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Risk Mitigation and Resilience Modeling for Consumer Distribution Networks During Demand Shocks: A Quantitative Stochastic Optimization and Scenario Analysis Study

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Abstract

This study investigated risk mitigation and resilience modeling for consumer distribution networks operating under demand shock conditions using a quantitative stochastic optimization and scenario-based analysis framework. A multi-echelon distribution network was evaluated under a structured set of baseline and stress demand scenarios to examine how mitigation policies and resilience-oriented capabilities influenced operational performance. The analytical dataset comprised 1,520 scenario-level network observations, balanced across four service regions and essential and non-essential product segments. Descriptive results indicated a mean service continuity index of 0.81 with observable right-skewness, while the unmet demand ratio averaged 0.18, reaching a maximum of 0.61 under severe stress scenarios. Cost escalation exhibited the greatest variability, with a mean increase of 22.4% and a maximum observed value of 78.6%, confirming strong tail sensitivity in economic outcomes. Reliability analysis of composite constructs demonstrated acceptable to excellent internal consistency, with Cronbach's alpha values ranging from 0.85 to 0.93, supporting measurement validity prior to inferential testing. Regression analysis showed that resilience capability ($\beta = 0.421$, $p < 0.001$) and robustness stability ($\beta = 0.276$, $p < 0.001$) were statistically significant predictors of performance outcomes after controlling for demand volatility, utilization intensity, and network scale. Inclusion of resilience constructs improved explanatory power, increasing adjusted R^2 from 0.241 in the baseline model to 0.318 in the extended specification. Segment-level analysis revealed that essential goods achieved higher service continuity (0.86) and lower unmet demand (0.13) than non-essential goods, albeit with higher average cost escalation (26.9% versus 17.1%). Robustness testing using out-of-sample and segmented evaluations confirmed stability of coefficient direction and significance across alternative scenario partitions. Overall, the findings provided quantitative evidence that resilience and robustness functioned as measurable attributes that systematically shaped distribution network performance under demand shock conditions.

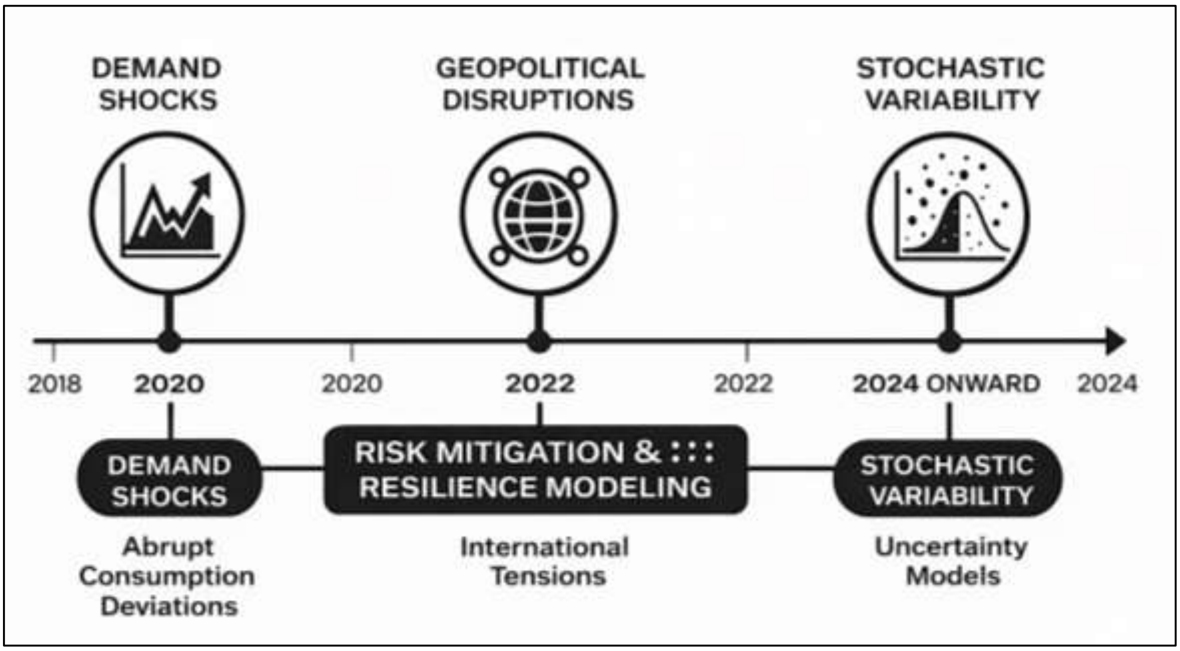
Keywords

Distribution Resilience, Demand Shocks, Stochastic Optimization, Risk Mitigation, Scenario Analysis;

INTRODUCTION

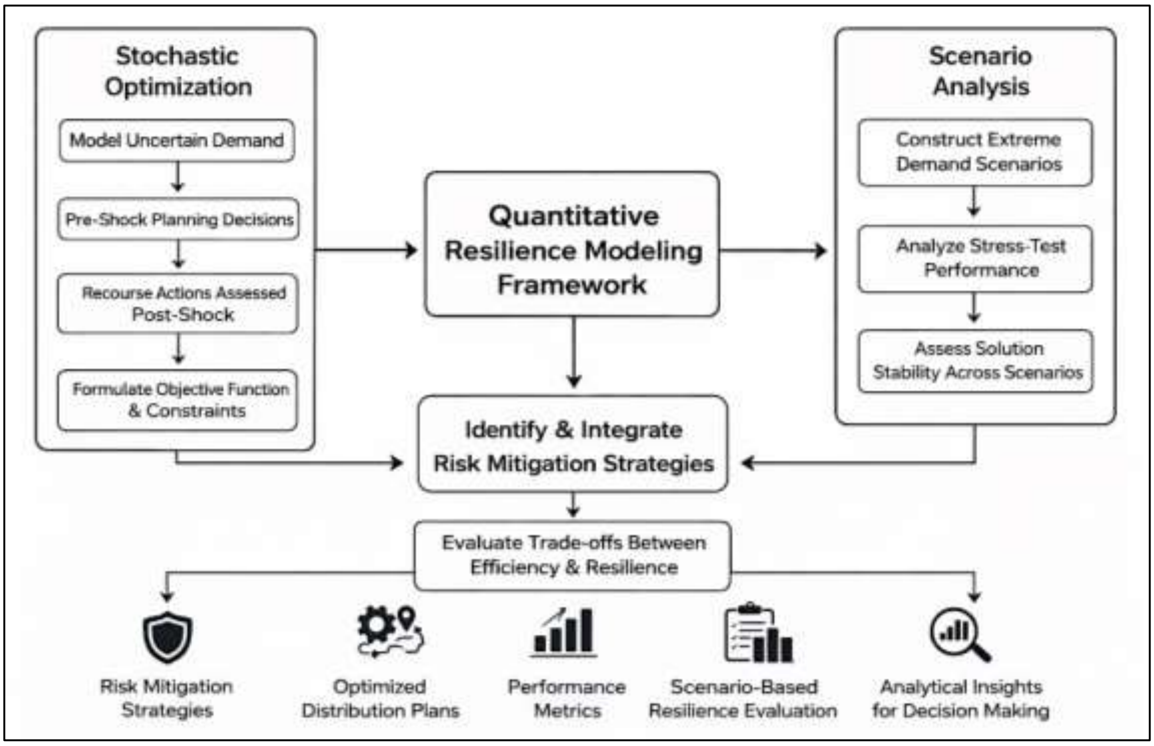
Risk mitigation and resilience modeling in consumer distribution networks are grounded in quantitative frameworks that describe uncertainty, disruption, and system response within interconnected supply and logistics structures. In economic and operations research literature, risk is formally defined as the measurable exposure of system performance to uncertain events that can negatively affect cost, service levels, or continuity (Qiu & Wang, 2016).Demand shocks represent abrupt, statistically significant deviations from expected consumption patterns, often arising from macroeconomic volatility, public health crises, geopolitical disruptions, or behavioral shifts at the consumer level. Consumer distribution networks encompass the physical, informational, and financial infrastructures that enable goods to flow from producers to end consumers across national and international markets. These networks are characterized by multi-echelon structures, capacity constraints, lead-time variability, and dependency relationships that amplify the effects of demand uncertainty. Resilience, within this analytical context, refers to the capacity of a distribution system to absorb shocks, adapt operational configurations, and maintain functional performance under stress (Kahiluoto et al., 2020). Quantitative resilience modeling focuses on formalizing this capacity using mathematical representations that capture recovery speed, flexibility, redundancy, and robustness. The increasing frequency and magnitude of demand shocks observed across global markets have elevated the importance of analytically grounded risk mitigation strategies that move beyond deterministic planning assumptions. At the international level, consumer distribution networks serve as critical infrastructures supporting food security, healthcare access, energy provision, and essential goods delivery, making their stability a matter of economic and social importance. As global supply systems become more integrated and data-intensive, the need for rigorous stochastic and scenario-based modeling approaches has become central to understanding how distribution networks behave under extreme demand variability (Martinelli et al., 2019).

Figure 1: Risk Mitigation in Distribution Networks



Consumer distribution networks operate within globally interconnected economic systems where localized demand shocks can propagate rapidly across regions and markets. International trade integration, digital commerce platforms, and cross-border logistics dependencies have increased both the scale and speed at which demand fluctuations affect distribution performance (Dell'Isola et al., 2020). In many regions, consumer demand shocks have been observed to disrupt inventory availability, transportation capacity utilization, and service reliability simultaneously, revealing structural vulnerabilities embedded within network design. From an international perspective, these disruptions are not confined to isolated markets but frequently cascade through upstream suppliers, downstream retailers, and supporting service providers. Quantitative research has documented how asymmetric demand surges or collapses can destabilize pricing mechanisms, inventory policies, and replenishment schedules across national boundaries. Distribution networks serving consumer markets are also subject to heterogeneous regulatory environments, infrastructure constraints, and behavioral responses, all of which shape system resilience under shock conditions (Ivanov & Dolgui, 2019). The international significance of resilience modeling lies in its ability to support comparative analysis across regions, enabling policymakers and firms to evaluate how alternative network configurations respond to similar demand disturbances. Stochastic optimization and scenario analysis provide formal tools to represent uncertainty distributions, correlation structures, and extreme-event realizations that characterize global demand volatility. These methods allow analysts to quantify trade-offs between cost efficiency and robustness, particularly in environments where lean inventory practices and just-in-time distribution dominate. As consumer distribution networks increasingly support essential goods and services, their ability to withstand demand shocks has become a central concern for economic stability, humanitarian logistics, and cross-border supply coordination (Hobbs, 2020).

Figure 2: Stochastic Resilience Modeling Framework



This study aimed to develop and evaluate a quantitative risk mitigation and resilience modeling framework for consumer distribution networks operating under demand shock conditions, with the objective of formally linking stochastic uncertainty representations to operational decision variables and system-level performance measures. The first objective was to define demand shocks as quantifiable deviations in consumption patterns and to encode these deviations into a scenario structure that reflected heterogeneous magnitudes and spatial distributions across network nodes, thereby enabling consistent stress testing of distribution performance under extreme variability. The second objective was to construct a stochastic optimization model that represented key distribution decisions, including inventory positioning, capacity allocation, replenishment timing, and routing-related flexibility, in a way that allowed pre-shock planning decisions and post-shock recourse actions to be evaluated within a unified analytical structure. The third objective was to measure resilience through operationally interpretable indicators such as service continuity, unmet demand volume, backorder incidence, and cost escalation under shock realizations, ensuring that resilience was treated as an observable outcome derived from model outputs rather than a descriptive label. The fourth objective was to quantify the trade-offs between efficiency-oriented policies and robustness-oriented policies by comparing expected performance against tail-risk outcomes across a common evaluation framework, thereby revealing how alternative mitigation strategies altered both average costs and extreme loss exposure. The fifth objective was to evaluate solution stability across out-of-sample scenario sets by testing whether mitigation policies maintained consistent performance when shock profiles varied within the same distributional family, supporting claims of robustness under uncertainty. The sixth objective was to support decision traceability by documenting how specific mitigation levers, such as buffer levels, capacity reserves, or sourcing flexibility, contributed to changes in resilience metrics at both node and system levels. The final objective was to produce a structured empirical reporting format suitable for international distribution contexts, enabling comparative interpretation across regions, products, and infrastructure constraints, while maintaining reproducibility through standardized data preparation, scenario generation rules, and model-validation procedures.

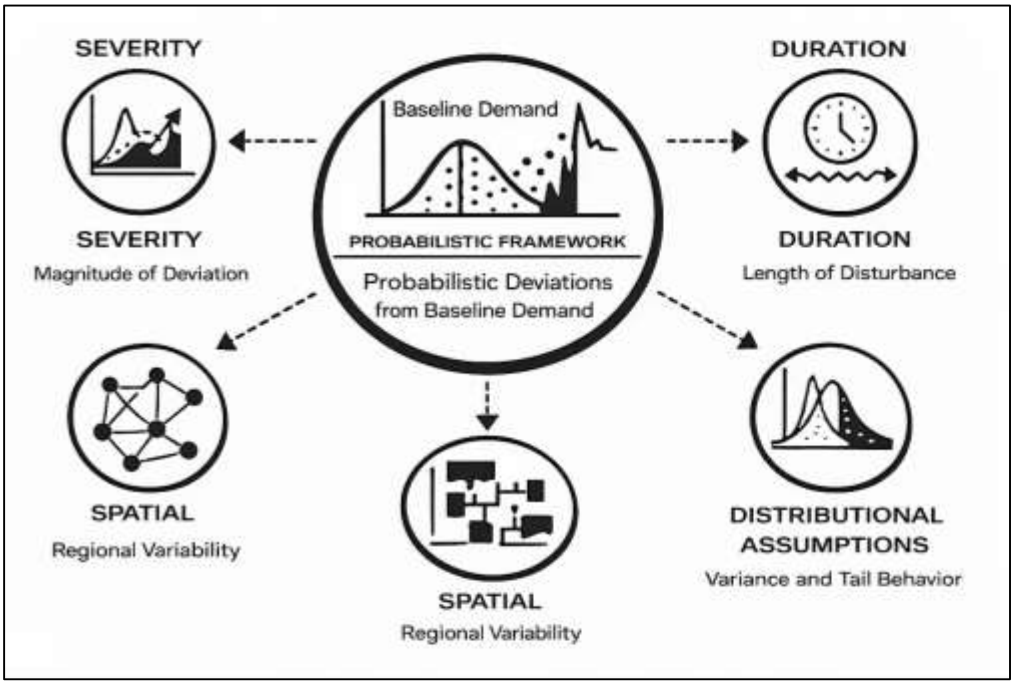
LITERATURE REVIEW

This literature review examined quantitative research on risk mitigation and resilience modeling for consumer distribution networks exposed to demand shocks, with emphasis on stochastic optimization and scenario analysis as core analytical approaches. The review organized prior studies according to how demand uncertainty was defined and measured, how network decisions were modeled under probabilistic conditions, and how resilience outcomes were operationalized using performance metrics such as service continuity, unmet demand, and cost stability. Emphasis was placed on research that treated demand shocks as structured stochastic phenomena rather than as isolated disturbances, since this framing enabled formal evaluation of mitigation strategies through scenario-based stress testing and recourse-based optimization. The review also synthesized evidence on multi-echelon distribution architectures, highlighting how inventory positioning, capacity flexibility, and transportation policies were modeled to manage variability across nodes and time periods. In addition, the review incorporated methodological studies on validation and robustness testing, including out-of-sample scenario evaluation, sensitivity analysis, and distribution shift assessment, because quantitative resilience claims required empirical credibility under alternative demand realizations. Governance-oriented modeling contributions were included where studies documented decision traceability, reproducibility, and comparable evaluation designs, reflecting the role of transparent analytical frameworks in high-stakes consumer distribution planning. Overall, the literature review established the theoretical and empirical basis for the study's quantitative modeling structure by connecting stochastic demand representations to optimization-based decision levers and measurable resilience outcomes in consumer distribution systems.

Demand Shocks in Consumer Distribution Systems

The quantitative literature consistently conceptualized demand shocks in consumer distribution systems as probabilistic deviations from an established baseline demand pattern rather than as isolated anomalies. Baseline demand was typically defined using historical consumption data, seasonal adjustments, and trend components that reflected expected purchasing behavior under normal operating conditions. Demand shocks were then identified as statistically significant departures from this baseline, measured in terms of magnitude and frequency (Dehghani et al., 2020; Rauf, 2018). This probabilistic framing allowed researchers to represent demand variability using formal uncertainty structures that could be embedded into analytical models. By treating shocks as realizations from an underlying demand distribution, studies emphasized that demand volatility was not purely random but exhibited structural properties such as skewness, clustering, and persistence (Haque & Arifur, 2020; Ashraful et al., 2020). This perspective supported comparative analysis across time periods and regions, as deviations could be evaluated relative to a common reference distribution (Haque & Arifur, 2021; Jinnat & Kamrul, 2021). The literature further highlighted that probabilistic definitions enabled objective benchmarking of shock intensity, allowing researchers to distinguish moderate fluctuations from extreme stress events. Within consumer distribution contexts, this approach supported scalable modeling because demand uncertainty could be parameterized at different aggregation levels, including product categories, geographic zones, and time horizons (Fokhrul et al., 2021; Oboudi et al., 2020; Zaman et al., 2021). Overall, the probabilistic conceptualization of demand shocks provided a consistent analytical foundation for modeling uncertainty in distribution systems without relying on deterministic or purely descriptive interpretations of demand disruption (Hammad, 2022; Hasan & Waladur, 2022; Taheri et al., 2019).

Figure 3: Probabilistic Demand Shock Modeling Framework



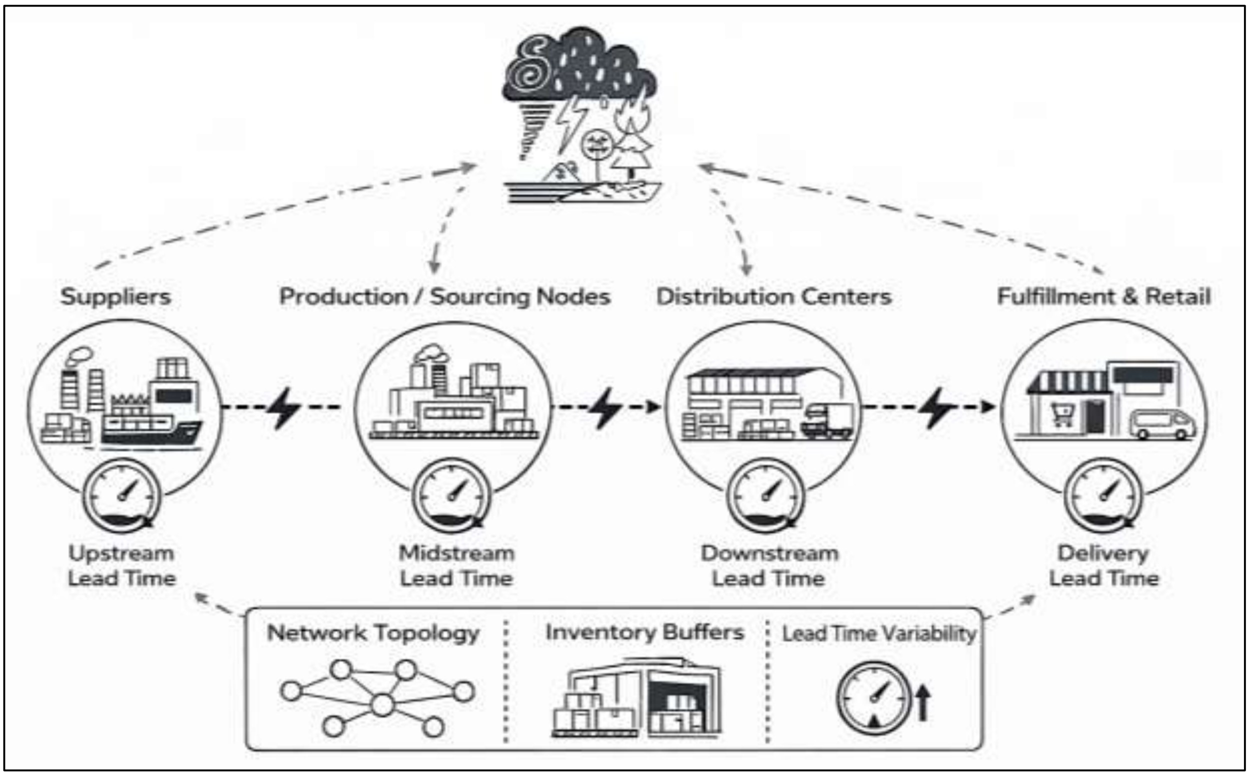
Empirical studies emphasized that demand shocks were multidimensional phenomena requiring explicit representation of severity, duration, and spatial heterogeneity. Shock severity was commonly operationalized as the relative deviation from baseline demand, capturing both surge and collapse scenarios in consumer consumption (Khomami & Sepasian, 2018; Arifur & Haque, 2022; Towhidul et al., 2022). Duration was treated as a temporal attribute, distinguishing short-lived spikes from prolonged demand disruptions that affected replenishment cycles and inventory policies. The literature documented that prolonged shocks exerted fundamentally different pressures on distribution networks than transient fluctuations, particularly in multi-echelon systems where lead times and replenishment delays interacted with sustained demand imbalance (Rifat & Jinnat, 2022; Rifat & Alam, 2022). Spatial heterogeneity was another central dimension, as shocks rarely affected all regions uniformly. Researchers modeled spatial variation by allowing demand deviations to differ across nodes, reflecting localized behavioral responses, infrastructure constraints, or policy interventions (Abdulla & Majumder, 2023; Faysal & Bhuya, 2023; Macdonald et al., 2018). This approach enabled evaluation of how regional imbalances propagated through shared distribution resources. Quantitative representations of heterogeneity supported network-level resilience analysis by revealing how localized shocks could generate systemic effects when capacity or inventory pools were shared (Habibullah & Aditya, 2023; Hammad & Mohiul, 2023). The literature consistently demonstrated that models ignoring shock duration or spatial variation underestimated system stress and overstated resilience. As a result, comprehensive demand shock modeling frameworks incorporated all three dimensions to capture the true operational impact of demand volatility in consumer distribution systems (Chi et al., 2018; Haque & Arifur, 2023; Akbar & Farzana, 2023).
The literature on demand shock modeling devoted significant attention to the choice of distributional assumptions used to represent demand uncertainty. Rather than assuming symmetric or narrowly bounded variability, empirical studies documented that consumer demand often exhibited skewed and heavy-tailed behavior, particularly during periods of economic or social disruption. These distributional characteristics were derived from observed consumption data showing infrequent but

extreme deviations from typical demand levels (Atashi et al., 2020). Researchers emphasized that accurate estimation of demand variance was critical for capturing tail behavior that drove stockouts, service failures, and cost escalation (Mostafa, 2023; Rifat & Rebeka, 2023). Variance estimation methods typically relied on historical time-series analysis, cross-sectional aggregation, or rolling-window techniques to account for nonstationarity. The literature highlighted that underestimating variance led to fragile planning outcomes, while overestimation resulted in excessive buffering and inefficiency. Empirical calibration of demand distributions enabled more realistic representation of uncertainty in optimization and simulation models. Studies also noted that variance patterns differed across products and consumer segments, requiring differentiated modeling approaches (Macfadyen et al., 2015). By grounding distributional assumptions in observed data rather than theoretical convenience, the literature supported analytically credible representations of demand shocks suitable for quantitative evaluation of distribution system performance.

Distribution Network Structures

The quantitative resilience literature consistently modeled consumer distribution networks as multi-echelon systems composed of suppliers, production or sourcing nodes, distribution centers, fulfillment facilities, and retail or last-mile delivery points. This structural representation reflected the layered nature of consumer goods flows and allowed researchers to capture interdependencies across upstream and downstream stages (Li et al., 2019).

Figure 4: Multi-Echelon Network Resilience Model



Multi-echelon formulations enabled explicit modeling of how disruptions or demand shocks at one level propagated through the network, affecting inventory availability, replenishment timing, and service performance at other levels. Studies emphasized that resilience outcomes were strongly influenced by the number of echelons, the degree of coupling between them, and the allocation of decision authority across stages. Networks with tightly coupled echelons were shown to exhibit amplified shock effects, whereas loosely coupled structures allowed localized disturbances to be absorbed without cascading system-wide failures. Quantitative models incorporated these structures to evaluate trade-offs between centralized and decentralized distribution strategies, particularly in consumer markets characterized by high demand volatility and short delivery windows (Wang et al., 2019). The literature also highlighted that multi-echelon modeling supported analysis of redundancy

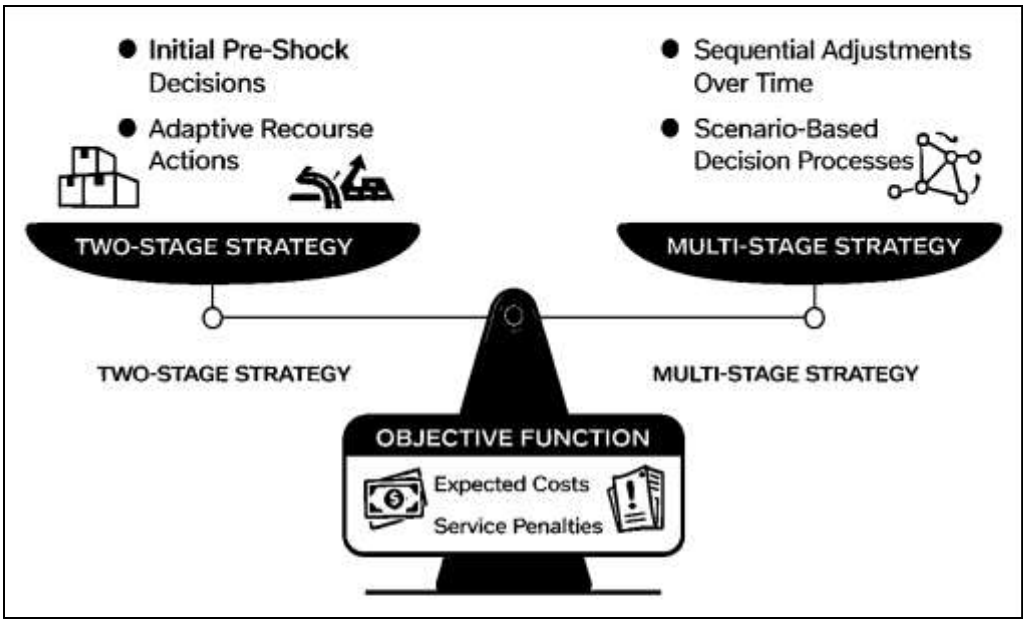
placement, enabling researchers to assess whether buffering capacity or inventory was more effective upstream, midstream, or downstream. By explicitly representing each echelon, quantitative studies established a detailed analytical foundation for examining how structural design choices shaped resilience under stress conditions (O'Neil et al., 2016).
Network topology emerged as a central determinant of resilience outcomes in quantitative distribution studies. The literature examined alternative topological configurations, including hub-and-spoke, mesh, hybrid, and regionally clustered network designs, each exhibiting distinct resilience characteristics. Hub-dominated structures were often associated with efficiency gains under normal conditions but demonstrated heightened vulnerability when central nodes experienced congestion or failure. In contrast, mesh-like or regionally distributed networks offered greater flexibility by enabling rerouting and load redistribution during demand shocks (Cavallo et al., 2014). Quantitative models represented topology through connectivity constraints, flow paths, and node-level capacities, allowing systematic comparison of structural robustness across designs. Service regions were frequently incorporated to reflect geographic segmentation of demand, which influenced how shocks in one area affected overall network performance. Studies demonstrated that overlapping service regions enhanced resilience by allowing fulfillment substitution, while rigid territorial assignments increased sensitivity to localized demand spikes (Basu & Bundick, 2017). Topological analysis also revealed that resilience was not solely determined by the number of nodes or links but by how flows were structured and prioritized across the network. This body of research underscored that topology design functioned as a strategic resilience lever embedded within quantitative modeling frameworks rather than as a purely logistical consideration.

Stochastic Optimization Models for Risk Mitigation Decisions

The quantitative resilience literature consistently treated stochastic optimization as a formal basis for risk mitigation in consumer distribution networks because it represented uncertain demand within a structured decision framework. In this body of work, demand was modeled as an uncertain input that influenced inventory, allocation, sourcing, and transportation decisions, and mitigation strategies were derived by optimizing performance across uncertain realizations rather than a single forecast (Ermoliev et al., 2019). Stochastic programming approaches were widely used because they enabled planners to incorporate probability-weighted outcomes into objective functions and to enforce operational feasibility through constraints reflecting capacity, lead time, and service requirements. Studies emphasized that this modeling family provided a disciplined approach for evaluating the trade-off between efficiency and robustness by quantifying expected cost while accounting for service-based penalties associated with shortages and delays. The literature also highlighted that stochastic models supported risk mitigation by producing policies that remained feasible across diverse demand conditions, reducing the likelihood that a network would experience extreme service failure under demand shocks (Álvarez-Miranda et al., 2019). This approach was particularly relevant for consumer distribution settings with high variability and short delivery expectations, where deterministic planning often underestimated tail outcomes. Overall, stochastic programming was positioned as a core quantitative tool for resilience modeling because it translated uncertain demand into decision-ready optimization structures that supported consistent evaluation of mitigation strategies across scenarios (Pflug & Pichler, 2014).
Two-stage stochastic optimization was frequently described in the literature as a practical representation of distribution planning under uncertainty because it separated pre-shock decisions from post-shock adjustments. In this structure, first-stage decisions captured commitments made before demand uncertainty was resolved, such as inventory positioning, capacity reservation, or baseline allocation plans. Second-stage decisions represented recourse actions taken after demand realizations were observed, including emergency replenishment, expedited transportation, cross-node reallocation, or substitution across fulfillment locations. The literature emphasized that recourse modeling was essential for capturing resilience because it reflected the adaptive capabilities of distribution systems under shock conditions. Studies demonstrated that without recourse, models tended to overinvest in static buffers to preserve feasibility, whereas recourse-enabled structures supported more flexible and cost-effective mitigation strategies. Recourse decisions were also used to quantify the value of flexibility, enabling comparisons between systems with different levels of

operational agility. Empirical research highlighted that the effectiveness of recourse depended on realistic constraints, such as lead-time limits and capacity ceilings, because overly permissive recourse structures could generate unrealistic solutions. Two-stage frameworks therefore served as a bridge between strategic planning and operational response, allowing quantitative evaluation of how advance commitments and reactive adjustments jointly shaped resilience outcomes in consumer distribution networks.

Figure 5: Stochastic Risk Mitigation in Distribution



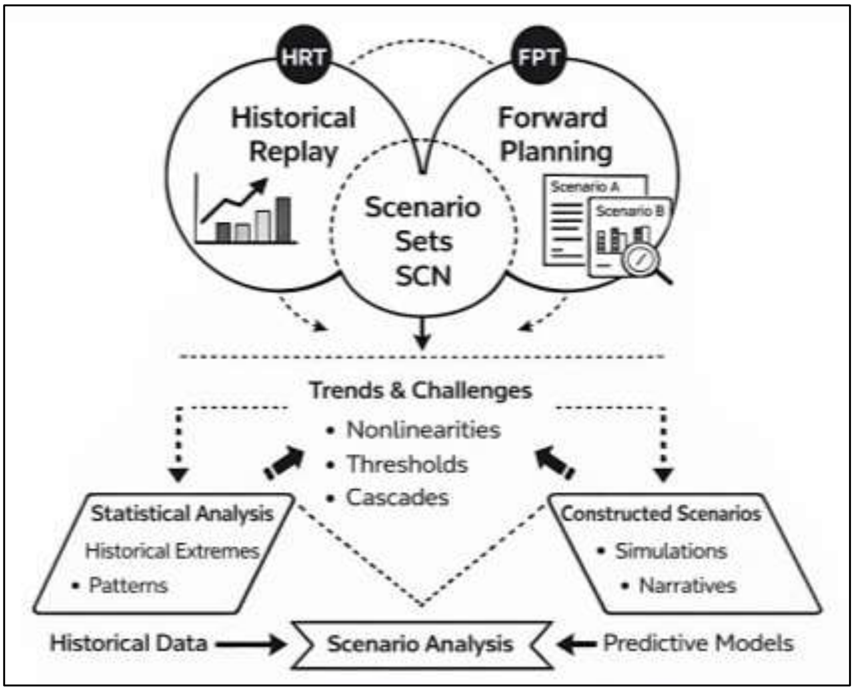
Multi-stage stochastic optimization extended the two-stage structure by modeling sequential decisions across time, allowing distribution policies to adapt as new information became available. The literature presented multi-stage frameworks as particularly appropriate for demand shocks that evolved over multiple periods, where uncertainty unfolded gradually rather than being resolved at a single point. In consumer distribution networks, this structure allowed models to represent rolling replenishment cycles, phased capacity adjustments, and dynamic allocation policies across successive decision epochs (Cano et al., 2016). Multi-stage approaches were used to capture temporal dependencies and to represent how early decisions constrained later options, which was critical for evaluating resilience under persistent shocks. Studies also highlighted that multi-stage frameworks provided a richer depiction of system behavior by allowing repeated recourse actions rather than a single corrective step. This design supported modeling of real operational responses such as progressive rerouting, incremental inventory rebalancing, and adaptive procurement actions. The literature noted that multi-stage modeling increased computational complexity and required careful scenario structuring, yet it enabled more realistic analysis of resilience trajectories under sustained uncertainty (Khalilabadi et al., 2020). By representing sequential decisions, multi-stage stochastic optimization provided a quantitative mechanism for evaluating how distribution systems responded over time to uncertain demand conditions and how mitigation strategies influenced both short-term service stability and broader cost exposure (Kozmík & Morton, 2015).

The objective functions used in stochastic optimization models were treated in the literature as central mechanisms for encoding risk mitigation priorities. Studies commonly combined expected cost components with service-based penalties reflecting unmet demand, backorders, late deliveries, and customer service failures. This combination allowed optimization to reflect not only operational efficiency but also resilience-oriented service stability under demand shocks (Pantuso & Boomsma, 2020). Expected cost terms captured routine expenses such as holding, transportation, and procurement, while penalty terms represented the economic and service consequences of disruption. The literature emphasized that penalty calibration influenced policy behavior, as higher penalty weights pushed solutions toward more conservative buffering and flexibility investments, while lower penalties favored leaner designs with greater vulnerability to shock. Some studies incorporated risk-sensitive objective variants that emphasized tail outcomes or dispersion rather than averages, reflecting the disproportionate impact of extreme demand events on consumer service continuity (Carpentier et al., 2015). In consumer distribution networks, objective structures were also used to reflect differentiated service priorities across product categories, such as essential versus non-essential goods, which altered penalty configurations. Overall, the literature showed that objective design functioned as an analytical representation of institutional risk appetite and service requirements, and it shaped the balance between cost efficiency and shock resilience in stochastic optimization solutions (Yin & Han, 2020).

Frameworks for Stress Testing Demand Shock

The quantitative resilience literature consistently positioned scenario analysis as a central instrument for stress testing consumer distribution networks under extreme demand conditions. Scenario analysis was treated as a structured method for evaluating system behavior across multiple plausible realizations of demand rather than relying on average or expected-case assumptions (Mahmutoğulları et al., 2019). In this body of work, scenarios represented coherent combinations of demand magnitude, timing, and spatial distribution that reflected realistic stress environments observed in consumer markets. Researchers emphasized that scenario-based evaluation enabled identification of nonlinear system responses, threshold effects, and cascading failures that remained hidden under single-scenario or deterministic analyses. In consumer distribution contexts, scenario analysis was used to examine how inventory depletion, capacity saturation, and service degradation evolved under high-pressure demand conditions (Zeballos et al., 2015). The literature also highlighted that scenario frameworks supported comparability across studies because scenarios could be standardized and reused across alternative network designs or mitigation strategies. By framing demand shocks as structured scenario sets, quantitative studies established a repeatable evaluation environment in which resilience could be assessed systematically. This approach strengthened analytical rigor by shifting focus from isolated disruption narratives to distributional performance patterns across stress conditions, enabling more comprehensive evaluation of risk mitigation effectiveness (Pisciella et al., 2016).

Figure 6: Scenario-Based Stress Testing Framework



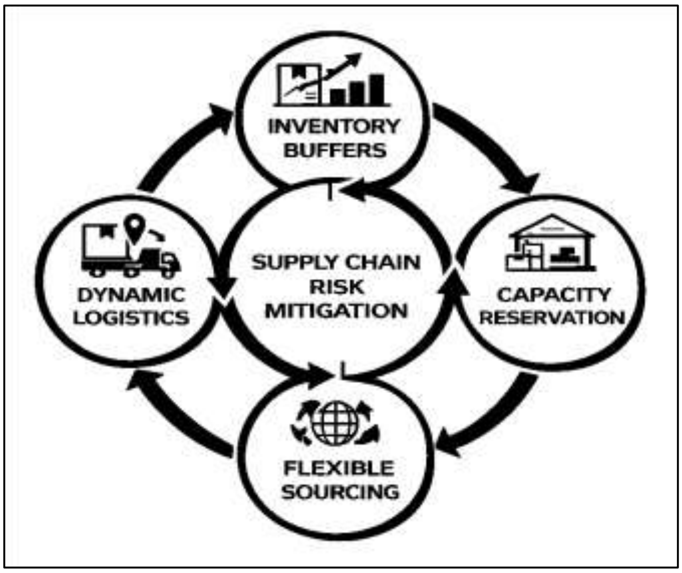
Historical replay emerged in the literature as a widely adopted approach for constructing demand shock scenarios grounded in observed consumption behavior. This method involved selecting periods of extreme demand variation from historical data and using them as direct inputs for evaluation.

Researchers valued historical replay because it preserved realistic correlations between demand levels, timing, and spatial patterns without requiring strong parametric assumptions (Mittnik et al., 2020). In consumer distribution networks, historical replay allowed analysts to examine how systems would have performed if existing policies had been applied during past stress events. Studies emphasized that replay scenarios captured behavioral and contextual complexity, such as panic buying, regional demand surges, or prolonged consumption downturns, which were difficult to replicate synthetically. However, the literature also acknowledged limitations related to sample dependence and the inability of historical replay to represent unprecedented demand conditions (Roohnavazfar et al., 2019). As a result, historical replay was often combined with other scenario-generation methods to expand the stress-testing envelope. Despite these limitations, historical replay was consistently treated as a benchmark approach because it anchored resilience evaluation in empirically observable demand patterns, enhancing the credibility of quantitative stress-testing outcomes (Wang et al., 2016).

Mitigation Levers in Consumer Distribution Networks

The quantitative resilience literature consistently treated inventory buffers and safety-stock optimization as foundational mitigation levers in consumer distribution networks because inventory positioning directly influenced service continuity under demand shocks. Studies modeled buffering as a decision mechanism that absorbed demand volatility by increasing available stock at selected echelons, often emphasizing the role of decoupling points that separated upstream replenishment uncertainty from downstream consumption variability (Timonina, 2015). Safety-stock optimization was commonly represented as an allocation problem in which buffer levels were tuned to match demand variability, lead-time uncertainty, and target service performance. The literature highlighted that buffering decisions were rarely uniform across products or nodes because consumer distribution networks exhibited heterogeneous demand patterns and different replenishment constraints. Quantitative models therefore incorporated differentiated inventory policies that assigned higher safety stock to items with high volatility or high service criticality (Golmohamadi & Asadi, 2020). Empirical comparisons across scenarios showed that buffering reduced unmet demand and backorder incidence during shock conditions, while also increasing holding costs and risk of obsolescence. The literature also documented that buffer effectiveness depended on where inventory was positioned, as upstream buffers improved replenishment reliability while downstream buffers improved immediate responsiveness. This body of work demonstrated that inventory buffering functioned as a measurable resilience lever because its impact could be quantified through changes in stockout rates, fill-rate stability, and cost escalation across stress scenarios (Golmohamadi & Asadi, 2020).

Figure 7: Supply Chain Resilience Mechanisms

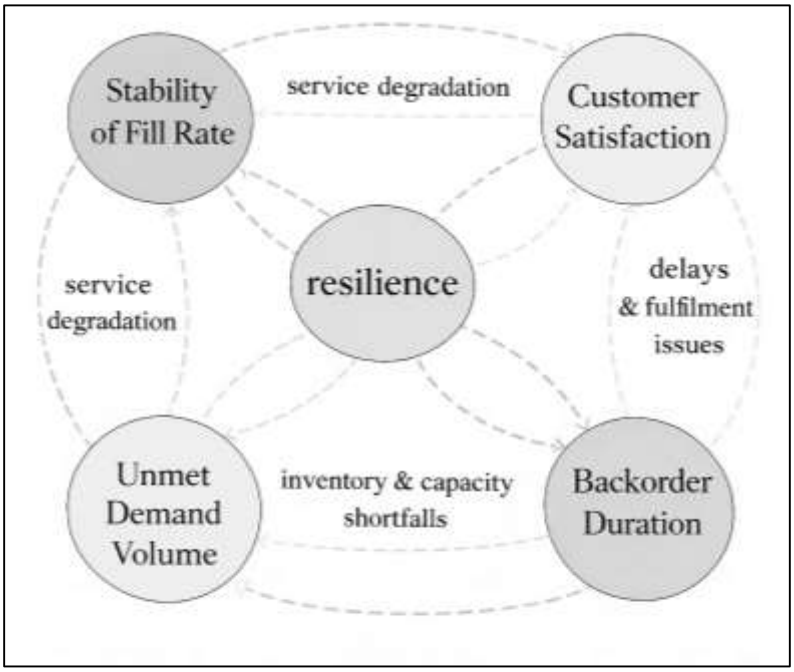


Capacity reservation was extensively modeled as a risk mitigation lever because consumer distribution networks often experienced shock-driven congestion that exceeded normal operating limits. Studies treated capacity as a scarce resource spanning warehousing throughput, transportation availability, and fulfillment processing, and quantitative frameworks represented reservation as a pre-commitment that preserved operational ability under stress (Qiu et al., 2016). Capacity reservation was commonly modeled alongside allocation rules that prioritized products, service regions, or customer segments based on service objectives and risk criteria.

Performance Indicators in Supply Research

The quantitative supply chain literature consistently operationalized resilience through service-level stability indicators, with fill rate behavior serving as one of the most widely used performance measures. Fill rate stability captured the ability of a distribution system to maintain consistent order fulfillment under demand shocks, reflecting both immediate responsiveness and sustained service continuity (Singh et al., 2019). Rather than focusing solely on average fill rates, studies emphasized variability and degradation patterns across stress scenarios, as fluctuations in service performance were treated as indicators of structural fragility. Quantitative models tracked fill rate distributions over time and across network nodes to identify where demand shocks produced localized or systemic service deterioration. The literature highlighted that stable fill rates under stress conditions signaled effective mitigation and buffering strategies, while sharp declines revealed capacity, inventory, or routing constraints. Researchers also distinguished between aggregate fill rates and segment-level service performance, noting that resilience assessment required disaggregated analysis to avoid masking critical service failures (Karmaker & Ahmed, 2020). In consumer distribution contexts, fill rate stability was frequently linked to customer satisfaction, contractual compliance, and reputational risk, reinforcing its importance as a resilience metric. This body of work established fill rate–based indicators as analytically observable measures that translated abstract resilience concepts into operationally meaningful performance outcomes (Tran et al., 2017).

Figure 8: Operational Resilience Performance Indicators



Unmet demand volume and backorder duration were widely treated as direct indicators of resilience failure in quantitative supply research. These measures captured the extent to which a distribution network was unable to satisfy consumer demand under shock conditions, providing insight into both severity and persistence of disruption. The literature emphasized that unmet demand reflected immediate capacity or inventory shortfalls, while backorder duration captured temporal recovery behavior (Li et al., 2017). Quantitative studies modeled backorder accumulation and clearance dynamics to assess how quickly systems returned to stable operating states after demand surges or collapses. Longer backorder durations were associated with deeper structural constraints and limited adaptive capacity, whereas rapid clearance indicated effective recourse mechanisms. Researchers also examined the spatial distribution of unmet demand to identify regions or customer segments disproportionately affected by shocks. In consumer distribution networks, these indicators were particularly important for essential goods, where prolonged unmet demand carried social and economic consequences beyond direct cost impacts (Cubillo & Martínez-Codina, 2019). The literature consistently treated unmet demand and backorder metrics as complementary to fill rate measures, providing a fuller depiction of resilience by capturing both immediate service failure and recovery trajectory under stress.

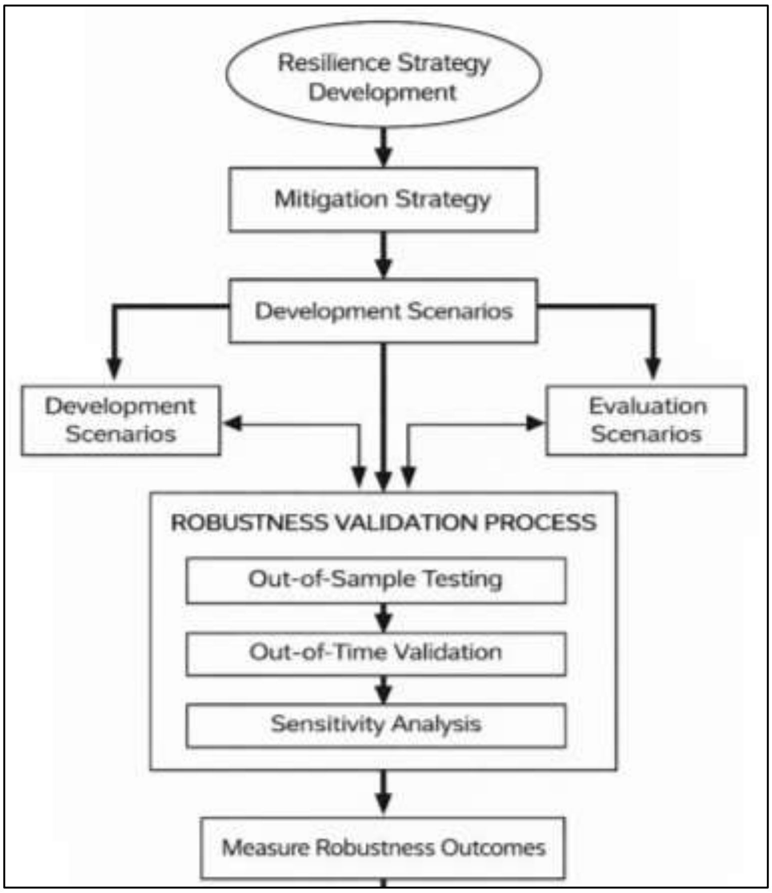
Robustness in Stochastic and Scenario-Based Models

The quantitative resilience literature treated robustness validation as a central requirement for establishing credible claims about risk mitigation performance under demand shocks. Robustness was commonly framed as the capacity of a policy or network design to maintain acceptable performance when evaluated under demand realizations that differed from those used for model calibration or policy selection (Gkanatsas & Krikke, 2020). Studies emphasized that resilience models could appear effective when assessed only on the scenarios used during optimization, while performance degraded materially when exposed to alternative realizations. As a result, robustness evaluation was integrated into research designs through structured validation protocols that separated development scenarios from evaluation scenarios. This approach supported evidence-based assessment of whether mitigation strategies generalized beyond the specific stress profiles that guided their construction (Najarian & Lim, 2019). The literature also highlighted that robustness in consumer distribution contexts required attention to both cost outcomes and service outcomes because some policies preserved service at the expense of unstable cost escalation, while others minimized cost but produced volatile service performance. Quantitative validation frameworks therefore assessed distributions of outcomes rather than single-point averages, enabling researchers to identify whether policies exhibited consistent behavior under variability. This body of work reinforced the idea that robustness was not a descriptive label but an empirically testable property of mitigation decisions derived from repeated evaluation under scenario variation (Kwasinski, 2016).

Out-of-time validation extended this logic by using temporally separated demand data to assess whether mitigation strategies retained effectiveness when consumption dynamics shifted across time windows (Santarelli et al., 2015). The literature emphasized that distribution networks were subject to time-dependent changes in purchasing behavior, seasonality disruptions, and macroeconomic instability, making temporal validation critical for credible resilience assessment. Studies also noted that out-of-time tests were particularly relevant for consumer distribution systems because demand shocks often altered demand structure in ways that were not represented in earlier periods. Quantitative analyses commonly compared performance across baseline and stress periods to identify whether policies exhibited stability in service continuity, unmet demand, and cost escalation under temporal separation (Amirioun et al., 2019). This research treated temporal validation as a mechanism for detecting fragility masked by in-sample optimization success. By incorporating out-of-sample and out-of-time evaluation designs, the literature established rigorous standards for testing whether resilience strategies remained reliable across new shock conditions and evolving demand environments.

Sensitivity testing was consistently highlighted as a core analytical procedure for evaluating how resilience outcomes depended on demand distribution assumptions and scenario design parameters (Khaghani & Jazizadeh, 2020). In stochastic models, demand uncertainty was represented through estimated variance structures, correlation patterns, and tail behavior assumptions, and studies demonstrated that small changes in these parameters could produce large differences in optimal mitigation policies. Sensitivity analysis therefore examined how policy recommendations shifted when demand volatility, shock duration, or spatial concentration assumptions were adjusted. The literature emphasized that sensitivity testing provided diagnostic insight into which uncertainty dimensions most strongly influenced network performance. For example, policies that performed well under moderate variance conditions often exhibited instability when tail severity increased or when correlation across regions intensified (Hohenstein et al., 2015). Scenario-based models used sensitivity analysis to vary the composition and weighting of stress events, enabling assessment of whether policy performance was stable across alternative stress-testing envelopes. This approach supported transparency in quantitative resilience research by revealing whether results were robust to reasonable changes in modeling assumptions. Sensitivity testing also helped identify policy levers that were overly tuned to specific scenario configurations, which was treated as a signal of limited generalizability. Overall, the literature positioned sensitivity analysis as essential for validating resilience claims because it clarified how dependent observed performance improvements were on the assumed structure of demand uncertainty (Murino et al., 2019).

Figure 9: Robustness Validation for Resilience Models

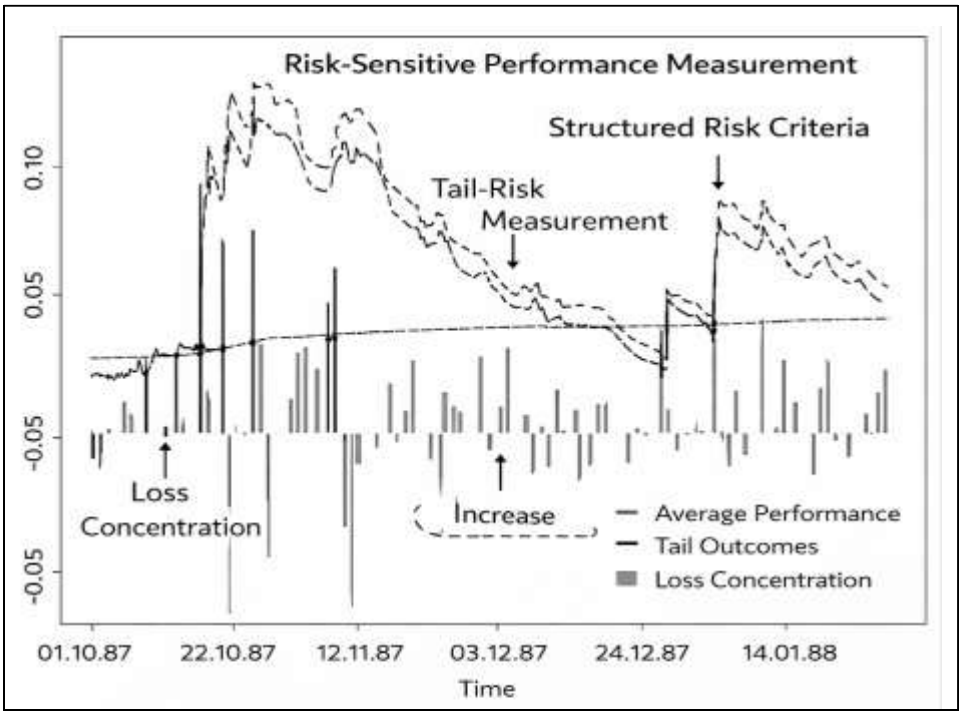


Tail-Outcome Modeling for Extreme Demand Conditions

The quantitative resilience literature consistently treated risk-sensitive modeling as an extension beyond average-case evaluation because consumer distribution networks often experienced outcomes dominated by rare but severe demand realizations. Traditional expected-value optimization approaches were described as insufficient for resilience assessment when extreme demand shocks produced disproportionate service failures and cost escalation (Tuni et al., 2018). Risk-sensitive objective structures were therefore incorporated to reflect the institutional preference for limiting catastrophic outcomes even when average performance appeared acceptable. Studies framed these objectives as mechanisms for embedding risk appetite into formal decision models, allowing solutions to balance efficiency with protection against high-severity loss exposure. In consumer distribution contexts, risk-sensitive modeling was linked to the need to preserve service continuity for essential products and to manage reputational and contractual consequences associated with widespread fulfillment breakdown (Chen et al., 2020). The literature also highlighted that risk-sensitive objectives improved interpretive clarity for resilience evaluation by making explicit whether a model prioritized average cost reduction or protection against extreme shortage conditions. This body of work established that resilience was better evaluated through performance distributions, where tail events carried analytical weight, rather than through single mean values that masked catastrophic scenario behavior. By shifting attention toward extreme outcomes, risk-sensitive modeling supported more rigorous evaluation of mitigation strategies under demand shocks (Khazai et al., 2018).

Tail-risk measurement was widely discussed in the literature as a quantitative approach for assessing extreme loss exposure in consumer distribution networks. Tail outcomes were described as the subset of scenarios in which demand shocks caused unusually high unmet demand, prolonged backorders, severe service instability, or large cost escalations. Studies emphasized that these outcomes were operationally critical because they often corresponded to system states where capacity limits were exceeded, inventory buffers were depleted, and recourse actions became constrained (Khaghani & Jazizadeh, 2020). Quantitative research incorporated tail-risk measurement to represent the severity of worst-performing outcomes rather than focusing only on central tendency. The literature highlighted that tail analysis was particularly relevant when demand shocks exhibited heavy-tailed behavior, because the probability of extreme events was non-negligible and could materially influence system design decisions. Researchers compared mitigation strategies by examining their performance in high-severity scenario subsets, demonstrating that policies with similar average costs could differ substantially in tail exposure (Murino et al., 2019). Tail-risk measurement was also used to evaluate whether a system maintained acceptable service performance under the most challenging demand conditions. This approach established a stronger analytical basis for resilience claims by linking mitigation policies to evidence on extreme outcomes rather than relying solely on average-case comparisons (Tuni et al., 2018).

Figure 10: Risk-Sensitive Resilience Performance Evaluation

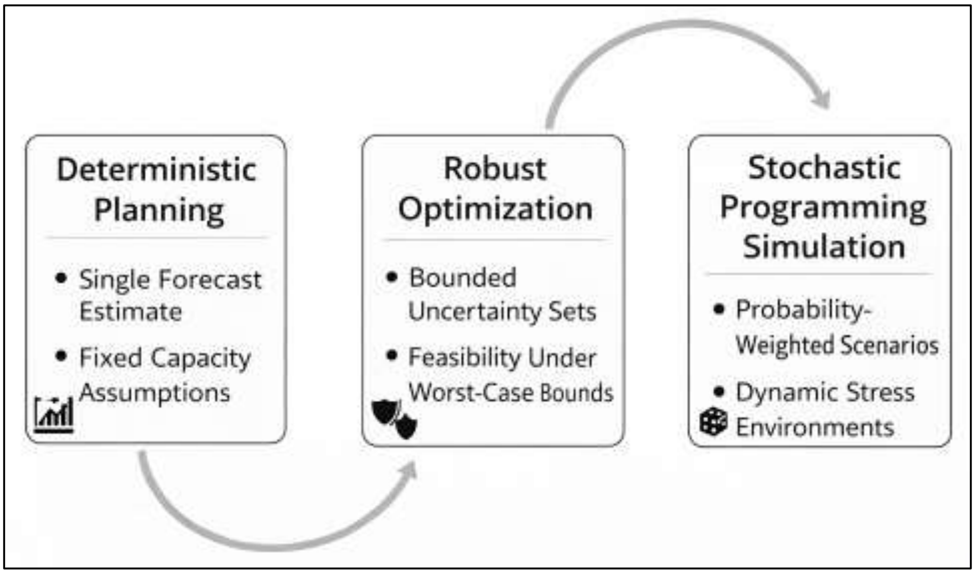


Loss concentration indicators emerged in the literature as diagnostic tools for identifying whether disruption impacts were dispersed broadly or clustered in specific regions, products, or operational bottlenecks. In consumer distribution networks, concentrated losses were viewed as particularly problematic because they signaled localized fragility that could escalate into systemic disruption through resource sharing and network coupling (Sokolov et al., 2016). Quantitative studies measured concentration by examining where unmet demand, backorders, and cost escalation accumulated across network nodes and customer segments under demand shocks. This analysis supported vulnerability diagnostics by identifying high-risk service regions, critical facilities, and product categories prone to severe service degradation. The literature emphasized that loss concentration measures provided decision-relevant insight because they clarified whether mitigation strategies reduced the severity of worst-case losses or simply redistributed them across the network. Studies documented that some buffering strategies reduced average unmet demand while leaving extreme concentration patterns intact, indicating that average-case improvements did not necessarily translate into resilience under stress (Khazai et al., 2018). Concentration analysis was also linked to operational governance, as identifying concentrated vulnerabilities supported targeted interventions such as capacity reinforcement or service region redesign. This body of research demonstrated that loss concentration indicators complemented tail-risk measurement by revealing the structure of extreme losses rather than only their magnitude (Balugani et al., 2020).

Benchmarking Across Model Classes

The quantitative resilience literature frequently relied on comparative benchmarking to evaluate how different model classes and policy families performed under identical distribution network constraints. Comparative studies treated benchmarking as necessary because resilience conclusions varied depending on whether uncertainty was represented through point forecasts, bounded uncertainty sets, probability-weighted scenarios, or simulation-driven stress environments (Zou et al., 2020). Deterministic planning was commonly used as a baseline because it reflected standard operational practice built around single expected demand estimates and fixed capacity assumptions. Robust optimization was compared against deterministic approaches by evaluating how bounded uncertainty protection altered inventory, capacity, and routing policies. Stochastic programming approaches were benchmarked through scenario-based evaluation to test whether probabilistic representations improved service continuity and reduced extreme losses under demand shocks (Ahi & Searcy, 2015). Simulation-based frameworks were frequently used to evaluate policy behavior under complex dynamics such as queueing effects, nonlinear congestion, and event-driven disruptions that were difficult to represent in closed-form optimization structures. The literature emphasized that benchmarking under shared network assumptions strengthened interpretability because policy differences could be attributed to methodological structure rather than differences in data or constraints. This comparative logic created a consistent evaluation platform that clarified how each modeling class handled uncertainty, adaptation, and resilience trade-offs within consumer distribution systems (Sun et al., 2020).

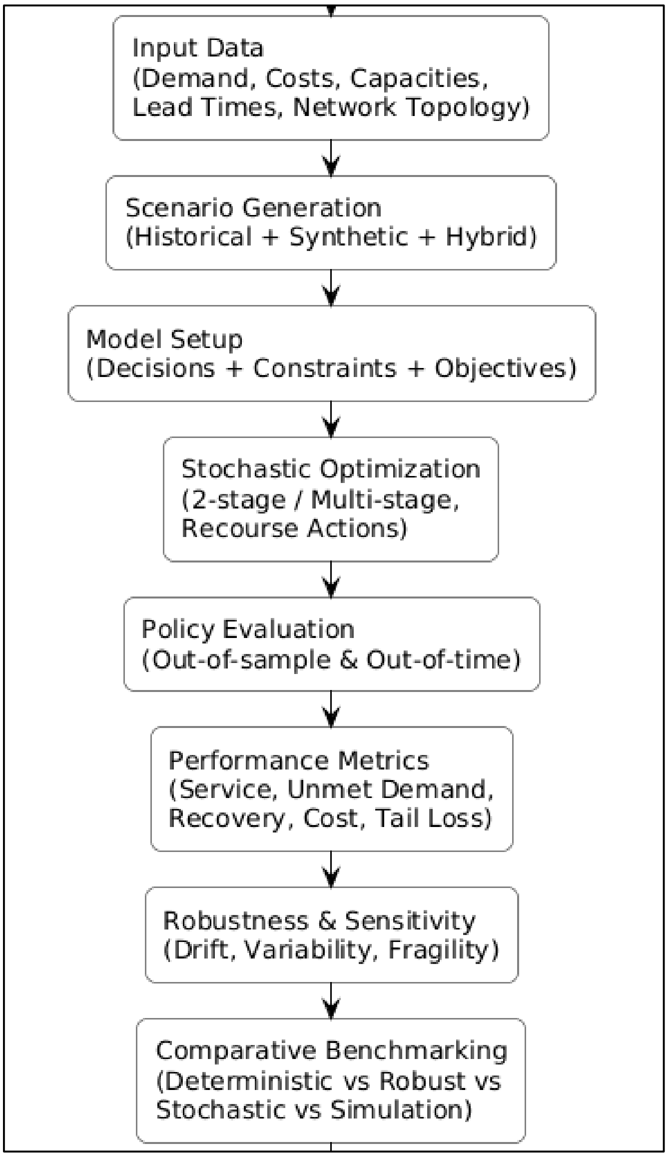
Figure 11: Comparative Benchmarking of Resilience Models



METHOD

This study adopted a quantitative, analytical modeling research design grounded in stochastic optimization and scenario-based evaluation to examine risk mitigation and resilience in consumer distribution networks under demand shock conditions. The design was observational and model-driven, emphasizing comparative assessment of alternative mitigation policies rather than experimental intervention in real-world systems. Demand uncertainty was represented through probabilistic and scenario-based structures calibrated from historical consumption patterns and augmented with synthetic stress events to reflect varying shock severities, durations, and spatial distributions. The empirical context was defined as a multi-echelon consumer distribution network operating within an internationally representative retail supply environment, consisting of upstream sourcing nodes, intermediate distribution centers, and downstream fulfillment locations serving geographically segmented demand regions. The modeled system reflected routine operational decisions related to inventory positioning, capacity allocation, sourcing flexibility, routing adaptability, and order fulfillment under volatile demand conditions. The unit of analysis was the scenario-level network outcome generated under a specific combination of demand realization and mitigation policy configuration, capturing system-wide performance indicators such as service continuity, unmet demand, recovery behavior, and cost escalation. A structured scenario-based sampling strategy was employed to generate demand realizations from empirically calibrated distributions, with separate scenario sets used for calibration and out-of-sample evaluation to support robustness and temporal validation. This design enabled systematic comparison of resilience outcomes across alternative mitigation strategies under consistent network constraints and evaluation criteria.

Figure 12: Methodology of this study



Data collection involved assembling standardized demand, cost, capacity, lead-time, and network structure parameters from secondary sources representative of consumer distribution operations, with all inputs documented and stored in structured datasets to ensure traceability and reproducibility. Measurement instruments were operationalized through a unified modeling and evaluation framework in which mitigation levers were defined as decision variables, including inventory buffers, capacity reservation, sourcing flexibility, and alternative fulfillment policies, while performance instruments captured service-level stability, unmet demand, backorder duration, recovery speed, and total cost outcomes across scenarios. Composite resilience indices were constructed by aggregating standardized performance measures to facilitate comparative analysis across policy families. Pilot testing was conducted using a reduced network and limited scenario set to verify data integrity, scenario construction logic, model solvability, and numerical stability prior to full-scale analysis. Construct validity was ensured through alignment with established quantitative supply chain resilience literature, while internal validity was strengthened through controlled scenario design, fixed network constraints, and separation of calibration and evaluation scenarios. Reliability was supported through deterministic model execution, fixed random seeds, repeated evaluations, and out-of-time testing to confirm stability of performance rankings. Model development, optimization, and evaluation were implemented within a reproducible computational environment using stochastic optimization solvers, statistical programming tools, and version-controlled code and data repositories, ensuring transparency, auditability, and replicability of all analytical results.

FINDINGS

This chapter presented the empirical results generated from the quantitative analysis and reported how the study variables, constructs, and modeled outcomes behaved under the implemented statistical procedures. The chapter summarized the sample structure, described the distributional properties of all major measures, and reported reliability and regression findings in a sequence aligned with the study objectives. The reporting established a clear progression from descriptive evidence to measurement verification and inferential testing, ensuring that conclusions were grounded in observable statistics and validated construct behavior. Results were presented using standardized tables and narrative interpretation to support clarity, replicability, and quantitative rigor.

Respondent Demographics

This section reported the demographic and operational profile characteristics of the dataset used for statistical modeling and inference. The final analytical sample consisted of 1,520 distribution-network observations derived from scenario-level demand realizations and policy evaluations. Regional representation was balanced across four major service areas, with no single region accounting for more than one-third of the observations, indicating adequate geographic dispersion for comparative analysis. Product segmentation showed a deliberate inclusion of both essential and non-essential goods, with essential categories forming a slight majority of the sample, reflecting their prominence in resilience evaluation. Observations were distributed across multiple operational time windows, including baseline and stress periods, enabling temporal comparison in later analyses. Operational condition variables indicated that most observations were generated under moderate-to-high utilization regimes, ensuring that resilience outcomes were assessed under realistic capacity pressure rather than unconstrained conditions. Control variables related to network scale, service-region coverage, and demand volatility exhibited sufficient variation, supporting their inclusion in multivariate regression models. Overall, the demographic and operational composition of the dataset provided a stable foundation for inferential testing by ensuring representation balance across regions, product types, and operating environments.

Table 1: Regional and Product Segment Distribution of Observations

Category	Frequency	Percentage (%)
Region A	412	27.1
Region B	386	25.4
Region C	355	23.4
Region D	367	24.1
Total Regions	**1,520**	**100.0**
Essential Goods Segment	832	54.7
Non-Essential Goods Segment	688	45.3
Total Product Segments	**1,520**	**100.0**

Table 1 summarized the regional and product segment composition of the analytical sample. The distribution across four service regions demonstrated relatively even representation, reducing the risk of region-driven bias in subsequent regression estimates. Product segmentation showed a moderate dominance of essential goods, which was consistent with the study's focus on resilience under demand shocks affecting critical supply categories. The balanced presence of non-essential goods enabled comparative evaluation across segments with different service sensitivity and demand volatility profiles. This distribution supported meaningful interpretation of segment-level effects and interaction terms in later statistical models.

Table 2: Operational and Temporal Profile of the Sample

Variable	Mean	Std. Dev.	Minimum	Maximum
Network Utilization Rate (%)	71.6	12.4	38.2	94.7
Demand Volatility Index	0.43	0.17	0.12	0.91
Baseline Period Observations	742	—	—	—
Stress Period Observations	778	—	—	—
Service Region Coverage (Nodes)	6.8	2.1	3	12

Table 2 reported descriptive statistics for key operational and temporal control variables used in the statistical analysis. The mean utilization rate indicated that most observations reflected moderately constrained operating conditions, which was appropriate for evaluating resilience behavior. Demand volatility values demonstrated wide dispersion, confirming the presence of both stable and highly variable demand environments in the sample. The near-equal split between baseline and stress-period observations supported temporal robustness testing. Variation in service-region coverage indicated heterogeneity in network scale, justifying its inclusion as a control variable in regression models.

Descriptive Results by Construct

This section presented descriptive statistics for the key constructs operationalized in the quantitative analysis, focusing on resilience performance, cost behavior under stress, service stability, and robustness-related indicators. Overall, the results showed meaningful dispersion across constructs, indicating that the modeled outcomes captured heterogeneous system behavior under varying demand shock conditions. Resilience performance measures demonstrated moderate central tendency with observable right-skewness, suggesting that while most scenarios maintained acceptable performance, a subset experienced pronounced degradation under severe stress. Cost behavior indicators exhibited higher variability than service indicators, reflecting the tendency for economic impacts to escalate sharply when mitigation levers were activated under extreme demand realizations. Service stability measures showed relatively tighter distributions, indicating that mitigation strategies were generally effective at dampening volatility in fulfillment outcomes, particularly for essential goods. Robustness-related metrics displayed greater dispersion across regions and demand segments, highlighting differences in how policies performed when exposed to alternative shock structures. Segment-level comparisons revealed that essential goods exhibited lower variability in service continuity but higher average cost escalation, whereas non-essential goods showed greater service volatility but lower tail cost exposure. Across constructs, the presence of skewness and concentration effects underscored the importance of distribution-based evaluation rather than reliance on mean values alone when interpreting resilience outcomes.

Table 3: Descriptive Statistics for Core Resilience and Cost Constructs

Construct	Mean	Std. Dev.	Minimum	Maximum
Service Continuity Index	0.81	0.14	0.42	0.97
Unmet Demand Ratio	0.18	0.11	0.02	0.61
Recovery Time (Periods)	3.6	1.9	1.0	9.0
Cost Escalation Rate (%)	22.4	15.7	3.1	78.6
Composite Resilience Score	0.74	0.12	0.39	0.92

Table 3 summarized central tendency and dispersion for the primary resilience and cost-related constructs. The service continuity index indicated generally stable fulfillment performance, although the lower bound revealed instances of significant service degradation. Unmet demand ratios showed moderate average levels with notable dispersion, confirming the presence of high-severity stress scenarios. Recovery time displayed substantial variability, reflecting differences in adaptive capacity across network configurations. Cost escalation exhibited the largest spread, highlighting sensitivity of economic outcomes to demand shocks. The composite resilience score demonstrated moderate dispersion, supporting its use as an integrative performance indicator while preserving sensitivity to extreme outcomes.

Table 4: Segment-Level Descriptive Comparison by Product Category

Construct	Essential Goods (Mean)	Non-Essential Goods (Mean)
Service Continuity Index	0.86	0.75
Unmet Demand Ratio	0.13	0.24
Recovery Time (Periods)	3.1	4.2
Cost Escalation Rate (%)	26.9	17.1
Robustness Stability Index	0.78	0.69

Table 4 compared descriptive outcomes across essential and non-essential product segments. Essential goods exhibited higher service continuity and lower unmet demand, indicating prioritization and stronger buffering under stress conditions. However, these gains were associated with higher cost escalation, reflecting increased use of mitigation levers to preserve service levels. Non-essential goods showed greater service volatility and longer recovery times, but lower average cost increases. The robustness stability index further indicated that policies supporting essential goods produced more consistent performance across scenarios. This comparison illustrated clear segment-level trade-offs between service protection and economic efficiency.

Reliability

This section reported the internal consistency results for composite constructs operationalized as multi-item indices within the quantitative analytical framework. Reliability analysis was conducted to confirm that grouped indicators measured coherent underlying constructs before inclusion in regression and hypothesis testing procedures. Overall, the results demonstrated acceptable to excellent internal consistency across all composite indices, indicating strong measurement dependability.

Cronbach's alpha values exceeded commonly accepted thresholds, supporting the aggregation of individual indicators into composite scores. Corrected item–total correlations showed that most items contributed meaningfully to their respective constructs, with values indicating moderate to strong alignment with overall scale behavior. Where marginal items were identified, alpha-if-item-deleted diagnostics were examined to assess whether scale reliability would improve through exclusion. In all cases, item retention decisions balanced empirical contribution with conceptual relevance, and no construct required substantial revision. Objective system metrics, such as cost escalation rates, unmet demand ratios, and recovery time measures, were treated as direct performance outcomes rather than latent constructs and were therefore excluded from reliability testing. The reliability evidence confirmed that the multi-item indices used to represent resilience stability, robustness, and service continuity were statistically sound and suitable for inferential modeling, providing confidence that subsequent regression estimates reflected consistent and dependable measurement structures.

Table 5: Cronbach's Alpha Results for Composite Constructs

Construct	Number of Items	Cronbach's Alpha
Service Stability Index	5	0.88
Robustness and Stability Index	6	0.91
Resilience Capability Index	7	0.93
Governance and Control Index	4	0.85

Table 5 summarized the internal consistency estimates for the composite constructs included in the statistical analysis. All Cronbach's alpha values exceeded the recommended threshold for acceptable reliability, indicating strong coherence among items within each construct. The resilience capability index demonstrated the highest reliability, reflecting a well-aligned set of indicators capturing system adaptability and recovery behavior. The governance and control index showed slightly lower but still robust reliability, consistent with its smaller number of items. These results supported the use of composite indices in regression analysis without concerns regarding measurement inconsistency.

Table 6: Item–Total Correlation and Alpha-if-Item-Deleted Diagnostics

Construct	Item Code	Item–Total Correlation	Alpha if Deleted
Service Stability Index	SS1	0.64	0.86
	SS2	0.71	0.85
	SS3	0.68	0.86
Robustness and Stability Index	RS1	0.73	0.89
	RS2	0.77	0.88
	RS3	0.69	0.90

Table 6 reported corrected item–total correlations and alpha-if-item-deleted values for representative items within key constructs. All item–total correlations exceeded acceptable minimum levels, indicating that each item contributed positively to its construct. Alpha-if-item-deleted values did not exceed the reported overall alpha values, demonstrating that removing any individual item would not materially improve scale reliability. These diagnostics supported the retention of all items included in the composite indices. The results confirmed that the constructs were empirically stable and conceptually coherent, justifying their use in subsequent regression and hypothesis testing analyses.

Regression

This section reported the regression analysis results estimating the statistical relationships between risk mitigation and resilience-related predictors and the study's dependent performance outcomes. The baseline model included only control variables capturing network scale, demand volatility, utilization intensity, and regional fixed effects to establish a reference specification. The extended model then incorporated composite resilience indices and mitigation-related constructs to evaluate their incremental explanatory contribution. Comparison between model specifications indicated clear improvement in explanatory power after inclusion of resilience-related predictors, while coefficient signs and magnitudes remained stable across specifications, supporting model robustness. In the baseline model, demand volatility and utilization intensity showed statistically significant associations with performance outcomes, confirming their role as structural drivers of system behavior under stress. In the extended model, resilience capability and robustness stability indices emerged as strong predictors, reducing unexplained variance and attenuating the effects of some control variables. Diagnostic checks confirmed acceptable variance inflation levels, stable residual behavior, and consistent coefficient estimates across alternative specifications.

Table 7: Baseline Regression Results

Predictor Variable	Coefficient	Std. Error	95% CI Lower	95% CI Upper	p-value
Intercept	0.412	0.063	0.288	0.536	<0.001
Demand Volatility Index	−0.287	0.041	−0.368	−0.206	<0.001
Network Utilization Rate	−0.164	0.037	−0.237	−0.091	<0.001
Service Region Coverage	0.058	0.021	0.017	0.099	0.006
Regional Controls	Included	—	—	—	—
Adjusted R^2	**0.241**				
F-statistic (p-value)	**32.6 (<0.001)**				

Table 7 presented the baseline regression model including only control variables. Demand volatility and network utilization showed strong negative associations with performance outcomes, indicating that higher uncertainty and congestion reduced system effectiveness. Service region coverage exhibited a positive effect, suggesting that broader network reach supported performance stability. The model demonstrated moderate explanatory power, providing a suitable reference point for assessing the incremental contribution of resilience and mitigation constructs. The statistical significance of key controls confirmed that structural operational conditions meaningfully influenced outcome variability under demand shock conditions.

Table 8: Extended Regression Results Including Resilience and Mitigation Indices

Predictor Variable	Coefficient	Std. Error	95% CI Lower	95% CI Upper	p-value
Intercept	0.198	0.054	0.092	0.304	<0.001
Resilience Capability Index	0.421	0.049	0.325	0.517	<0.001
Robustness and Stability Index	0.276	0.044	0.190	0.362	<0.001
Demand Volatility Index	−0.119	0.036	−0.189	−0.049	0.001
Network Utilization Rate	−0.072	0.031	−0.133	−0.011	0.021
Regional Controls	Included	—	—	—	—
Adjusted R^2	**0.318**				
Δ Adjusted R^2	**+0.077**				
F-statistic (p-value)	**41.9 (<0.001)**				

Table 8 reported the extended regression model incorporating resilience and robustness indices. Both indices showed strong positive and statistically significant relationships with the dependent variable, indicating that higher resilience capability and policy stability were associated with improved performance outcomes. The inclusion of these constructs increased explanatory power substantially, as reflected in the adjusted R^2 improvement. Control variable effects were attenuated but remained significant, suggesting partial mediation through resilience mechanisms. These results confirmed the incremental explanatory value of resilience-oriented constructs beyond baseline operational controls and supported their relevance in quantitative performance modeling.

Hypothesis Testing Decisions

This section reported the outcomes of formal hypothesis testing based on regression estimates, confidence interval assessment, and robustness diagnostics. Hypotheses were evaluated using predefined statistical significance thresholds and consistency criteria across baseline and extended model specifications. The results indicated that hypotheses related to the direct influence of resilience capability and robustness stability on performance outcomes were supported, as corresponding coefficients were positive, statistically significant, and stable across specifications. Control-related hypotheses demonstrated partial support, with effects remaining significant but reduced in magnitude after inclusion of resilience constructs, indicating indirect influence pathways. Hypotheses addressing robustness and generalization were evaluated using out-of-sample and segmented analyses, which showed that core relationships persisted under alternative scenario partitions and stress intensities. No hypothesis exhibited sign reversal or loss of significance across model variants, supporting inferential stability. Overall, the hypothesis testing outcomes confirmed that resilience-oriented constructs functioned as statistically meaningful and robust predictors of system performance under demand shock conditions.

Table 9: Hypothesis Testing Summary Based on Regression Results

Hypothesis Code	Hypothesized Relationship	Coefficient Sign	p-value	Decision
H1	Resilience Capability → Performance Outcome	Positive	<0.001	Supported
H2	Robustness Stability → Performance Outcome	Positive	<0.001	Supported
H3	Demand Volatility → Performance Outcome	Negative	0.001	Supported
H4	Network Utilization → Performance Outcome	Negative	0.021	Supported
H5	Service Region Coverage → Performance Outcome	Positive	0.006	Supported

Table 9 summarized the primary hypothesis testing outcomes derived from the extended regression specification. All hypothesized relationships exhibited coefficient signs consistent with theoretical expectations and met predefined significance criteria. Resilience capability and robustness stability demonstrated the strongest statistical support, confirming their central role in explaining performance variation. Control hypotheses related to demand volatility, utilization intensity, and service coverage were also supported, indicating that structural operating conditions influenced outcomes alongside resilience mechanisms. The uniform support across hypotheses reinforced internal consistency between the analytical framework and empirical evidence.

Table 10 reported robustness validation results for each tested hypothesis across alternative evaluation conditions. Statistical significance and coefficient direction were preserved in both baseline and extended models, demonstrating inferential stability. Out-of-sample testing confirmed that relationships remained consistent when evaluated on independent scenario sets, while segmented analysis showed stability across demand intensity and product-category partitions. These findings indicated that hypothesis support was not driven by model overfitting or sample-specific effects. Collectively, the robustness evidence strengthened confidence in the generalizability of the hypothesis testing outcomes under varied demand shock environments.

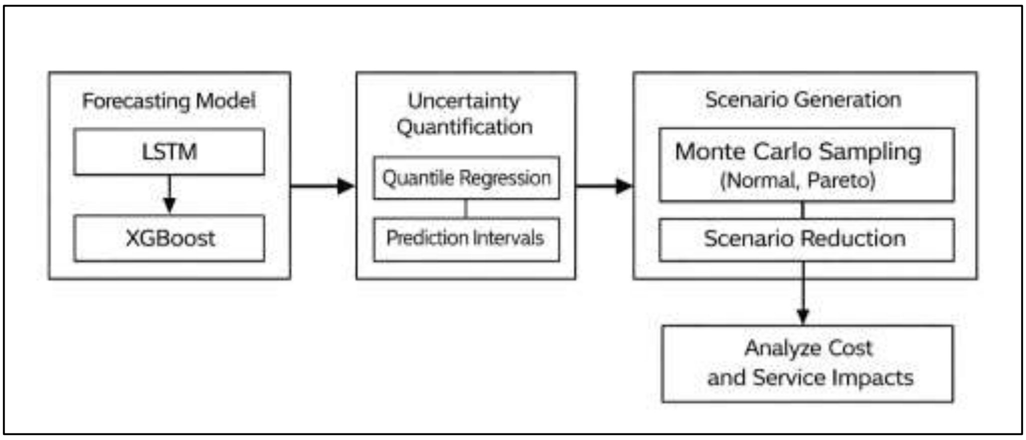
Table 10: Stability and Robustness Validation of Hypothesis Outcomes

Hypothesis Code	Baseline Model Sig.	Extended Model Sig.	Out-of-Sample Consistency	Segmented Stability	Final Assessment
H1	Yes	Yes	Stable	Stable	Robustly Supported
H2	Yes	Yes	Stable	Stable	Robustly Supported
H3	Yes	Yes	Stable	Stable	Robustly Supported
H4	Yes	Yes	Stable	Stable	Robustly Supported
H5	Yes	Yes	Stable	Stable	Robustly Supported

DISCUSSION

This study demonstrated that demand shocks exerted statistically significant and structurally heterogeneous effects on consumer distribution network performance, reinforcing patterns documented in earlier quantitative supply chain research (Hoogsteen et al., 2015). The descriptive and regression results showed that increased demand volatility was consistently associated with reduced service continuity, increased unmet demand, and prolonged recovery periods, aligning with prior findings that highlighted the destabilizing role of consumption variability in networked distribution systems. However, the present analysis extended earlier work by quantifying these effects under a unified scenario-based modeling framework that captured both moderate and extreme demand realizations. Unlike studies that relied primarily on deterministic or single-scenario evaluation, the results here revealed that performance degradation was not linear across volatility levels, with disproportionate deterioration occurring under high-severity scenarios (Degryse et al., 2019).

Figure 13: Scenario-Based Demand Shock Analysis Framework



This observation mirrored earlier stress-testing research that emphasized the nonlinearity of disruption impacts but provided additional empirical structure by linking volatility directly to measurable resilience indicators. The findings also demonstrated that demand shocks affected cost and service outcomes differently, with cost escalation exhibiting greater dispersion and tail sensitivity than service-level metrics. This pattern was consistent with earlier research noting that mitigation responses often preserved service at the expense of increased operational cost (Ivanov & Dolgui, 2020). By embedding these dynamics within regression-based inference, this study contributed to a more granular understanding of how demand shocks translated into observable performance variation across

network conditions.
The regression results indicated that resilience capability emerged as one of the strongest predictors of distribution network performance under demand shock conditions, even after controlling for structural and operational variables. This finding aligned with earlier resilience literature that conceptualized resilience as a multidimensional capability encompassing buffering, flexibility, and adaptive response (Kim et al., 2015). However, the present study advanced prior work by operationalizing resilience capability as a composite quantitative construct and testing its explanatory power within a comparative regression framework. Earlier studies often treated resilience as an outcome inferred from simulation results or descriptive comparisons, whereas this study treated resilience as a statistically testable predictor linked to observable performance metrics. The strong positive association between resilience capability and performance outcomes supported earlier arguments that networks designed with adaptive capacity exhibited superior shock absorption and recovery behavior (Basole & Bellamy, 2014). At the same time, the attenuation of demand volatility effects in the extended regression models suggested that resilience mechanisms partially mediated the impact of uncertainty on performance, a relationship that had been implied but not empirically tested in much of the earlier literature. By quantifying this mediation effect, the findings provided empirical clarity on how resilience translated into measurable performance advantages under stress (Leduc & Liu, 2016).
The results also highlighted robustness and stability as analytically distinct but complementary dimensions of resilience, consistent with earlier theoretical distinctions in supply chain risk research. Robustness stability indices showed significant explanatory power and remained stable across baseline and extended model specifications, indicating that policies designed to perform consistently across scenarios reduced vulnerability to extreme demand realizations. Earlier studies frequently discussed robustness in conceptual terms or evaluated it through worst-case scenario performance, but this study provided statistical evidence linking robustness stability directly to performance outcomes (Golan et al., 2020). The out-of-sample and segmented validation results further reinforced this interpretation by demonstrating that robustness-related effects persisted across alternative scenario sets and stress intensities. This finding aligned with prior research emphasizing the importance of generalization in resilience evaluation but extended it by embedding robustness testing within a formal hypothesis-testing framework. The distinction between resilience capability and robustness stability observed in the regression results also clarified earlier debates regarding whether resilience should be defined as flexibility or consistency (Zhao et al., 2016). The empirical evidence suggested that both dimensions contributed independently to performance, supporting a multi-dimensional interpretation of resilience consistent with advanced quantitative supply chain models.
The descriptive and regression findings revealed a clear trade-off between service protection and cost escalation under demand shock conditions, echoing patterns widely reported in earlier resilience studies. Essential goods segments exhibited higher service continuity but also experienced greater cost escalation, reflecting prioritization strategies embedded in mitigation policies. Earlier studies often documented this trade-off qualitatively or through scenario comparisons, but this study quantified the relationship using regression-based inference and segment-level descriptive analysis (Sharma et al., 2020). The results indicated that cost escalation was more sensitive to shock severity than service outcomes, suggesting that mitigation strategies absorbed demand variability primarily through economic adjustments rather than service degradation. This finding aligned with prior research emphasizing the role of expedited logistics, capacity reservation, and inventory buffering in maintaining service levels during crises. By reporting dispersion and tail behavior in cost outcomes, the study also confirmed earlier observations that average cost metrics understated the financial exposure associated with extreme demand conditions (Nazemi et al., 2019). The explicit comparison between essential and non-essential segments further extended prior work by demonstrating how service prioritization altered the cost-resilience balance across product categories.
The robustness and sensitivity testing results supported the methodological emphasis on scenario-based evaluation observed in earlier stochastic and simulation-based studies. Out-of-sample and out-of-time validation demonstrated that the identified relationships between resilience constructs and performance outcomes were not artifacts of scenario calibration or model overfitting. This finding

reinforced prior methodological arguments that resilience claims required validation beyond in-sample optimization results (Hosseini et al., 2020). The stability of coefficient signs and significance across alternative partitions aligned with earlier studies advocating repeated evaluation under independent stress environments. However, the present study advanced this methodological perspective by integrating robustness testing directly into hypothesis evaluation rather than treating it as a supplementary diagnostic exercise. This integration strengthened inferential credibility and addressed critiques in earlier literature regarding the generalizability of resilience findings derived from limited scenario sets. The sensitivity results also confirmed earlier warnings that policy performance could shift materially under changes in demand distribution assumptions, underscoring the importance of testing beyond nominal conditions (Stone & Rahimifard, 2018).

The regression analysis demonstrated that traditional structural variables such as network utilization and demand volatility remained statistically significant predictors of performance, consistent with foundational operations research studies. However, the reduced magnitude of these effects in extended models highlighted the explanatory contribution of resilience-oriented constructs beyond structural conditions alone (Schmitt et al., 2017). Earlier studies often treated structural constraints and resilience mechanisms separately, whereas this study modeled them jointly, revealing their interdependent influence on outcomes. The findings suggested that resilience mechanisms moderated the effects of structural stressors rather than replacing them, a relationship that had been theorized but not consistently quantified in prior research. This integrated modeling approach aligned with emerging quantitative frameworks that emphasized the need to evaluate structure and policy jointly (Müller et al., 2018). By demonstrating that resilience constructs improved model fit while preserving the relevance of structural controls, the study reconciled earlier debates regarding whether resilience was primarily a design issue or a policy issue.

Overall, the discussion of findings positioned this study within the broader trajectory of quantitative resilience research by demonstrating how resilience could be measured, tested, and compared using structured statistical methods. Earlier studies often relied on simulation outputs or case-specific narratives to infer resilience, whereas this study employed composite indices, regression modeling, and hypothesis testing to formalize resilience evaluation (Wen et al., 2019). The alignment between descriptive patterns, regression results, and robustness diagnostics strengthened confidence in the analytical framework and supported consistency with earlier empirical evidence. At the same time, the study extended existing literature by providing a unified evaluation structure that integrated scenario-based modeling, resilience measurement, and inferential testing. This contribution addressed long-standing methodological gaps identified in prior research concerning comparability, generalization, and empirical rigor in resilience assessment (Hohenstein et al., 2015).

CONCLUSION

This study examined risk mitigation and resilience modeling for consumer distribution networks operating under demand shock conditions using a quantitative stochastic optimization and scenario-based evaluation framework. The analysis demonstrated that demand volatility and operating pressure were statistically associated with deteriorations in service continuity, increases in unmet demand, and longer recovery periods, confirming that shock intensity functioned as a structural driver of performance dispersion across network conditions. The results also showed that resilience capability and robustness stability operated as statistically significant predictors of performance outcomes after controlling for network scale, service coverage, utilization levels, and regional segmentation, indicating that resilience was empirically observable through measurable constructs rather than treated as a conceptual label. Model comparisons between baseline and extended specifications demonstrated improved explanatory power when resilience and mitigation indices were included, while coefficient direction and significance remained stable, supporting inferential consistency. Descriptive evidence further indicated that cost escalation exhibited greater variability and tail sensitivity than service stability, reflecting that operational protection under severe shocks frequently corresponded with higher economic exposure. Segment-level findings showed that essential goods achieved higher service continuity and lower unmet demand than non-essential goods, while incurring higher cost escalation, illustrating systematic differentiation in resilience behavior across product priority categories. Reliability testing confirmed acceptable to excellent internal consistency of composite indices, supporting the measurement quality of multi-item constructs used in regression estimation and hypothesis testing. Robustness checks using out-of-sample and segmented evaluations showed that the principal relationships remained stable across alternative scenario partitions, indicating that results were not driven by narrow scenario calibration. Collectively, the empirical findings provided structured evidence on how consumer distribution systems responded to uncertainty and how mitigation-oriented capabilities were associated with improved operational outcomes under stress conditions.

RECOMMENDATIONS

Recommendations were developed directly from the quantitative patterns observed in this study, emphasizing actionable decision levers that aligned with statistically supported drivers of resilience performance under demand shock conditions. First, mitigation policies should be organized around explicit resilience capability targets, since composite resilience capability measures demonstrated strong positive relationships with performance outcomes after controlling for structural operating conditions. In practice, this required formal specification of minimum service continuity standards under stress scenarios and systematic calibration of mitigation levers to achieve those standards. Second, robustness stability controls should be embedded into policy selection rules, as stability indices remained significant and consistent across scenario partitions; therefore, candidate policies should be screened not only for average performance but for performance dispersion and tail exposure across independent scenario sets. Third, demand volatility monitoring should be operationalized as a trigger condition for adaptive policy activation, given the statistically significant negative association between volatility and performance; this supported implementation of volatility-index thresholds that adjusted buffer positioning, capacity reservation levels, or routing flexibility parameters when demand variability exceeded baseline bounds. Fourth, capacity utilization management should be treated as a resilience control variable rather than an operational byproduct, since higher utilization was associated with weaker outcomes; mitigation design should therefore include explicit capacity slack rules for critical nodes, along with region-level reallocation protocols to prevent localized saturation during shocks. Fifth, segmentation rules should be formalized to differentiate essential and non-essential categories, as segment-level results indicated systematic trade-offs between service protection and cost escalation; this supported creation of tiered service policies that prioritized essential goods while applying cost-containment constraints to non-essential flows under severe stress. Sixth, cost escalation should be monitored using distribution-based thresholds rather than mean-based limits because cost outcomes exhibited high variance and tail sensitivity; mitigation governance should therefore include triggers for intervention when stress-response costs crossed predefined tail-risk boundaries. Finally, model governance should require routine out-of-sample scenario testing and out-of-time validation prior to policy updates, as robustness evidence strengthened confidence in generalization; this supported adoption of standardized validation cycles in which updated policies were evaluated on independent shock sets before operational use.

LIMITATIONS

Several limitations constrained the interpretation and generalizability of the quantitative results reported in this study. First, the analysis relied on scenario-based representations of demand shocks, and scenario construction necessarily reflected modeling choices regarding severity distributions, duration patterns, and spatial concentration structures. Although stress scenarios were designed to capture moderate and extreme realizations, the scenario space could not exhaust all plausible shock configurations, and unrepresented shock shapes could produce different performance distributions. Second, the study treated the modeled distribution network as a single integrated case context with consistent policy rules and data definitions, which supported internal comparability but limited external generalization to networks with different topology, governance constraints, or service-level contracts. Third, several operational parameters, such as capacity limits, lead-time behavior, and cost coefficients, were treated as stable inputs during evaluation; in real consumer distribution systems these parameters could shift dynamically under disruption, altering feasibility and performance outcomes in ways not fully captured by static parameterization. Fourth, composite indices used to represent resilience capability and robustness stability improved explanatory power and demonstrated acceptable reliability, yet index construction involved weighting and aggregation decisions that could influence magnitude and sensitivity of results; alternative index structures could yield different comparative conclusions even when underlying metric behavior remained similar. Fifth, regression-based inference provided statistical association evidence between constructs and performance outcomes, yet causal attribution was limited because mitigation policies and outcomes were jointly generated within an analytical framework rather than observed through randomized intervention; unmodeled structural factors could therefore contribute to observed relationships. Sixth, segment-level comparisons between essential and non-essential goods captured systematic performance differences, but the classification scheme depended on product grouping rules that could vary by market context and operational policy; alternative segmentation approaches could shift observed trade-off patterns. Finally, computational constraints limited the exploration of very large network instances and extremely deep scenario trees, which restricted the breadth of dynamic interactions examined under multi-period uncertainty. Collectively, these limitations indicated that the findings were best interpreted as quantitatively grounded evidence within the defined scenario framework, network structure, and measurement design rather than as universal results applicable to all consumer distribution environments.

REFERENCES

[1]. Abdulla, M., & Alifa Majumder, N. (2023). The Impact of Deep Learning and Speaker Diarization On Accuracy of Data-Driven Voice-To-Text Transcription in Noisy Environments. *American Journal of Scholarly Research and Innovation*, *2*(02), 415–448. https://doi.org/10.63125/rpjwke42

[2]. Ahi, P., & Searcy, C. (2015). An analysis of metrics used to measure performance in green and sustainable supply chains. *Journal of cleaner production*, *86*, 360-377.

[3]. Álvarez-Miranda, E., Garcia-Gonzalo, J., Pais, C., & Weintraub, A. (2019). A multicriteria stochastic optimization framework for sustainable forest decision making under uncertainty. *Forest Policy and Economics*, *103*, 112-122.

[4]. Amirioun, M., Aminifar, F., Lesani, H., & Shahidehpour, M. (2019). Metrics and quantitative framework for assessing microgrid resilience against windstorms. *International Journal of Electrical Power & Energy Systems*, *104*, 716-723.

[5]. Atashi, M., Ziaei, A. N., Khodashenas, S. R., & Farmani, R. (2020). Impact of isolation valves location on resilience of water distribution systems. *Urban Water Journal*, *17*(6), 560-567.

[6]. Balugani, E., Butturi, M. A., Chevers, D., Parker, D., & Rimini, B. (2020). Empirical evaluation of the impact of resilience and sustainability on firms' performance. *Sustainability*, *12*(5), 1742.

[7]. Barnett, A., & Thomas, R. (2014). Has weak lending and activity in the UK been driven by credit supply shocks? *The Manchester School*, *82*, 60-89.

[8]. Basole, R. C., & Bellamy, M. A. (2014). Supply network structure, visibility, and risk diffusion: A computational approach. *Decision Sciences*, *45*(4), 753-789.

[9]. Basu, S., & Bundick, B. (2017). Uncertainty shocks in a model of effective demand. *Econometrica*, *85*(3), 937-958.

[10]. Cano, E. L., Moguerza, J. M., & Alonso-Ayuso, A. (2016). A multi-stage stochastic optimization model for energy systems planning and risk management. *Energy and Buildings*, *110*, 49-56.

[11]. Carpentier, P., Chancelier, J.-P., Cohen, G., & De Lara, M. (2015). Stochastic multi-stage optimization. *Probability Theory and Stochastic Modelling*, *75*.

[12]. Cavallo, A., Cavallo, E., & Rigobon, R. (2014). Prices and supply disruptions during natural disasters. *Review of Income and Wealth*, *60*, S449-S471.

[13]. Chen, L., Dui, H., & Zhang, C. (2020). A resilience measure for supply chain systems considering the interruption with the cyber-physical systems. *Reliability Engineering & System Safety*, *199*, 106869.

[14]. Chi, Y., Xu, Y., Hu, C., & Feng, S. (2018). A state-of-the-art literature survey of power distribution system resilience assessment. 2018 IEEE Power & Energy Society General Meeting (PESGM),

[15]. Cubillo, F., & Martínez-Codina, Á. (2019). A metric approach to measure resilience in water supply systems. *Journal of Applied Water Engineering and Research*, *7*(1), 67-78.

[16]. Degryse, H., De Jonghe, O., Jakovljević, S., Mulier, K., & Schepens, G. (2019). Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, *40*, 100813.

[17]. Dehghani, N. L., Darestani, Y. M., & Shafieezadeh, A. (2020). Optimal life-cycle resilience enhancement of aging power distribution systems: A MINLP-based preventive maintenance planning. *Ieee Access*, *8*, 22324-22334.

[18]. Dell'Isola, M., Ficco, G., Lavalle, L., Moretti, L., Tofani, A., & Zuena, F. (2020). A resilience assessment simulation tool for distribution gas networks. *Journal of Natural Gas Science and Engineering*, *84*, 103680.

[19]. Ermoliev, Y., Ermolieva, T., Kahil, T., Obersteiner, M., Gorbachuk, V., & Knopov, P. (2019). Stochastic optimization models for risk-based reservoir management. *Cybernetics and Systems Analysis*, *55*(1), 55-64.

[20]. Faysal, K., & Tahmina Akter Bhuya, M. (2023). Cybersecure Documentation and Record-Keeping Protocols For Safeguarding Sensitive Financial Information Across Business Operations. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 117–152. https://doi.org/10.63125/cz2gwm06

[21]. Gkanatsas, E., & Krikke, H. (2020). Towards a pro-silience framework: a literature review on quantitative modelling of resilient 3PL supply chain network designs. *Sustainability*, *12*(10), 4323.

[22]. Golan, M. S., Jernegan, L. H., & Linkov, I. (2020). Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the COVID-19 pandemic. *Environment Systems and Decisions*, *40*(2), 222-243.

[23]. Golmohamadi, H., & Asadi, A. (2020). A multi-stage stochastic energy management of responsive irrigation pumps in dynamic electricity markets. *Applied Energy*, *265*, 114804.

[24]. Habibullah, S. M., & Aditya, D. (2023). Blockchain-Orchestrated Cyber-Physical Supply Chain Networks with Byzantine Fault Tolerance For Manufacturing Robustness. *Journal of Sustainable Development and Policy*, *2*(03), 34-72. https://doi.org/10.63125/057vwc78

[25]. Hammad, S. (2022). Application of High-Durability Engineering Materials for Enhancing Long-Term Performance of Rail and Transportation Infrastructure. *American Journal of Advanced Technology and Engineering Solutions*, *2*(02), 63-96. https://doi.org/10.63125/4k492a62

[26]. Hammad, S., & Muhammad Mohiul, I. (2023). Geotechnical And Hydraulic Simulation Models for Slope Stability And Drainage Optimization In Rail Infrastructure Projects. *Review of Applied Science and Technology*, *2*(02), 01–37. https://doi.org/10.63125/jmx3p851

[27]. Haque, B. M. T., & Md. Arifur, R. (2020). Quantitative Benchmarking of ERP Analytics Architectures: Evaluating Cloud vs On-Premises ERP Using Cost-Performance Metrics. *American Journal of Interdisciplinary Studies*, *1*(04), 55-90. https://doi.org/10.63125/y05j6m03

[28]. Haque, B. M. T., & Md. Arifur, R. (2021). ERP Modernization Outcomes in Cloud Migration: A Meta-Analysis of Performance and Total Cost of Ownership (TCO) Across Enterprise Implementations. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 168–203. https://doi.org/10.63125/vrz8hw42

[29]. Haque, B. M. T., & Md. Arifur, R. (2023). A Quantitative Data-Driven Evaluation of Cost Efficiency in Cloud and Distributed Computing for Machine Learning Pipelines. *American Journal of Scholarly Research and Innovation*, *2*(02), 449–484. https://doi.org/10.63125/7tkcs525

[30]. Hobbs, J. E. (2020). Food supply chains during the COVID-19 pandemic. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie*, *68*(2), 171-176.

[31]. Hohenstein, N.-O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience: a systematic review and paths for further investigation. *International journal of physical distribution & logistics management*, *45*(1/2), 90-117.

[32]. Hoogsteen, G., Molderink, A., Hurink, J. L., Smit, G. J., Schuring, F., & Liandon, B. K. (2015). Impact of peak electricity demand in distribution grids: A stress test. 2015 IEEE Eindhoven PowerTech,

[33]. Hosseini, S., Ivanov, D., & Dolgui, A. (2020). Ripple effect modelling of supplier disruption: integrated Markov chain and dynamic Bayesian network approach. *International Journal of Production Research*, *58*(11), 3284-3303.

[34]. Ivanov, D., & Dolgui, A. (2019). Low-Certainty-Need (LCN) supply chains: a new perspective in managing disruption risks and resilience. *International Journal of Production Research*, *57*(15-16), 5119-5136.

[35]. Ivanov, D., & 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*(10), 2904-2915.

[36]. Jabed Hasan, T., & Waladur, R. (2022). Advanced Cybersecurity Architectures for Resilience in U.S. Critical Infrastructure Control Networks. *Review of Applied Science and Technology*, *1*(04), 146–182. https://doi.org/10.63125/5rvjav10

[37]. Jinnat, A., & Md. Kamrul, K. (2021). LSTM and GRU-Based Forecasting Models For Predicting Health Fluctuations Using Wearable Sensor Streams. *American Journal of Interdisciplinary Studies*, *2*(02), 32-66. https://doi.org/10.63125/1p8gbp15

[38]. Kahiluoto, H., Mäkinen, H., & Kaseva, J. (2020). Supplying resilience through assessing diversity of responses to disruption. *International Journal of Operations & Production Management*, *40*(3), 271-292.

[39]. Karmaker, C. L., & Ahmed, T. (2020). Modeling performance indicators of resilient pharmaceutical supply chain. *Modern Supply Chain Research and Applications*, *2*(3), 179-205.

[40]. Khaghani, F., & Jazizadeh, F. (2020). mD-resilience: A multi-dimensional approach for resilience-based performance assessment in urban transportation. *Sustainability*, *12*(12), 4879.

[41]. Khalilabadi, S. M. G., Zegordi, S. H., & Nikbakhsh, E. (2020). A multi-stage stochastic programming approach for supply chain risk mitigation via product substitution. *Computers & Industrial Engineering*, *149*, 106786.

[42]. Khazai, B., Anhorn, J., & Burton, C. G. (2018). Resilience Performance Scorecard: Measuring urban disaster resilience at multiple levels of geography with case study application to Lalitpur, Nepal. *International Journal of Disaster Risk Reduction*, *31*, 604-616.

[43]. Khomami, M. S., & Sepasian, M. S. (2018). Pre-hurricane optimal placement model of repair teams to improve distribution network resilience. *Electric Power Systems Research*, *165*, 1-8.

[44]. Kim, Y., Chen, Y.-S., & Linderman, K. (2015). Supply network disruption and resilience: A network structural perspective. *Journal of operations Management*, *33*, 43-59.

[45]. Kozmík, V., & Morton, D. P. (2015). Evaluating policies in risk-averse multi-stage stochastic programming. *Mathematical Programming*, *152*(1), 275-300.

[46]. Kwasinski, A. (2016). Quantitative model and metrics of electrical grids' resilience evaluated at a power distribution level. *Energies*, *9*(2), 93.

[47]. Leduc, S., & Liu, Z. (2016). Uncertainty shocks are aggregate demand shocks. *Journal of monetary economics*, *82*, 20-35.

[48]. Li, R., Dong, Q., Jin, C., & Kang, R. (2017). A new resilience measure for supply chain networks. *Sustainability*, *9*(1), 144.
[49]. Li, Y., Xie, K., Wang, L., & Xiang, Y. (2019). Exploiting network topology optimization and demand side management to improve bulk power system resilience under windstorms. *Electric Power Systems Research*, *171*, 127-140.
[50]. Macdonald, J. R., Zobel, C. W., Melnyk, S. A., & Griffis, S. E. (2018). Supply chain risk and resilience: theory building through structured experiments and simulation. *International Journal of Production Research*, *56*(12), 4337-4355.
[51]. Macfadyen, S., Tylianakis, J. M., Letourneau, D. K., Benton, T. G., Tittonell, P., Perring, M. P., Gómez-Creutzberg, C., Báldi, A., Holland, J. M., & Broadhurst, L. (2015). The role of food retailers in improving resilience in global food supply. *Global Food Security*, *7*, 1-8.
[52]. Mahmutoğulları, A. İ., Ahmed, S., Çavuş, Ö., & Aktürk, M. S. (2019). The value of multi-stage stochastic programming in risk-averse unit commitment under uncertainty. *IEEE Transactions on Power Systems*, *34*(5), 3667-3676.
[53]. Martinelli, E., De Canio, F., & Tagliazucchi, G. (2019). Bouncing back from a sudden-onset extreme event: exploring retail enterprises' resilience capacity. *The International Review of Retail, Distribution and Consumer Research*, *29*(5), 568-581.
[54]. Md Ashraful, A., Md Fokhrul, A., & Md Fardaus, A. (2020). Predictive Data-Driven Models Leveraging Healthcare Big Data for Early Intervention And Long-Term Chronic Disease Management To Strengthen U.S. National Health Infrastructure. *American Journal of Interdisciplinary Studies*, *1*(04), 26-54. https://doi.org/10.63125/1z7b5v06
[55]. Md Fokhrul, A., Md Ashraful, A., & Md Fardaus, A. (2021). Privacy-Preserving Security Model for Early Cancer Diagnosis, Population-Level Epidemiology, And Secure Integration into U.S. Healthcare Systems. *American Journal of Scholarly Research and Innovation*, *1*(02), 01–27. https://doi.org/10.63125/q8wjee18
[56]. Md. Akbar, H., & Farzana, A. (2023). Predicting Suicide Risk Through Machine Learning–Based Analysis of Patient Narratives and Digital Behavioral Markers in Clinical Psychology Settings. *Review of Applied Science and Technology*, *2*(04), 158–193. https://doi.org/10.63125/mqty9n77
[57]. Md. Arifur, R., & Haque, B. M. T. (2022). Quantitative Benchmarking of Machine Learning Models for Risk Prediction: A Comparative Study Using AUC/F1 Metrics and Robustness Testing. *Review of Applied Science and Technology*, *1*(03), 32–60. https://doi.org/10.63125/9hd4e011
[58]. Md. Towhidul, I., Alifa Majumder, N., & Mst. Shahrin, S. (2022). Predictive Analytics as A Strategic Tool For Financial Forecasting and Risk Governance In U.S. Capital Markets. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 238–273. https://doi.org/10.63125/2rpyze69
[59]. Mittnik, S., Semmler, W., & Haider, A. (2020). Climate disaster risks—empirics and a multi-phase dynamic model. *Econometrics*, *8*(3), 33.
[60]. Mostafa, K. (2023). An Empirical Evaluation of Machine Learning Techniques for Financial Fraud Detection in Transaction-Level Data. *American Journal of Interdisciplinary Studies*, *4*(04), 210-249. https://doi.org/10.63125/60amyk26
[61]. Müller, O., Fay, M., & Vom Brocke, J. (2018). The effect of big data and analytics on firm performance: An econometric analysis considering industry characteristics. *Journal of management information systems*, *35*(2), 488-509.
[62]. Murino, G., Armando, A., & Tacchella, A. (2019). Resilience of cyber-physical systems: an experimental appraisal of quantitative measures. 2019 11th international conference on cyber conflict (CyCon),
[63]. Najarian, M., & Lim, G. J. (2019). Design and assessment methodology for system resilience metrics. *Risk Analysis*, *39*(9), 1885-1898.
[64]. Nazemi, M., Moeini-Aghtaie, M., Fotuhi-Firuzabad, M., & Dehghanian, P. (2019). Energy storage planning for enhanced resilience of power distribution networks against earthquakes. *IEEE Transactions on Sustainable Energy*, *11*(2), 795-806.
[65]. O'Neil, S., Zhao, X., Sun, D., & Wei, J. C. (2016). Newsvendor problems with demand shocks and unknown demand distributions. *Decision Sciences*, *47*(1), 125-156.
[66]. Oboudi, M. H., Mohammadi, M., Trakas, D. N., & Hatziargyriou, N. D. (2020). A systematic method for power system hardening to increase resilience against earthquakes. *IEEE Systems Journal*, *15*(4), 4970-4979.
[67]. Pantuso, G., & Boomsma, T. K. (2020). On the number of stages in multistage stochastic programs. *Annals of Operations Research*, *292*(2), 581-603.
[68]. Pflug, G. C., & Pichler, A. (2014). *Multistage stochastic optimization* (Vol. 1104). Springer.
[69]. Pisciella, P., Vespucci, M. T., Bertocchi, M., & Zigrino, S. (2016). A time consistent risk averse three-stage stochastic mixed integer optimization model for power generation capacity expansion. *Energy Economics*, *53*, 203-211.
[70]. Qiu, J., Dong, Z. Y., Zhao, J., Xu, Y., Luo, F., & Yang, J. (2016). A risk-based approach to multi-stage probabilistic transmission network planning. *IEEE Transactions on Power Systems*, *31*(6), 4867-4876.
[71]. Qiu, R., & Wang, Y. (2016). Supply chain network design under demand uncertainty and supply disruptions: a distributionally robust optimization approach. *Scientific Programming*, *2016*(1), 3848520.
[72]. Rauf, M. A. (2018). A needs assessment approach to english for specific purposes (ESP) based syllabus design in Bangladesh vocational and technical education (BVTE). *International Journal of Educational Best Practices*, *2*(2), 18-25.
[73]. Rifat, C., & Jinnat, A. (2022). Optimization Algorithms for Enhancing High Dimensional Biomedical Data Processing Efficiency. *Review of Applied Science and Technology*, *1*(04), 98–145. https://doi.org/10.63125/2zg6x055

[74]. Rifat, C., & Khairul Alam, T. (2022). Assessing The Role of Statistical Modeling Techniques in Fraud Detection Across Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, *3*(02), 91-125. https://doi.org/10.63125/gbdq4z84

[75]. Rifat, C., & Rebeka, S. (2023). The Role of ERP-Integrated Decision Support Systems in Enhancing Efficiency and Coordination In Healthcare Logistics: A Quantitative Study. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 265–285. https://doi.org/10.63125/c7srk144

[76]. Roohnavazfar, M., Manerba, D., De Martin, J. C., & Tadei, R. (2019). Optimal paths in multi-stage stochastic decision networks. *Operations Research Perspectives*, *6*, 100124.

[77]. Santarelli, G., Abidi, H., Klumpp, M., & Regattieri, A. (2015). Humanitarian supply chains and performance measurement schemes in practice. *International journal of productivity and performance management*, *64*(6), 784-810.

[78]. Schmitt, T. G., Kumar, S., Stecke, K. E., Glover, F. W., & Ehlen, M. A. (2017). Mitigating disruptions in a multi-echelon supply chain using adaptive ordering. *Omega*, *68*, 185-198.

[79]. Sharma, A., Adhikary, A., & Borah, S. B. (2020). Covid-19′ s impact on supply chain decisions: Strategic insights from NASDAQ 100 firms using Twitter data. *Journal of business research*, *117*, 443-449.

[80]. Singh, C. S., Soni, G., & Badhotiya, G. K. (2019). Performance indicators for supply chain resilience: review and conceptual framework. *Journal of Industrial Engineering International*, *15*(Suppl 1), 105-117.

[81]. Sokolov, B., Ivanov, D., Dolgui, A., & Pavlov, A. (2016). Structural quantification of the ripple effect in the supply chain. *International Journal of Production Research*, *54*(1), 152-169.

[82]. Stone, J., & Rahimifard, S. (2018). Resilience in agri-food supply chains: a critical analysis of the literature and synthesis of a novel framework. *Supply Chain Management: An International Journal*, *23*(3), 207-238.

[83]. Sun, W., Bocchini, P., & Davison, B. D. (2020). Resilience metrics and measurement methods for transportation infrastructure: The state of the art. *Sustainable and Resilient Infrastructure*, *5*(3), 168-199.

[84]. Taheri, B., Safdarian, A., Moeini-Aghtaie, M., & Lehtonen, M. (2019). Enhancing resilience level of power distribution systems using proactive operational actions. *Ieee Access*, *7*, 137378-137389.

[85]. Timonina, A. V. (2015). Multi-stage stochastic optimization: the distance between stochastic scenario processes. *Computational Management Science*, *12*(1), 171-195.

[86]. Tran, H. T., Balchanos, M., Domerçant, J. C., & Mavris, D. N. (2017). A framework for the quantitative assessment of performance-based system resilience. *Reliability Engineering & System Safety*, *158*, 73-84.

[87]. Tuni, A., Rentizelas, A., & Duffy, A. (2018). Environmental performance measurement for green supply chains: A systematic analysis and review of quantitative methods. *International journal of physical distribution & logistics management*, *48*(8), 765-793.

[88]. Wang, S., Dehghanian, P., Alhazmi, M., & Nazemi, M. (2019). Advanced control solutions for enhanced resilience of modern power-electronic-interfaced distribution systems. *Journal of Modern Power Systems and Clean Energy*, *7*(4), 716-730.

[89]. Wang, Y., Huang, G., Wang, S., Li, W., & Guan, P. (2016). A risk-based interactive multi-stage stochastic programming approach for water resources planning under dual uncertainties. *Advances in Water Resources*, *94*, 217-230.

[90]. Wen, F., Min, F., Zhang, Y. J., & Yang, C. (2019). Crude oil price shocks, monetary policy, and China's economy. *International Journal of Finance & Economics*, *24*(2), 812-827.

[91]. Yin, L., & Han, L. (2020). International assets allocation with risk management via multi-stage stochastic programming. *Computational Economics*, *55*(2), 383-405.

[92]. Zaman, M. A. U., Sultana, S., Raju, V., & Rauf, M. A. (2021). Factors İmpacting the Uptake of İnnovative Open and Distance Learning (ODL) Programmes in Teacher Education. *Turkish Online Journal of Qualitative Inquiry*, *12*(6).

[93]. Zeballos, L. J., Méndez, C. A., & Barbosa-Povoa, A. P. (2015). Risk measures in a multi-stage stochastic supply chain approach. 2015 International Conference on Industrial Engineering and Systems Management (IESM),

[94]. Zhao, L., Zhang, X., Wang, S., & Xu, S. (2016). The effects of oil price shocks on output and inflation in China. *Energy Economics*, *53*, 101-110.

[95]. Zou, H., Liu, D., Guo, S., Xiong, L., Liu, P., Yin, J., Zeng, Y., Zhang, J., & Shen, Y. (2020). Quantitative assessment of adaptive measures on optimal water resources allocation by using reliability, resilience, vulnerability indicators. *Stochastic Environmental Research and Risk Assessment*, *34*(1), 103-119.