersediaan sumber daya. Model prediktif digunakan untuk mengidentifikasi potensi risiko, sedangkan analisis kausal digunakan untuk mengevaluasi kemungkinan dampak intervensi, seperti penyesuaian persediaan, penggantian pemasok, dukungan transportasi, dan realokasi sumber daya. Analisis skenario memungkinkan organisasi layanan kesehatan membandingkan berbagai respons alternatif sebelum diterapkan serta mempersiapkan diri menghadapi gangguan tunggal maupun gangguan gabungan. Kerangka kerja yang diusulkan memberikan pendekatan terstruktur untuk mengubah manajemen rantai pasok layanan kesehatan dari respons reaktif terhadap gangguan menjadi perencanaan ketahanan yang proaktif dan berbasis bukti.

Kata Kunci:

Kecerdasan Buatan, Analisis Kausal, Analisis Skenario, Rantai Pasok Layanan Kesehatan, Ketahanan, Pembelajaran Mesin, Jaringan Bayesian, Analisis Kontrafaktual.

Abstract

Healthcare supply chains operate in highly uncertain environments where supplier disruptions, fluctuating demand, inventory shortages, transportation failures, and capacity constraints can threaten the continuous availability of essential medical resources. Artificial intelligence provides new opportunities for monitoring these conditions, predicting emerging risks, and supporting more responsive supply-chain management. This study develops an AI-driven causal scenario-analysis framework for healthcare supply-chain resilience. The framework combines machine-learning prediction, causal reasoning, Bayesian scenario modelling, and counterfactual analysis to examine how supply-chain conditions may change under alternative disruption and intervention scenarios. Key variables include demand, supplier reliability, inventory levels, transportation capacity, facility requirements, procurement conditions, and resource availability. Predictive models are used to identify potential risks, while causal analysis is used to examine the likely effects of interventions such as inventory adjustments, supplier substitution, transportation support, and resource reallocation. Scenario analysis allows healthcare organizations to compare alternative responses before implementation and prepare for both individual and compound disruptions. The proposed framework provides a structured approach for moving healthcare supply-chain management from reactive disruption response toward proactive and evidence-based resilience planning.

Keyword:

Artificial Intelligence, Causal Analysis, Scenario Analysis, Healthcare Supply Chains, Resilience, Machine Learning, Bayesian Networks, Counterfactual Analysis.

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INTRODUCTION

Healthcare supply chains are critical to the functioning of modern health systems because they connect manufacturers, suppliers, distributors, healthcare facilities, and patients. These networks must maintain reliable flows of medicines, medical equipment, vaccines, consumables, and other essential resources despite considerable uncertainty. Disruptions affecting one part of the network can propagate through other components and create shortages, delays, and inefficient resource utilization.

Artificial intelligence (AI) has increasingly emerged as a tool for improving supply-chain visibility, prediction, and decision-making. AI can process large volumes of operational information and identify patterns associated with demand changes, inventory pressure, supplier instability, and logistics disruptions. The broader application of AI to healthcare innovation provides a technological basis for extending intelligent analytics into healthcare supply-chain management (Kopparthi, 2022).

Recent work has increasingly emphasized the use of AI to strengthen healthcare supply-chain resilience. Thiagarajan et al. (2026) identify AI, digital technologies, simulation, and scenario analysis as increasingly important capabilities for building agile and resilient healthcare supply chains. Their review also highlights persistent challenges involving data quality, legacy systems, interpretability, workforce capabilities, and governance.

Although predictive AI can identify likely disruptions, prediction alone does not explain which intervention is likely to be most effective. A healthcare organization may know that a shortage is probable but still need to determine whether it should increase inventory, substitute a supplier, improve transportation, redistribute resources, or change procurement priorities. This distinction creates a role for causal AI, which focuses on the potential consequences of interventions rather than prediction alone.

Uddandarao and Mahajan (2023) provide a strong methodological foundation through their use of causal Bayesian networks and Double Machine Learning for counterfactual supply-chain capacity allocation. Their study explicitly treats capacity reallocation as a causal intervention and evaluates what could happen when capacity is reassigned across nodes.

The present study extends this logic to healthcare supply chains by integrating AI-based prediction with causal and scenario-based reasoning. The framework is designed to identify supply-chain vulnerabilities, evaluate alternative disruption conditions, and estimate how different interventions may influence resilience outcomes.

Healthcare supply chains differ from many conventional commercial supply chains because disruptions can directly affect healthcare delivery. Shortages of essential medicines, vaccines, medical equipment, and consumables can create operational pressure for hospitals and healthcare providers. Maintaining resilience therefore requires organizations to anticipate disruptions and develop strategies for responding to uncertain conditions.

Traditional supply-chain planning often uses historical demand, inventory policies, supplier contracts, and predefined contingency plans. These mechanisms remain important, but they may be insufficient when disruptions involve several interconnected factors. For example, an increase in pharmaceutical demand may coincide with a supplier production problem and a transportation delay. Each event can reinforce the others, producing a larger effect than would be expected from considering them separately.

AI can improve the ability of healthcare organizations to detect such patterns. Machine-learning models can analyse historical and real-time data to estimate demand, detect unusual changes, and identify facilities or products with increasing exposure to disruption. The recent systematic review by Thiagarajan et al. (2026) shows that AI is increasingly being positioned as a strategic enabler of healthcare supply-chain agility, resilience, and proactive risk mitigation.

However, the quality of prediction does not automatically determine the quality of a management decision. A predictive system may identify a facility as high risk without distinguishing which intervention would be most effective. This is particularly important when available resources are limited. The organization may have enough capacity for only one intervention and therefore needs evidence about the likely consequences of different choices.

Causal analysis addresses this issue by estimating relationships between interventions and outcomes. Instead of asking whether a shortage is likely, causal analysis allows the organization to ask what may happen if additional inventory is introduced, a supplier is replaced, or transportation capacity is increased.

Counterfactual analysis provides a practical extension of causal reasoning. It allows decision-makers to compare a baseline condition with alternative hypothetical interventions. Uddandarao and Mahajan (2023) demonstrate this approach in supply-chain capacity allocation using causal Bayesian networks and Double Machine Learning. Their published article appeared in 2023 and provides a particularly relevant methodological basis for the current framework.

Scenario analysis is also important because healthcare supply-chain disruptions are not always isolated. Organizations may need to evaluate normal operations, sudden demand surges, supplier disruption, inventory shortages, transportation failures, and combinations of these conditions. AI-driven scenario analysis can support the preparation of alternative strategies before a disruption occurs.

The emerging literature also indicates that resilience should be treated as a dynamic capability rather than simply a static buffer. AI can support continuous monitoring and adaptation, while causal analysis can connect observed risks to potential interventions. The combination creates an analytical pathway from risk detection to intervention selection.

The background of this study therefore lies in the convergence of artificial intelligence, machine learning, causal inference, Bayesian reasoning, and scenario analysis. Integrating these approaches can help healthcare organizations move from reactive disruption management toward proactive resilience planning.

Artificial Intelligence in Healthcare Supply Chains

AI is increasingly being applied to healthcare operations because of its ability to process large and complex datasets. Supply-chain applications include demand prediction, inventory monitoring, supplier assessment, transportation optimization, disruption detection, and decision support.

Kopparthi (2022) establishes the wider healthcare context for AI-driven innovation. More recent healthcare supply-chain research demonstrates that the role of AI is moving beyond isolated prediction tasks toward integrated resilience and decision-support capabilities.

Thiyagarajan et al. (2026) provide particularly strong recent evidence through a systematic scoping review of AI-enabled healthcare supply chains. Their study identifies AI, digital twins, Internet of Things technologies, and simulation as strategic tools for real-time sensing, scenario analysis, and proactive risk mitigation.

The implications are important for healthcare organizations because resilience requires early awareness of changing conditions. AI systems can continuously examine new information and generate updated risk estimates as supply-chain conditions evolve.

Predictive Analytics for Supply-Chain Risk

Predictive analytics focuses on estimating future states using historical and current information. In healthcare supply chains, potential applications include forecasting pharmaceutical demand, estimating inventory shortages, predicting supplier failures, and identifying facilities likely to experience capacity constraints.

Prediction can improve preparation by providing earlier warnings. However, a risk score by itself does not identify the most effective response. For example, two facilities could have similar predicted shortage probabilities but require completely different interventions because the underlying causal conditions differ.

This limitation creates a need for analytical systems that connect predictive information with intervention analysis.

Causal AI and Counterfactual Reasoning

Causal AI complements predictive modelling by examining how interventions may affect outcomes. This is particularly relevant to supply-chain decisions because managers are often choosing among alternative actions.

Uddandarao and Mahajan (2023) provide a direct methodological example. Their study uses causal Bayesian networks and Double Machine Learning to evaluate counterfactual capacity reallocation. The article was published in August 2023 and has DOI 10.29284/hx0afm50.

The methodological logic can be extended to healthcare. A model can estimate the expected outcome under existing conditions and compare it with the expected outcome after a proposed intervention. This supports more evidence-based decision-making.

Bayesian Scenario Analysis

Bayesian models are useful for representing uncertainty and dependencies among multiple variables. In healthcare supply chains, a Bayesian network could represent relationships among demand, inventory, suppliers, transportation, capacity, and shortages.

Scenario analysis can then modify selected variables and assess how those changes affect the probability of disruption. The approach is particularly useful when information is incomplete or uncertain because probability distributions can be updated when new evidence becomes available.

Combining Bayesian reasoning with machine learning can therefore create a system in which prediction, uncertainty assessment, and causal analysis are integrated rather than treated as separate activities.

Resilience-Oriented Healthcare Supply Chains

Recent evidence suggests that AI-enabled healthcare supply chains increasingly focus on agility and resilience. Thiyagarajan et al. (2026) report that the literature is shifting toward proactive risk mitigation, real-

time sensing, scenario analysis, and digitally enabled resilience. They also identify challenges such as data quality, interpretability, legacy infrastructure, and governance.

This suggests that the implementation of AI-driven causal systems requires more than technical model development. Healthcare organizations must also establish appropriate data infrastructure, validation procedures, governance mechanisms, and human oversight.

Table 1. Literature Supporting the Proposed Framework

Main contribution	Relevance
AI, agility, resilience, and scenario analysis in healthcare supply chains	Very strong
Causal Bayesian networks and counterfactual supply-chain allocation	Very strong
AI and healthcare innovation	Strong supporting
Probabilistic AI and Bayesian inference diagnostics	Methodological supporting
AI and global supply-chain resilience	Supporting
AI and pharmaceutical supply-chain agility	Supporting
AI-powered risk mitigation and resilience	Supporting

METHODS

This study proposes a conceptual AI-driven causal scenario-analysis framework for healthcare supply-chain resilience. The framework combines operational data, machine learning, Bayesian modelling, causal inference, counterfactual analysis, and strategic decision support.

Data Collection

The framework considers data from healthcare facilities, pharmaceutical suppliers, distributors, warehouses, transportation systems, and procurement platforms. The principal variables include:

Table 2. Variables in Healthcare Supply Chain Risk Prediction

Variable	Description
Demand	Current and forecast healthcare requirements
Inventory	Available stock and replenishment levels
Supplier reliability	Probability of supplier disruption
Transportation	Delivery capacity and delay conditions
Facility capacity	Available operational capacity
Procurement	Lead time and purchasing conditions
Emergency requirements	Additional demand during disruptions

Machine-Learning Risk Prediction

Machine-learning models are first used to identify patterns associated with disruption. The predictive stage can estimate future demand, shortage probability, supplier risk, and transportation disruption. The output can be represented as a facility- or product-level risk score:

$$R_i = f(D_i, I_i, S_i, T_i, C_i)$$

Where R_i represents disruption risk for facility or product i , D_i represents demand, I_i inventory, S_i supplier reliability, T_i transportation conditions, and C_i facility capacity.

Bayesian Network Modelling

A Bayesian network is then used to represent dependencies between the major supply-chain variables. Nodes can represent demand, inventory, supplier conditions, transportation, capacity, and shortage outcomes. The probability of an outcome can be updated as new evidence becomes available:

$$P(Y | X) = \frac{P(X | Y)P(Y)}{P(X)}$$

This allows the system to update risk estimates when new information about demand, inventory, suppliers, or transportation becomes available.

Causal Intervention Analysis

The next stage identifies potential interventions. These can include increasing inventory, changing suppliers, adding transportation capacity, reallocating resources, adjusting procurement, or rerouting distribution. For intervention A , the framework estimates:

$$\tau = E[Y(1) - Y(0)]$$

Where $Y(1)$ represents the expected outcome under the intervention and $Y(0)$ represents the expected outcome without the intervention. The objective is to distinguish potential intervention effects from simple observational associations.

Counterfactual Scenario Analysis

Counterfactual scenarios are generated to compare alternative strategies.

Table 3. Illustrative Scenarios

Scenario	Condition	Intervention
Baseline	Normal supply and demand	No additional action
Demand surge	Demand increases substantially	Increase inventory
Supplier disruption	Primary supplier unavailable	Substitute supplier
Transport disruption	Distribution delays increase	Reroute shipments
Inventory shortage	Critical stock falls below threshold	Emergency redistribution
Compound disruption	Multiple risks occur together	Combined intervention

This process follows the counterfactual decision logic demonstrated by Uddandarao and Mahajan (2023).

Strategic Resilience Decision

The final stage ranks the interventions according to expected effectiveness, resource requirements, urgency, and operational feasibility. The overall process is:

Data collection → Machine-learning prediction → Bayesian risk modelling → Causal estimation → Counterfactual scenarios → Intervention comparison → Strategic decision → Resilience monitoring

RESULTS AND DISCUSSION

Results

The proposed framework provides a structured mechanism for integrating prediction and intervention analysis in healthcare supply-chain management.

First, the machine-learning component can identify emerging risks. Increasing demand, decreasing inventory, unreliable suppliers, and transportation constraints can be analysed simultaneously to determine where disruption exposure is increasing.

Second, Bayesian modelling can provide an updated representation of uncertainty. When new evidence becomes available, such as a supplier failure or sudden increase in demand, the estimated probabilities of shortages and other outcomes can be recalculated.

Third, causal analysis can distinguish between risk detection and intervention selection. A high-risk facility can be evaluated according to different response strategies rather than automatically receiving a predefined intervention.

Table 4. Illustrative Decision Outputs

Output	Decision implication
Demand forecast	Estimate future resource requirements
Shortage probability	Identify vulnerable products or facilities
Supplier-risk estimate	Prioritize procurement alternatives
Transportation-risk estimate	Consider rerouting or extra capacity
Causal intervention effect	Identify potentially effective responses
Counterfactual outcome	Compare alternative strategies
Resilience score	Evaluate overall supply-chain preparedness

The framework can also evaluate compound disruptions. For instance, a demand surge occurring simultaneously with supplier disruption and transportation failure may create substantially greater risk than any individual event.

This allows organizations to test whether a combined intervention is more effective than a single response. For example, the model could compare emergency inventory redistribution against supplier substitution plus transportation support.

Discussion

The proposed AI-driven causal scenario-analysis framework represents a transition from conventional predictive supply-chain analytics toward intervention-oriented resilience management. Its primary strength is the integration of multiple analytical capabilities rather than relying on prediction alone.

Predictive AI provides the early-warning component. Machine-learning models can analyse large quantities of healthcare supply-chain information and identify patterns associated with future shortages or disruptions. This capability is especially valuable in healthcare because delays in identifying a supply problem can have operational and clinical consequences.

The second major contribution is Bayesian reasoning. Healthcare supply chains involve uncertainty, and information is often incomplete. A Bayesian framework allows uncertainty to be explicitly represented and updated when new evidence becomes available. This is useful when a supplier suddenly becomes unavailable or demand changes unexpectedly.

The causal layer adds a different form of intelligence. Rather than stopping at prediction, the framework evaluates interventions. This distinction is fundamental because healthcare organizations generally have to make decisions about how to respond to identified risks.

The approach developed by Uddandarao and Mahajan (2023) is particularly relevant because it treats capacity allocation as a causal intervention and uses counterfactual analysis to compare alternative outcomes. Their published study provides a direct methodological bridge between machine learning, causal reasoning, and supply-chain allocation.

The framework is also consistent with recent developments in healthcare supply-chain AI. Thiagarajan et al. (2026) identify scenario analysis, real-time sensing, AI, digital twins, and simulation as increasingly important technologies for healthcare supply-chain resilience. Their review also identifies data quality, interpretability, legacy systems, governance, and human–AI collaboration as continuing barriers to implementation.

These limitations are important. An AI model cannot produce reliable causal recommendations when the underlying data are incomplete, biased, or inconsistent. Healthcare organizations should therefore establish data-quality controls and continuously validate model performance.

Interpretability is also necessary. Supply-chain managers may be reluctant to implement a recommendation if the system cannot explain why it considers one intervention preferable to another. Bayesian network structures can help because they provide an explicit representation of relationships among variables.

Human oversight should remain part of the framework. Healthcare decisions may involve clinical priorities, regulatory considerations, ethical requirements, and emergency conditions that are not fully represented in historical data. AI should therefore support managerial judgment rather than automatically replace it.

Another important consideration is compound risk. Healthcare disruptions often interact. A supplier failure can reduce inventory, which can increase emergency procurement, while transportation delays can prevent replacement supplies from arriving. AI-driven scenario analysis can model these interactions and help organizations prepare for them in advance.

The framework also supports proactive resilience. Rather than waiting for a shortage to become visible, organizations can use predictive signals to identify emerging risks and evaluate interventions before the disruption reaches a critical level. This may reduce response time and improve the efficiency of limited resources.

The inclusion of counterfactual analysis further strengthens strategic planning because it allows decision-makers to compare hypothetical alternatives before implementation. This is especially valuable when interventions are costly or when resources are insufficient to support all possible responses.

Overall, the proposed framework combines predictive intelligence with causal decision support in a way that is particularly relevant to healthcare supply-chain resilience. Its main contribution is the integration of risk prediction, causal explanation, scenario evaluation, and intervention selection within a single analytical framework.

CONCLUSION

AI-driven causal scenario analysis provides a promising approach for strengthening healthcare supply-chain resilience under uncertain and changing conditions. By combining machine-learning prediction with Bayesian reasoning and causal analysis, healthcare organizations can identify emerging risks while also examining how alternative interventions may influence supply availability and operational performance. Scenario and counterfactual analysis can further support comparison of different responses before resources are committed. The framework can help organizations anticipate shortages, prepare for compound disruptions, prioritize critical interventions, and allocate limited resources more effectively. Overall, integrating predictive intelligence with causal decision support can move healthcare supply-chain management from reactive disruption response toward proactive, adaptive, and evidence-based resilience planning.

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