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DATA-DRIVEN SUPPLY CHAIN RESILIENCE MODELING THROUGH STOCHASTIC SIMULATION AND SUSTAINABLE RESOURCE ALLOCATION ANALYTICS

Sudipto Roy[1]; Md. Hasan Imam[2];

[1]. *Department of Industrial and Systems Engineering, Lamar University, Texas, USA; Email: sudiptobd00@gmail.com*

[2]. *Master of Business Administration, Washington University of Science and Technology, Virginia, USA; Email: hasanimambulbul@gmail.com*

ABSTRACT
This study investigates how data-driven capabilities and sustainable resource-allocation policies jointly influence supply chain resilience (SCRes) under disruption and uncertainty. Adopting a quantitative, cross-sectional, multiple case-study design, the research integrates survey-based measurement, archival operational data, and stochastic simulation–optimization to link organizational capabilities—visibility, collaboration, flexibility, supplier diversification, redundancy, risk orientation, and allocation efficiency—to key resilience outcomes, including service recovery, time-to-recovery (TTR), backorder intensity, cost variance, and emissions. Data were collected from 190 professionals across four international firms in discrete manufacturing, FMCG, healthcare logistics, and electronics sectors, each providing both perceptual and objective data spanning 12–24 months of operations. Hierarchical multiple regression models, supported by mediation and moderation analyses, revealed that collaboration, digital visibility, and allocation efficiency were the strongest predictors of resilience performance, while flexibility and diversification contributed moderate incremental effects. Allocation efficiency partially mediated the impact of visibility and collaboration on outcomes, demonstrating that information and coordination enhance resilience primarily through improved resource allocation. Moreover, capability effects intensified under uncertainty—visibility's and collaboration's benefits were significantly amplified by demand volatility and lead-time variability. A composite Resilience Performance Index (RPI) was developed to align statistical and operational metrics, linking survey constructs to observed KPIs. Monte Carlo simulation experiments using empirically calibrated disruption parameters validated these statistical insights: sustainability-aware optimized policies improved mean service levels by 3–6 percentage points, reduced TTR by 15–27%, lowered backorder intensity by up to 24%, and cut emissions intensity by 6–11% compared to status quo. These findings confirm that resilience and sustainability can be jointly enhanced through data-driven allocation strategies. The study contributes an integrated, replicable framework that bridges measurement, inference, and decision experimentation—offering both theoretical clarity on capability mechanisms and practical guidance for managers seeking to design resilient, carbon-conscious supply chains under stochastic conditions.

KEYWORDS
Supply Chain Resilience, Sustainable Resource Allocation, Stochastic Simulation, Optimization, Visibility

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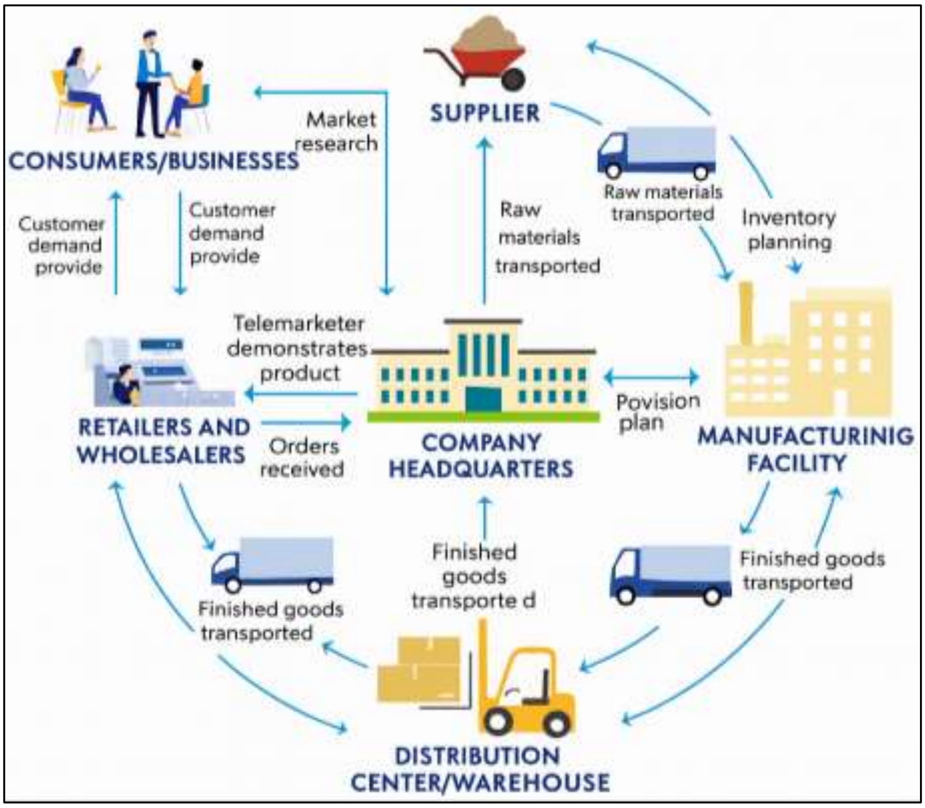
INTRODUCTION

Supply chain resilience (SCRes) is commonly defined as a supply chain's ability to prepare for, respond to, and recover from disruptions while maintaining continuity of operations and control over performance variability. In logistics and operations scholarship, SCRes is framed as an adaptive, multi-capability construct that draws on agility, robustness, flexibility, visibility, and collaboration to absorb shocks and return to targeted service and cost levels (or better) across global networks (Bektas & Laporte, 2011). Since 2005, research has matured from conceptual definitions to empirical models linking relational competencies, information sharing, and risk culture to measurable recovery, continuity, and performance outcomes (Tang, 2006). Parallel strands in sustainable supply chain management (SSCM) establish that resilience cannot be decoupled from responsible resource allocation because many disruptions co-evolve with environmental and social stressors (e.g., climate, regulation, labor welfare) that constrain capacity and material flows (Seuring & Müller, 2008). Stochastic simulation and quantitative risk modeling add explanatory power by capturing the uncertain propagation of shocks ("ripple effects") and testing alternative resource-allocation and mitigation policies under parameter uncertainty (Schmitt & Singh, 2012). Together, these literatures motivate a definition of data-driven supply chain resilience as the systematic use of probabilistic analytics and sustainable resource allocation to anticipate, absorb, and recover from disruptions while meeting service, cost, and environmental objectives (Wamba et al., 2017).

Figure 1: Data-Driven Supply Chain Resilience Framework



Building on these foundations, this study proposes and empirically tests an integrated resilience modeling approach that couples survey-based organizational capabilities with stochastic simulation and sustainable allocation analytics to offer statistically rigorous, managerially actionable insights (Tomlin, 2006). Across international contexts, disruptions originate from diverse sources natural hazards, geopolitical instability, pandemics, cyber events, supplier insolvencies, and logistics bottlenecks that propagate across multi-echelon networks (Scholten & Schilder, 2015). Empirical studies identify antecedents of SCRes such as relational competencies (communication, cooperation, integration), disruption orientation, learning orientation, and risk management culture that influence agility and robustness (Brandon-Jones et al., 2014). At the same time, complexity and

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interdependence measured through supply-base breadth, tiering depth, and product/process variety elevate disruption frequency and recovery time, making resource allocation decisions (buffers, redundancy, dual sourcing) more consequential (Abdul, 2021; Bode & Wagner, 2015). The sustainability literature highlights that resource allocation amidst disruptions must consider environmental constraints and carbon policies that shape inventory positioning, transport routing, and sourcing footprints (Benjaafar et al., 2013). Quantitative modeling has shown that emissions-aware inventory policies, pollution-routing, and carbon-constrained order sizing can align cost and environmental performance under cap-and-trade or tax regimes (Sanjid & Farabe, 2021; Snyder et al., 2016). Yet many firms still lack integrated, data-driven decision frameworks that couple risk-mitigation levers (e.g., safety stock, supplier diversification, postponement) with sustainable allocation (e.g., emissions-bounded transport and inventory) under realistic stochastic dynamics (Dubey et al., 2019; Omar & Rashid, 2021). This gap motivates the present study's focus on stochastic simulation–supported regression models that connect organizational resilience capabilities to performance, conditioned on sustainable resource choices. The problem addressed here is twofold. First, despite strong conceptual progress, there is limited quantitative evidence that jointly estimates how capability constructs (e.g., visibility, collaboration, flexibility) relate to outcome metrics (service recovery, cost variance reduction, emissions intensity) when decision makers face stochastic disruption processes (Hohenstein et al., 2015; Zaman & Momena, 2021). Second, sustainable resource allocation is often modeled separately from resilience even though the same levers (inventory, capacity, routing, sourcing) alter both service continuity and environmental performance (Mubashir, 2021; Tukamuhabwa et al., 2015).

Empirical works demonstrate that connectivity and information-sharing enhance resilience through visibility and coordination (Wieland & Wallenburg, 2013), while risk-management culture and learning orientation support proactive mitigation (Ponomarov & Holcomb, 2009; Rony, 2021). However, managers need integrated evidence linking these capabilities to quantitative improvements in recovery time, fill rate, cost stability, and emissions per unit served under probabilistic disruption scenarios (Carvalho et al., 2012; Zaki, 2021). In carbon-constrained systems, even basic operational decisions order quantities, shipment consolidation, modal choices change the feasible resilience frontier (Braunscheidel & Suresh, 2009; Danish & Zafor, 2022). Consequently, this study frames resilience not only as an organizational capability but also as a resource-constrained optimization problem where sustainability policies form boundary conditions for risk-mitigation efficacy. The purpose of this research is to develop and test a data-driven resilience modeling framework that integrates (a) survey-based measures of resilience capabilities using a Likert 5-point instrument, (b) descriptive and correlational analyses to establish construct relationships, (c) multiple regression models for performance outcomes, and (d) stochastic simulation experiments that quantify how sustainable allocation policies (e.g., carbon-aware inventory and routing choices) interact with capabilities to shape resilience results. Conceptually, the study synthesizes insights from contingency and relational views of the firm, which emphasize context-specific resource–capability alignment and inter-organizational competencies (Danish & Kamrul, 2022; Gunasekaran et al., 2017), with OR/MS models that evaluate mitigation value under disruption uncertainty (Ambulkar et al., 2015; Hozyfa, 2022). Methodologically, the design follows established scale-development and validity practices for structural measurement (Henseler et al., 2015; Arman & Kamrul, 2022), while leveraging simulation to reflect multi-echelon dynamics not easily observable in one cross-section (Carvalho et al., 2012). Practically, the framework positions sustainable allocation analytics as captured in carbon-constrained EOQ and pollution-routing formulations as levers that can be combined with buffers, redundancy, and collaboration to improve resilience KPIs without ignoring environmental constraints (Hasan & Omar, 2022; Pettit et al., 2010). The study is case-study–based and quantitative, cross-sectional, which enables sector-specific insights while maintaining statistical rigor.

Guided by the foregoing, the study addresses four research questions (RQ): RQ1: Which organizational resilience capabilities (e.g., visibility, collaboration, flexibility, risk culture) are most strongly associated with service recovery and cost-stability outcomes in supply chains? RQ2: How do data-driven practices (e.g., analytics use, information sharing, connectivity) relate to resilience performance when controlling for supply-base complexity and market turbulence? RQ3: To what extent do sustainable resource allocation choices (e.g., emissions-aware inventory and routing) moderate the relationships between resilience capabilities and operational outcomes? RQ4: Under stochastic disruption scenarios, what is the marginal effect of combining specific mitigation levers

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(e.g., safety stock, dual sourcing) with carbon-constrained policies on expected recovery time, fill rate, and emissions intensity? These questions are anchored in prior work that links capabilities to resilience (Jüttner & Maklan, 2011; Mohaiminul & Muzahidul, 2022), demonstrates the role of complexity and visibility (Pagell & Wu, 2009), and quantifies mitigation impacts via simulation and optimization (Brandon-Jones et al., 2014; Omar & Ibne, 2022), while aligning with SSCM insights on carbon-aware operations (Hua et al., 2011). From these research questions, the study proposes four testable hypotheses (H) using survey constructs measured on a Likert 5-point scale and operational outcomes obtained from the case context. H1: Resilience visibility (timely, accurate, shared information) is positively associated with service recovery and negatively associated with cost variance (Kleindorfer & Saad, 2005; Hasan, 2022). H2: Collaboration (communication, joint problem solving, integration) is positively associated with resilience outcomes, controlling for complexity (Henseler et al., 2015). H3: Risk-management culture/learning orientation is positively associated with resilience performance and mediates the effect of data-driven practices on outcomes (Dubey et al., 2019). H4: Sustainable allocation policies (emissions-aware inventory and routing) positively moderate the capability→outcome relationships i.e., the slope relating capabilities to resilience outcomes is steeper under carbon-constrained optimization than under unconstrained allocation (Hohenstein et al., 2015; Mominul et al., 2022). These hypotheses are consistent with OR/MS evidence that mitigation and contingency strategies (inventory, sourcing, flexibility) yield differential value depending on disruption characteristics and system constraints (Rabiul & Sai Praveen, 2022; Pettit et al., 2010).

This study's contributions and significance are threefold. First, it integrates organizational capabilities and sustainable resource allocation within a single data-driven resilience framework, advancing partial, parallel literatures that often analyze them separately (Gunasekaran et al., 2017). Second, it provides quantitative evidence via descriptive, correlational, and regression modeling on the effect sizes linking visibility, collaboration, and risk culture to operational outcomes under realistic cross-sectional conditions (Farabe, 2022; Wieland & Wallenburg, 2013). Third, it augments empirical associations with stochastic simulation that explores "what-if" scenarios for mitigation-policy mixes subject to carbon constraints, thereby connecting managerial levers to expected recovery time, fill rate, cost dispersion, and emissions intensity (Carvalho et al., 2012; Pankaz Roy, 2022). The synthesis is internationally relevant because resilience and sustainability pressures are transboundary, affecting procurement, manufacturing, and logistics across regions and tiers (Kleindorfer & Saad, 2005; Rahman & Abdul, 2022). Organization of the paper. Section 2 reviews the literature on (i) SCRes concepts and antecedents; (ii) data analytics and visibility; (iii) sustainable resource allocation under carbon constraints; and (iv) stochastic simulation and optimization for disruption risk. Section 3 details the methodology: research design, case selection, measurement instrument (Likert 5-point), participants and sampling, objective data capture, and the statistical plan (descriptives, correlations, regressions), including construct reliability and discriminant validity procedures (Carvalho et al., 2012; Razia, 2022). Section 4 reports results: sample/context description; descriptive and correlational findings; regression estimates; managerial insights; and simulation outcomes that quantify trade-offs between resilience and emissions under alternative policies. Section 5 provides a focused discussion connecting findings to prior theory and Section 6 closes with the conclusion and recommendations for practice, keeping analysis aligned with the study's quantitative, case-based scope (Brandon-Jones et al., 2014; Zaki, 2022).

This study pursues a set of integrated, concrete objectives that bind measurement, modeling, and decision experimentation into a single, data-driven roadmap for supply chain resilience under sustainability constraints. First, it will construct and validate a parsimonious measurement instrument for key resilience capabilities visibility, collaboration, flexibility, supplier diversification, redundancy, risk orientation, and resource-allocation efficiency using a Likert five-point scale tailored to cross-sectional, case-based contexts. Second, it will generate a transparent descriptive portrait of the participating firms and supply networks, establishing the empirical distributions, central tendencies, and variability of resilience capabilities and outcome metrics such as time-to-recovery, fill rate, backorder duration, expedited logistics cost, and emissions intensity. Third, it will estimate a hierarchy of regression models that quantify the relationships between capabilities and resilience outcomes, beginning with control-only baselines, advancing to main-effect specifications, and extending to mediation by allocation efficiency and moderation by uncertainty indicators such as demand volatility and lead-time coefficient of variation; model fit, stability, and diagnostics will be rigorously

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reported to ensure interpretability and replicability. Fourth, it will operationalize sustainable resource allocation through an optimization layer that encodes cost, service, and emissions objectives, and then embed the resulting policies inside a stochastic simulation environment to stress-test performance across disruption scenarios, including supplier failure, port closure, and demand spikes. Fifth, it will compare status quo policies against optimized, sustainability-aware policies using simulation replications to estimate expected performance, dispersion, and risk-sensitive metrics, thereby identifying robust policy mixes that elevate recovery while respecting environmental constraints. Sixth, it will synthesize the empirical and simulation findings into a compact set of decision rules and parameter thresholds that practitioners can implement using standard analytics and planning tools, accompanied by templates for data capture and analysis. Finally, it will document a reproducible workflow survey development, data cleaning, reliability and validity checks, correlation analysis, regression estimation, optimization modeling, simulation design, and sensitivity analysis so that researchers and managers can replicate the procedure in other sectors and geographies. By meeting these objectives, the study aims to deliver a validated measurement toolkit, calibrated statistical relationships, tested policy interventions, and an end-to-end analytical playbook that links organizational capabilities to resilience performance under realistic uncertainty while integrating sustainability into the resource-allocation core.

LITERATURE REVIEW

The literature on supply chain resilience, sustainability, and analytics has evolved along three converging streams that set the stage for this study's review. The first stream establishes what resilience is and how it is operationalized, moving from qualitative concepts such as agility, flexibility, redundancy, visibility, and collaboration to measurable outcome constructs like time-to-recovery, service level, backorder duration, and cost variance. This body of work clarifies that resilience is not a single capability but a portfolio of complementary practices that act at different phases of disruption readiness, response, and recovery, with organizational routines (e.g., information sharing, risk governance, cross-functional coordination) shaping the speed and stability of performance restoration. The second stream examines sustainable operations and resource allocation, showing that carbon, energy, and waste constraints increasingly define the feasible set of inventory, sourcing, and logistics decisions. Rather than treating resilience and sustainability as separate goals, this literature demonstrates that inventory positioning, supplier diversification, and transport-mode choices have simultaneous effects on continuity and environmental performance, creating a multi-objective decision space that requires explicit trade-off management. The third stream brings in quantitative analytics descriptive statistics, correlation, regression, optimization, and stochastic simulation to estimate relationships among capabilities and outcomes and to test the performance of policies under uncertainty. Studies in this vein argue that resilience mechanisms are context-dependent and that their value varies with demand volatility, lead-time variability, capacity tightness, and network structure, which are better explored through probabilistic methods than through static benchmarks. Across the three streams, several review articles and empirical papers highlight gaps that motivate an integrated approach: measurement instruments often stop at psychometric validation without linking to objective performance; sustainable allocation is modeled without empirical capability foundations; and simulation experiments are rarely calibrated with case-derived data. Consequently, this review will synthesize the theoretical roots and empirical findings across these streams, articulate a coherent set of constructs and measurable outcomes, and organize the evidence around how data-driven practices and sustainable resource allocation interact with resilience capabilities. This synthesis will directly inform the study's measurement model, the specification of regression analyses, and the design of simulation scenarios and optimization policies used to stress-test resilience under realistic uncertainty.

Supply Chain Resilience

The theoretical foundations of supply chain resilience (SCRes) begin with vulnerability analysis and systems thinking, which frame resilience as the capacity of a supply network to sustain target performance when exposed to stressors that exploit structural and behavioral weaknesses. Early theorization emphasizes that vulnerability is endogenously produced by the very features that often create competitive advantage global dispersion, specialization, lean buffers, and high interdependence and that these features interact with environmental turbulence to amplify exposure (Peck, 2005). In this view, resilience is not merely a post-shock property but a design attribute arising from choices about network configuration, governance, and information

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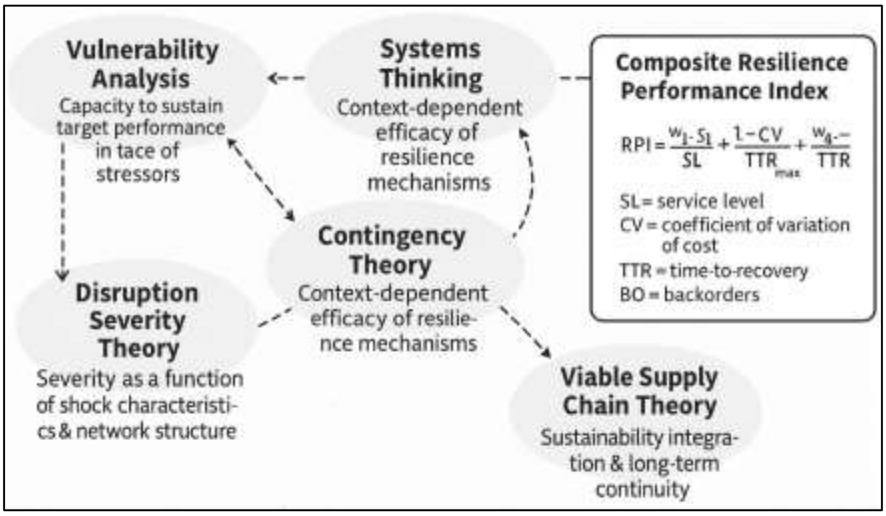
architecture that shape the system's controllability and recoverability. Contingency theory contributes by arguing that the efficacy of any resilience mechanism is context dependent; the same buffer or dual sourcing policy will have different value depending on product clockspeed, demand uncertainty, and supply base structure. Complementing this, the risk management literature models resilience as a portfolio of capabilities visibility, flexibility, redundancy, collaboration whose payoffs emerge through dynamic interactions across prevention, response, and recovery phases. Network perspectives add that topology matters: concentrated hubs, long paths, and low redundancy can increase the likelihood and propagation of failure, suggesting that resilience entails both structural and behavioral dimensions (Colicchia & Strozzi, 2012). Altogether, the theoretical baseline posits resilience as an emergent, multi-level property produced by the alignment of network design, organizational routines, and decision rules, with vulnerability and capability coevolving within global supply ecosystems (Colicchia & Strozzi, 2012; Peck, 2005).

Figure 2: Theoretical Foundations of Supply Chain Resilience



Building on these foundations, disruption severity theory specifies how shock characteristics and network structure combine to determine impact. Severity increases with the breadth (number of nodes affected), depth (tier level), and magnitude (loss of capacity/lead-time escalation), and with the lack of substitutability across upstream sources; these structural–behavioral interactions explain variance in interruption length, cost escalation, and service loss (Craighead et al., 2007). Empirical risk–performance models further show that distinct categories of risk supply, demand, process, and environmental affect performance through different pathways and that firms' mitigation portfolios (e.g., slack vs. flexibility) exhibit tradeoffs among cost, responsiveness, and quality (Wagner & Bode, 2008). These perspectives converge on a measurement implication: resilience should be observed in outcomes (e.g., recovery time, fill rate, backorders, cost variance) and also inferred from capabilities and configurations that causally precede those outcomes. To formalize this connection for quantitative analysis, a composite Resilience Performance Index (RPI) can be specified to aggregate normalized operational outcomes into a single metric for regression and simulation benchmarking:

$$RPI = w_1 \cdot SL + w_2 \cdot \left(1 - \frac{CV}{Cost}\right) + w_3 \cdot \left(1 - \frac{TTR_{max}}{TTR}\right) + w_4 \cdot \left(1 - \frac{BO_{max}}{BO}\right),$$

where SL is service level, $CV_{(Cost)}$ is the coefficient of variation of logistics/fulfillment cost, TTR is time-to-recovery, BO is backorders, terms with "max" are scenario-normalization constants, and w_k are stakeholder-agreed weights summing to one. The index provides a theoretically consistent bridge between capabilities (predictors) and resilience outcomes (responses), enabling hypothesis testing about how design choices and organizational routines map to performance under uncertainty (Craighead et al., 2007; Wagner & Bode, 2008).

More recently, viable supply chain theory extends resilience by emphasizing continuity under prolonged or repeated stress, not only single-shock recovery. Viability integrates resilience with

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adaptability and reconfiguration capacity, proposing that supply networks must dynamically adjust flows, structures, and governance modes to sustain goals in changing environments (Craighead et al., 2007; Ivanov & Dolgui, 2020). This perspective is compatible with sustainability-aware resource allocation because it treats operational constraints (e.g., carbon caps, energy intensity, regulatory limits) as boundary conditions that shape the feasible set of resilience policies (Danish, 2023b; Kanti & Shaikat, 2022). From a network science standpoint, viability depends on timely sensing (visibility), decoupling options (postponement, modularity), and alternative pathways (multi-sourcing, re-routing) that preserve flow feasibility when nodes or arcs fail; from an organizational standpoint, it depends on routines for synchronization and decision rights that enable rapid, coordinated reconfiguration (Danish, 2023a; Ivanov & Dolgui, 2020; Arif Uz & Elmoon, 2023). The theoretical implication is a design–governance duality: structural redundancy without governance agility can lock resources in the wrong places, while agile governance without structural options can produce rapid but ineffective responses. Vulnerability analysis thus remains relevant as a diagnostic lens, while disruption severity and risk–performance models provide causal scaffolds, and viability theory supplies the long-horizon criterion for continuous functioning. Taken together, these foundations justify modeling resilience as a data-driven, optimization-supported property of supply networks in which measurement (capabilities and outcomes), structural configuration, and sustainable allocation are treated as interdependent elements of one system (Colicchia & Strozzi, 2012; Peck, 2005).

Network Design as Resilience Antecedents

Digital visibility is widely regarded as a foundational antecedent of resilience because it governs the timeliness, accuracy, and scope of information available for coordinated action across tiers. Visibility encompasses who can see what, when, and at what level of granularity; in practice, it fuses event capture (e.g., sensing in plants, warehouses, and in-transit assets), data quality (accuracy and completeness), and dissemination (latency and accessibility across partners). Retail and manufacturing studies show that improving visibility reduces coordination lags, dampens demand and lead-time variability amplification, and shortens exception-resolution cycles by aligning partners' perceptions of the state of inventory, capacity, and transportation flows (Barratt & Oke, 2007; Muhammad & Redwanul, 2023; Razia, 2023). To operationalize visibility for empirical analysis, recent work proposes multi-attribute measurement that distinguishes coverage of nodes/lanes, latency to update, and fidelity of signals, acknowledging that uncertainty and "virtuality" (digital intermediation across organizational boundaries) change how value accrues from visibility investments (Caridi et al., 2014). A simple, additive Visibility Composite Index (VCI) that aligns with these insights can be specified as:

$$VCI = \alpha \cdot Coverage + \beta \cdot \left(1 - \frac{Latency_{max}}{Latency}\right) + \gamma \cdot Accuracy + \delta \cdot Granularity,$$

with $\alpha + \beta + \gamma + \delta = 1$, where Coverage is the share of critical nodes/lanes with near–real-time status, Latency scales updates to a common horizon, Accuracy captures data reliability, and Granularity reflects SKU- and shipment-level detail. The VCI serves as a tractable predictor for readiness and recovery outcomes because it captures both breadth and depth of observability that underpin decision quality, exception detection, and synchronized responses. In cross-sectional, case-based designs, VCI also facilitates comparison across heterogeneous digital architectures by normalizing disparate telemetry and ERP/transport events into a common, interpretable scale (Blome et al., 2013; Mesbaul, 2024).

Flexibility is the second major antecedent and functions as the behavioral counterpart to visibility: while visibility reveals the problem state, flexibility provides the option set to act on it. Flexibility can be decomposed into product, mix, volume, routing, and delivery flexibility, all supported by shared resources, modular processes, postponement, and multi-skilled labor. Empirical research on supply chain agility shows that information integration and process integration foster agility, which then translates into performance through rapid reconfiguration of flows and schedules; firms develop agility via both internal capabilities (IT integration, cross-functional process alignment) and external linkages (supplier/customer collaboration) (Reduanul, 2023; Sadia, 2023; Swafford et al., 2006). From a conceptual perspective, flexibility at the chain level differs from plant-level flexibility because it must span organizational boundaries and transportation infrastructures, implying that governance, contracts, and decision rights are as critical as technical changeover times. A comprehensive view treats flexibility as a portfolio of options contingent on context e.g., dual sourcing for critical

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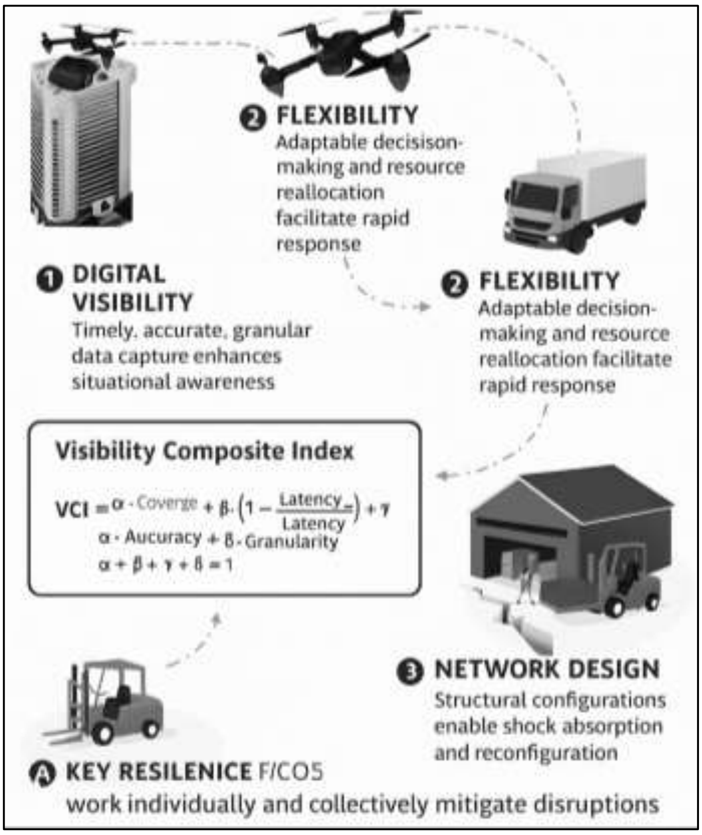
components, capacity pooling across facilities, modular product architectures, and multi-modal routing each with distinct cost and responsiveness profiles. Accordingly, the mechanisms by which flexibility yields resilience include substitution (supplier or mode), decoupling (inventory and postponement), and synchronizing (rapid plan revision) (Srinivas & Manish, 2023; Zayadul, 2023). A useful insight from the flexibility literature is that capabilities must be architected for scalability and range not only speed so that responses remain feasible under diverse disruption severities and geographies (Stevenson & Spring, 2007). In quantitative models, flexibility can be proxied by indices such as the fraction of SKUs with qualified alternates, the share of capacity that is cross-deployable across products or sites, and the lead-time penalty for plan changes, enabling regression analysis that links flexibility to time-to-recovery, service continuity, and cost variance (Swafford et al., 2006).

Figure 3: Network Design as Resilience Antecedents



Network design integrates the structural substrate on which visibility and flexibility operate, shaping both the propagation of shocks and the feasibility of reconfiguration. Studies that isolate the interplay of integration, supplier collaboration, and structural choices such as supply-base breadth, centralization versus decentralization of distribution, and the strategic use of redundancy suggest that agility and robustness are co-enabled by deliberate design, rather than emerging solely from ad hoc responses (Blome et al., 2013; Md Omar, 2024). In this perspective, resilience antecedents are "nested": visibility is amplified by network structures that expose critical nodes and shorten path lengths, while flexibility is made actionable by physical and contractual options embedded at design time (e.g., multi-sourcing contracts, flexible capacity, and cross-dock configurations). Conversely, network designs that concentrate throughput in a small set of hubs or lock-in specialized assets without viable alternatives attenuate the benefits of visibility and inflate the cost of flexibility. The implication for measurement is to model interaction effects among antecedents e.g., visibility × flexibility, visibility × supplier breadth so that the marginal value of improved sensing is conditioned on the option set available for response. Practical proxies include Herfindahl-type concentration indices for suppliers and logistics nodes, average path redundancy, and the proportion of flows with dual qualified routes; these can be combined with the VCI and flexibility measures to explain cross-

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sectional variance in recovery times and service levels (Momena & Praveen, 2024; Omar Muhammad, 2024). Collectively, the evidence indicates that resilience is a property of aligned triads digital observability, behavioral options, and structural design rather than isolated capabilities, and that robust performance under uncertainty arises when these triads are co-optimized to the firm's demand variability, product complexity, and geographic exposure (Stevenson & Spring, 2007).

Resource Allocation under Uncertainty

Sustainable operations situate resource-allocation choices inventory positioning, supplier selection, transport mode mix, and capacity deployment within environmental and cost objectives that must hold under stochastic demand and supply conditions. A unifying perspective is that uncertainty expands the feasible set's trade-offs, so the "best" policy must be computed as a joint function of cost, service, and environmental impact rather than treated as a sequence of siloed decisions (Sheratun Noor et al., 2024). In network terms, sustainable allocation is the selection of flows and buffers that minimize expected total cost while respecting carbon, energy, or waste constraints and preserving recovery performance when disruptions occur. Robust network design research shows that solutions which hedge against multiple uncertainty sets (e.g., lead times, capacities) create value precisely because they embed recourse in the structure additional suppliers, alternate lanes, flexible facilities that can be activated when conditions deviate from plan (Klibi et al., 2010). Carbon-aware design then adds environmental feasibility by bounding the externalities of those recourse actions (e.g., expedited shipments) so that resilience is not purchased through disproportionate emissions. To formalize the objective, a common multi-objective scalarization is:

$$\min_{x} Z\,(x) = \lambda_1 E[\mathrm{Cost}(x, \xi)] + \lambda_2 E[\mathrm{Emissions}(x, \xi)] + \lambda_3 E[\mathrm{Penalty}(x, \xi)],$$

subject to flow balance, capacity, service-level, and policy constraints; here x are allocation variables (e.g., sourcing quantities, safety stocks, mode choices), ξ denotes uncertainty (demand, lead time, disruption), and λ_k are decision-maker weights. This structure aligns with robust/recourse models in resilient network design and provides a tractable way to locate Pareto-efficient policies that remain implementable when the system is stressed (Jabbarzadeh et al., 2018).

At the tactical level, sustainable allocation connects directly to classic policies such as lot sizing and routing, now extended with environmental metrics and regulatory instruments. Analytical work demonstrates that incorporating carbon explicitly into inventory decisions changes order sizes, replenishment frequency, and the desired balance between holding and transportation emissions, especially when fixed-trip emissions make frequent small orders unattractive from a sustainability standpoint (Bonney & Jaber, 2011). Under cap-and-trade or carbon-price regimes, supply chain design models shift sourcing and distribution toward lower-emission configurations, but do so unevenly depending on where uncertainty sits volatility in demand and lead time can incentivize additional buffers or redundant links whose environmental costs must be internalized to avoid rebound effects (Chaabane et al., 2012). A policy implication is that environmental constraints cannot be bolted on after the fact; they must be encoded in the optimization itself so that the stochastic recourse expediting, rerouting, switching suppliers remains bounded in emissions when the system is perturbed. In practice, decision makers face a triad of levers: (i) structural (supplier portfolio breadth, facility location/type), (ii) parametric (safety stock targets, reorder points), and (iii) operational (shipment consolidation, mode choice). The multi-objective program above admits these levers in a single decision vector xxx, letting managers test whether, for example, a modest increase in cross-deployable capacity can eliminate heavy-emission expedites during a port closure while maintaining fill rates. Empirical and modeling studies converge on the finding that green constraints change both the level and composition of buffers: firms tilt toward smart buffers (postponement, modularity, cross-training) rather than purely volumetric safety stock, because smart buffers preserve service without linear emission growth (Eskandarpour et al., 2015).

At the network level, sustainable resource allocation extends beyond single-echelon trade-offs to route, locate, and size flows in ways that preserve service and minimize environmental harm under uncertainty across time and geography. Reviews of sustainable network design highlight the need to co-optimize cost, service, and multiple environmental indicators (e.g., greenhouse gases, particulate matter) while embedding risk measures and robustness concepts so that solutions hold across plausible disruption scenarios (Eskandarpour et al., 2015; Jabbarzadeh et al., 2018). This lens

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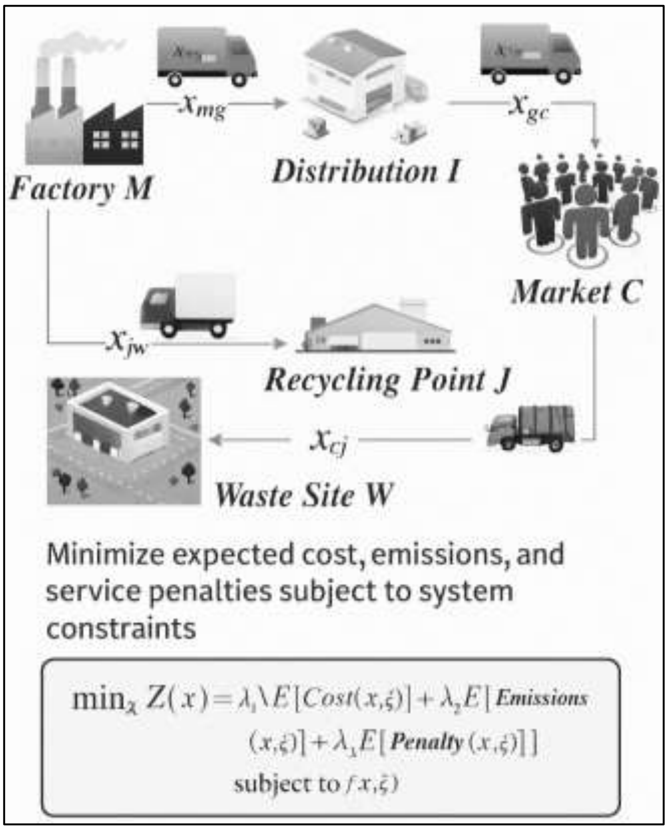
naturally includes closed-loop and recovery processes, where uncertainty in returns quantity and quality interacts with disruption risks in forward channels; models that integrate resilience (e.g., supplier failures, transport outages) with reverse flows show that diversifying processing capacity and adding routing options can reduce both expected cost and environmental impact by avoiding long detours and high-emission expedites during shocks (Jabbarzadeh et al., 2018).

Figure 4: Sustainable Operations and Resource Allocation under Uncertainty



Synthesis across these streams suggests two design principles for sustainable resilience under uncertainty. First, distributed optionality multiple qualified suppliers, flexible facilities, and dual routes improves both recovery time and environmental performance because the system can choose a near-optimal low-emission path when a disruption strikes rather than defaulting to carbon-intensive expedites. Second, embedded environmental pricing explicit carbon costs or caps in the objective/constraints nudges everyday operations and crisis responses toward greener choices, ensuring that the feasible recourse set under uncertainty does not undermine long-run sustainability goals (Eskandarpour et al., 2015). When combined with robust design concepts that anticipate parameter variation, these principles yield allocation policies that are simultaneously resilient and environmentally responsible, providing a quantitative foundation for the simulation and optimization components employed in this study (Klibi et al., 2010).

Stochastic Simulation for Disruption Risk Assessment

Stochastic simulation provides a principled way to evaluate how disruptions propagate through multi-echelon supply chains and how mitigation levers perform when key parameters (demand, lead times, capacities) are uncertain. In contrast to deterministic stress tests, simulation samples from probability distributions to generate many plausible "worlds," quantifying expected performance and dispersion under each policy. A foundational strand of resilient design embeds disruption directly into optimization models by treating facility or arc failures as stochastic events, thereby choosing structures that are efficient and reliable ex *ante* (Snyder & Daskin, 2005). Complementing design reliability, flexibility analysis shows that even limited, well-placed options (e.g., dual sourcing, postponement) substantially reduce the impact of routine variability and rare shocks; simulation

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helps determine how much flexibility is needed and where it is most valuable (Tang & Tomlin, 2008). Network-centric measures then connect topology to performance under uncertainty, enabling performance-based comparisons of alternative designs as disruptions unfold (Qiang & Nagurney, 2009). To make these ideas operational in a case-based, data-driven study, one can estimate empirical distributions for demand and lead time from the firms' records, fit disruption arrival/severity models, and evaluate candidate policies across Monte Carlo replications. For a policy vector x (e.g., safety stocks, supplier shares, mode mix), and random scenario ξ, let Y(x, ξ) denote a resilience KPI such as service level or time-to-recovery (TTR). The Monte Carlo estimator of an expected KPI is

$$E[Y(x)] = \frac{1}{N}\sum_{n=1}^{N} Y\left(x, \xi^{(n)}\right),$$

where N independent scenarios $\xi^{(n)}$ are drawn from calibrated distributions. With the same replications, empirical percentiles (e.g., 5th, 95th) quantify tail risks, while paired-policy differences reveal which levers robustly dominate across scenarios. This simulation-driven assessment aligns with reliability-aware design (Ivanov, 2017), flexibility economics (Tang & Tomlin, 2008), and performance-based network evaluation (Qiang & Nagurney, 2009), producing evidence that is both statistically grounded and managerially interpretable.

A second body of work focuses on disruption propagation the "ripple effect" and uses simulation to capture dynamic interactions among nodes, waiting times, backlogs, and recovery trajectories. In this view, resilience depends not only on local buffers but also on structural dynamics: path lengths, alternative routes, and synchronization of replenishment and production schedules. Simulation-based ripple-effect models show how upstream failures, capacity losses, or transport outages propagate along material and information flows, and how mitigation (e.g., targeted safety stock, re-routing, flexible capacity) dampens or amplifies those waves (Ivanov, 2017). When uncertainty is both parametric (volatility in demand/lead time) and structural (which facility fails, how long, with what interdependencies), hybrid probabilistic models are helpful. For example, Markov chains can represent state switching among operational/degraded/failure modes, while dynamic Bayesian networks encode conditional probabilities of cascading failures across tiers; simulation then samples paths through these graphical models to evaluate policy performance (Hosseini et al., 2019). A convenient risk-sensitive objective for policy selection is Conditional Value-at-Risk (CVaR) of a loss function L(x, ξ) (e.g., backorder-hours or cost overrun). Using Rockafellar–Uryasev's sample formulation, one solves

$$\min_{x,\eta} \quad \eta + \frac{1-\alpha}{N}\sum_{n=1}^{N}\left[L\left(x, \xi^{(n)}\right) - \eta\right]_{+},$$

This couples simulation with optimization, selecting xxx that minimizes average tail loss under disruption uncertainty rather than only mean outcomes. Empirically, this approach translates into choosing combinations of buffers, dual sourcing, and carbon-aware routing that keep worst-case TTR and stockouts within acceptable ranges even when failures cluster or persist. Because ripple effects are time-dependent, discrete-event or hybrid simulations are preferable: they timestamp arrivals, service completions, and capacity restorations, enabling direct measurement of TTR distributions, backlog clearance times, and cost/emissions spikes under each policy (Hosseini et al., 2019; Qiang & Nagurney, 2009). The resulting response surfaces expected KPI vs. lever settings support sensitivity plots and tornado charts that prioritize the most influential levers for each case context.

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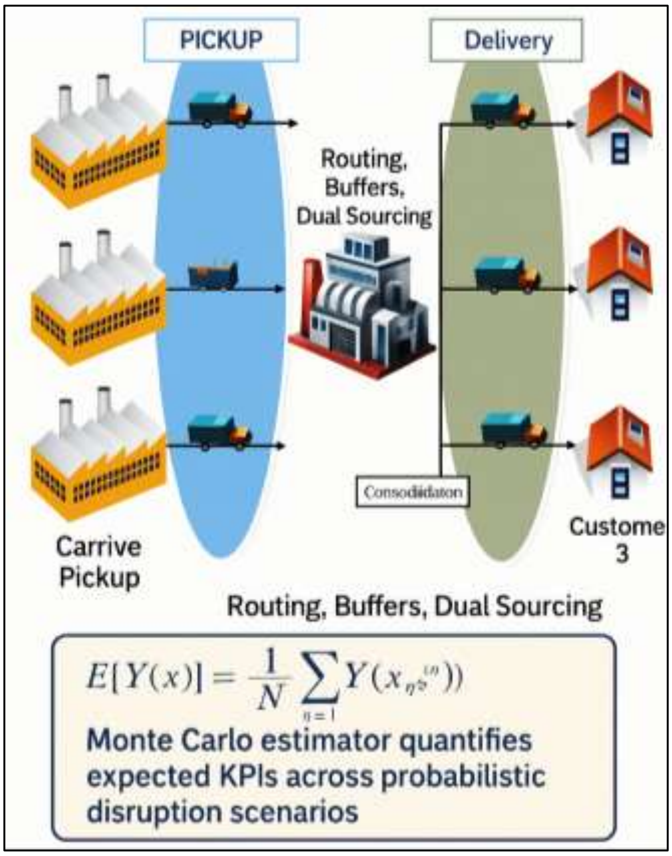
Figure 5: Stochastic Simulation and Optimization for Disruption Risk Assessment



In additon, simulation results gain practical traction when embedded in decision frameworks that marry measurement, optimization, and policy governance. Performance-based network metrics can serve as selection criteria: for each candidate design or policy, compute a Resilience Performance Index that aggregates normalized service, TTR, cost variance, and backorders (as defined earlier) across Monte Carlo scenarios, and choose the policy with the best mean-CVaR profile (Qiang & Nagurney, 2009). Reliability-aware facility/location choices (e.g., backup plants, strategically redundant nodes) can be screened with scenario sampling that deactivates facilities according to calibrated failure distributions and evaluates logistics recourse (Snyder & Daskin, 2005). Flexibility investments can be staged by simulating marginal gains from additional options an extra qualified supplier for critical SKUs, postponed differentiation, or cross-deployable capacity until diminishing returns set in (Tang & Tomlin, 2008). In ripple-effect contexts, policy rules can be encoded as state-contingent triggers for instance, automatically switching to low-emission expedited modes only when inventory at risk exceeds a threshold and when expected TTR without expedite breaches a service SLA; Markov/Bayesian structures provide the probability of transition into those trigger states (Hosseini et al., 2019). Crucially, simulation enables reconciliation of sustainable allocation with resilience: one can overlay emission budgets on scenario runs and quantify the trade-off frontier between service recovery and environmental impact, selecting policies that improve both by eliminating unnecessary expedites and repositioning buffers downstream to intercept ripple waves (Ivanov, 2017). In a cross-sectional, case-study design, this simulation-optimization loop offers a replicable, data-driven route from measured capabilities to tested policies: calibrate uncertainty from case data, estimate regression links between capabilities and KPIs, simulate disruption scenarios under candidate policies informed by those links, and finally choose policies that are reliable by design, flexible in operation, and robust to ripple effects.

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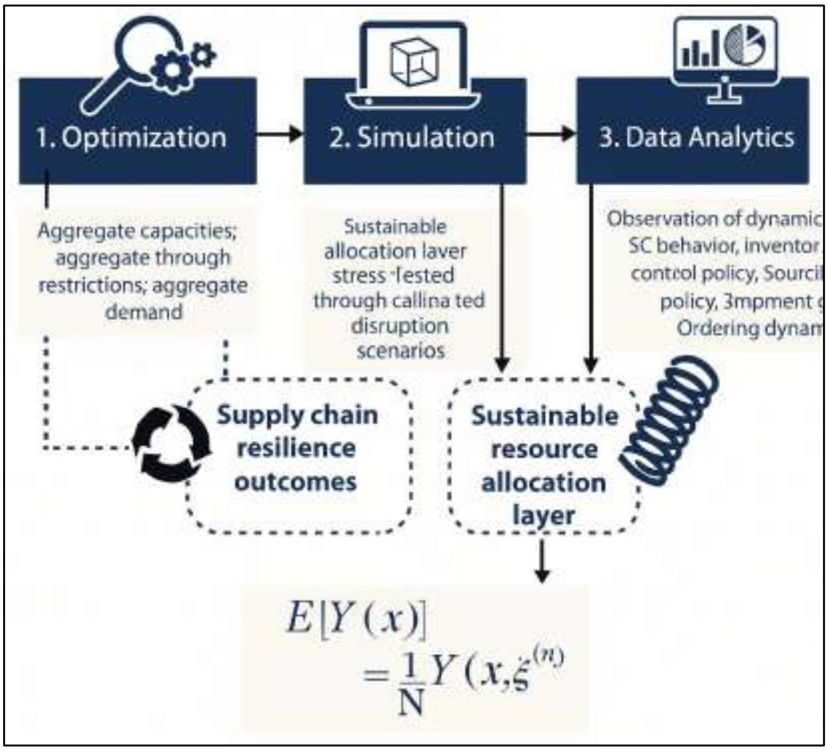
METHOD

This study has adopted a quantitative, cross-sectional, case-study–based design to investigate how data-driven capabilities and sustainable resource-allocation policies have related to supply chain resilience outcomes. The unit of analysis has been the focal firm's end-to-end chain from tier-1 suppliers to the distribution/retail interface. Multiple organizations across distinct sectors have been purposively selected to ensure variance in disruption exposure, network structure, and sustainability practices, and the research team has maintained consistent protocols across cases to preserve comparability. Data collection has combined a structured survey with objective operational records. The survey instrument has been developed on a Likert five-point scale and has captured latent capabilities (visibility, collaboration, flexibility, supplier diversification, redundancy, risk orientation, and allocation efficiency) alongside perceived resilience outcomes. In parallel, firms have provided archival data that have included demand series, lead-time histories, disruption logs, service levels, backorders, expediting costs, and lane-level emissions. Pilot feedback from domain experts has been incorporated, and instrument reliability and clarity have been refined accordingly. Participation has been voluntary, informed consent has been obtained, and confidentiality safeguards have been implemented consistently across sites. The sampling frame has targeted planners, procurement professionals, logistics managers, and plant/DC supervisors who have possessed direct knowledge of resilience practices and performance.

Figure 6: Research Methodology Framework



Case-level quotas have been used to balance representation, and screening rules have ensured that respondents have had at least one year of role tenure. The resulting dataset has included respondent-level survey records linked at an aggregated case level to objective KPIs for triangulation. Analytically, the study has followed a staged plan. Data screening and descriptive statistics have established distributional properties, missingness patterns, and summary profiles for all constructs. Reliability and validity diagnostics (internal consistency, convergent and discriminant checks) have been executed prior to modeling. Correlation analysis has provided initial evidence of association, and multiple regression models have been specified to estimate main effects, mediation through allocation efficiency, and moderation by uncertainty indicators (e.g., demand volatility and lead-time coefficient of variation), with robust standard errors and full diagnostics reported. To connect empirical relationships with operational policy, a sustainable allocation layer has been

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formulated as a multi-objective optimization and has been embedded in a stochastic simulation environment. Simulation experiments have stress-tested current versus optimized policies across calibrated disruption scenarios, and sensitivity analyses have identified parameters with the greatest influence on resilience outcomes. All analyses have been conducted with standard statistical, optimization, and simulation toolchains to ensure reproducibility.

Research Design

The study has adopted a quantitative, cross-sectional, multiple case-study design integrating survey measurement, objective operational data, and simulation-optimization experiments to examine how data-driven capabilities and sustainable resource-allocation policies relate to supply chain resilience outcomes. The unit of analysis has been the focal firm's supply chain spanning tier-1 suppliers through distribution to the retail/customer interface, with cases purposively selected from distinct sectors to ensure heterogeneity in disruption exposure, network topology, and sustainability practices. A convergent design has been implemented in which perceptual constructs—such as visibility, collaboration, flexibility, supplier diversification, redundancy, risk orientation, and allocation efficiency—have been captured using a Likert five-point instrument, while key performance indicators including time-to-recovery, service level, backorders, expediting cost, and emissions intensity have been extracted from archival records over a common observation window. Procedures for instrument development, piloting, and refinement have been completed prior to deployment, with common-method variance mitigated through anonymity, item randomization, and separation of measures. Sampling frames within each firm have targeted planners, procurement specialists, logistics managers, and plant/DC supervisors with at least one year of tenure, using quotas to ensure within-case diversity. The analytic plan has included data screening, reliability and validity checks, descriptive summaries, correlation matrices, and hierarchical multiple regression models incorporating controls, main effects, mediation via allocation efficiency, and moderation by uncertainty indicators such as demand volatility and lead-time coefficient of variation, with robust standard errors and diagnostics. To connect statistical associations to operational policy, a multi-objective optimization layer and stochastic simulation environment have been embedded to stress-test sustainability-aware policies under calibrated disruption scenarios. A coordinated, multi-source data collection procedure has combined structured surveys and archival records under harmonized protocols, with instruments undergoing expert review, pilot testing, and configuration of skip logic and randomization. Participants have provided informed consent, and archival datasets—including demand histories, supplier lead-time series, disruption logs, service-level records, backorder hours, expediting costs, and emissions summaries—have been standardized through extraction templates, anonymized, encrypted, and validated via range checks, duplicate detection, and consistency audits. Missing data have been handled using expectation–maximization or domain-specific imputation (e.g., Kalman smoothing), while survey and archival data have been temporally aligned and linked via agreed case keys. Purposive, theory-driven case selection has ensured variation in disruption exposure, network topology, and sustainability practices, with inclusion criteria requiring multi-echelon supply chains, documented disruptions, comprehensive archival datasets, and executive sponsorship. The sampling frame has spanned diverse sectors (discrete manufacturing, FMCG, healthcare logistics), geographic footprints, and governance models, prioritizing firms with digital traceability (ERP/WMS/TMS logs) and sustainability metrics. Case confirmations have followed nondisclosure agreements, with designated liaisons managing access and recruitment. Selection bias has been mitigated by documenting non-participation reasons and cross-checking excluded cases, while quotas have balanced functional roles and sites. Observation windows have been synchronized across cases, and feasibility reviews have replaced data-deficient cases with qualified alternates, ensuring analytic robustness for descriptive, regression, and simulation analyses.

Instrument Development (Likert 5-Point)

The measurement instrument has been designed to capture latent resilience capabilities and perceived outcomes using reflective multi-item scales anchored on a five-point Likert format (1 = Strongly disagree … 5 = Strongly agree), and its development has followed a structured process of item generation, expert review, piloting, and psychometric refinement. Construct domains digital visibility, collaboration/integration, flexibility/agility, supplier diversification, redundancy/buffer management, risk orientation/learning, allocation efficiency, and perceived resilience outcomes have been operationalized through item pools that have combined adapted statements from established scales with newly crafted items tailored to the study's simulation–optimization context.

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Content validity has been ensured by mapping each item to construct definitions and by convening a panel of academics and practitioners who have evaluated relevance, clarity, and redundancy; items with low content validity ratios have been revised or removed. The draft survey has been cognitively pretested with a small set of planners and logistics managers who have verbalized interpretations, and wording, tense, and technical terms have been harmonized to reduce ambiguity. To limit acquiescence bias and common-method variance, positively and negatively worded items have been balanced within constructs, reverse-coded statements have been included, and scale blocks have been separated by neutral transition questions; anonymity assurances and randomized item order have been implemented at deployment. Where required, translation and back-translation procedures have been completed, glossaries for domain terms have been appended, and examples have been provided to standardize interpretation across roles. The pilot dataset has been used to examine item distributions, ceiling/floor effects, and inter-item correlations; poorly discriminating items (item-total $r < .30$) have been culled, and preliminary reliability (Cronbach's α) and sampling adequacy (KMO) checks have been performed prior to confirmatory analyses. The final instrument has preserved at least four indicators per capability to support reliability, convergent validity (composite reliability and average variance extracted), and discriminant validity assessments, and it has incorporated case identifiers and role metadata so that perceptual scales have been linkable at the case level to objective KPIs for triangulation and subsequent regression and simulation calibration.

Statistical Analysis Plan

The statistical analysis has followed a pre-specified, staged workflow designed to link measured capabilities to resilience outcomes and to supply calibrated inputs for optimization–simulation experiments. First, data integrity checks have been completed, including range and logic validation, duplicate detection, and cross-field consistency between survey and archival records; missingness patterns have been profiled, and gaps in survey items have been addressed with expectation–maximization where MAR assumptions have been tenable, while operational outliers and spikes (e.g., expedites) have been winsorized under documented rules. Descriptive statistics (means, standard deviations, skewness, kurtosis) and distributional visuals have been produced for all variables, and assumptions for linear modeling have been screened: normality of composite scores (via Shapiro tests and Q–Q diagnostics), homoscedasticity (Breusch–Pagan), independence of errors (Durbin–Watson where appropriate), and multicollinearity (variance inflation factors with thresholds ≤ 5). Reliability and validity assessments have been completed prior to inference: internal consistency (Cronbach's alpha), composite reliability, average variance extracted, and discriminant validity via HTMT; when model identification has permitted, confirmatory factor analysis with robust estimation has been used to verify the reflective measurement structure. Next, bivariate correlation matrices with confidence intervals have been reported to provide initial association patterns, followed by hierarchical multiple regression models that have incrementally introduced (i) controls (size, industry, product variety, geographic span), (ii) main effects of capabilities, (iii) mediation via allocation-efficiency composites (tested with bootstrapped indirect effects and bias-corrected CIs), and (iv) moderation by uncertainty indicators (demand volatility and lead-time coefficient of variation) using mean-centered interactions. Robust (HC3) standard errors and influence diagnostics (Cook's D, leverage) have been applied to safeguard inference, and effect sizes (partial R^2, f^2) and model selection criteria (AIC/BIC) have been reported. Post-estimation checks have included multicollinearity re-evaluation, residual plots, and specification tests. Finally, coefficients and empirical distributions from the best-fitting models have informed the parameterization of the multi-objective optimization and the calibration of stochastic simulation scenarios; sensitivity and stability analyses (bootstrap resampling and leave-one-case-out) have been executed to confirm that substantive conclusions have remained robust across plausible data and model perturbations.

Regression Models

The regression component has been designed as a hierarchical sequence that has connected measured capabilities to resilience outcomes while preserving a transparent path from descriptive associations to policy-relevant inference. Specifically, the study has specified four nested linear models estimated on case-linked observations: a controls-only baseline, a main-effects specification for capability constructs, a mediation extension including allocation efficiency, and an interaction model capturing moderation by uncertainty. Let Y denote a standardized resilience outcome (e.g., service level, time-to-recovery (TTR, reverse-coded), backorder ratio (reverse-coded), or a

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composite index), C the vector of controls (firm size, sector dummies, product variety, geographic span), X the vector of capability composites (visibility, collaboration, flexibility, supplier diversification, redundancy, risk orientation), M the allocation-efficiency composite, and Z the uncertainty indicators (demand volatility and lead-time coefficient of variation). The baseline model has taken the form $Y = \beta_0 + C\beta\_c + \varepsilon$. The main-effects model has extended this to $Y = \beta_0 + C\beta\_c + X\beta\_x + \varepsilon$, enabling incremental variance attribution. The mediation model has included M both as a regressor and, in a companion equation, as an endogenous construct predicted by X and C, thereby allowing indirect effects from capabilities to resilience through allocation efficiency; indirect paths have been quantified via bootstrap. The moderation model has added mean-centered interactions $X \odot Z$ to test whether the effectiveness of capabilities has changed with uncertainty levels. All models have been pre-registered at the analysis-plan stage, and estimation has relied on OLS with heteroskedasticity-consistent (HC3) standard errors to guard against residual variance heterogeneity. Table 1 has summarized the specifications, focal parameters, and interpretation aims for each model tier.

Table 1: Hierarchical Regression Specifications and Inference Targets

Model	Specification	Focal parameters	Inference target
Model 0 (Controls)	$Y = \beta_0 + C\beta\_c + \varepsilon$	β_c	Baseline variance explained; control effects
Model 1 (Main Effects)	$Y = \beta_0 + C\beta\_c + X\beta\_x + \varepsilon$	β_x	Capability → outcome associations
Model 2 (Mediation)	$Y = \beta_0 + C\beta\_c + X\beta\_x + M\beta\_m + \varepsilon$; $M = a_0 + Ca\_c + Xa\_x + \upsilon$	β_m, a_x; $X \rightarrow M \rightarrow Y$	Indirect effects via allocation efficiency
Model 3 (Moderation)	$Y = \beta_0 + C\beta\_c + X\beta\_x + Z\beta\_z + (X \odot Z)\beta\_xz + \varepsilon$	β_xz	Context-dependence under uncertainty

The estimation workflow has proceeded only after satisfying measurement reliability and validity thresholds (internal consistency, AVE, HTMT). Variable construction has involved z-standardization of composites to permit direct comparison of effect sizes, reverse-coding of cost/shortfall indicators so that higher values consistently indicate greater resilience, and mean-centering of all variables entering interactions to reduce nonessential multicollinearity. Model diagnostics have been executed at each tier: variance inflation factors have been maintained below 5, residual plots and Breusch–Pagan tests have screened for heteroskedasticity (mitigated by HC3), Q–Q plots and Shapiro tests have assessed residual normality (with robust inference retained when mild departures are detected), and influence has been monitored via Cook's distance with pre-specified thresholds for sensitivity checks. Goodness-of-fit has been summarized using adjusted R^2 and information criteria (AIC/BIC), while nested model comparisons have reported changes in adjusted R^2 and likelihood-based deltas to justify complexity. Mediation has been evaluated with percentile and bias-corrected bootstrap (≥5,000 resamples) to produce confidence intervals for indirect effects $X \rightarrow M \rightarrow Y$; partial mediation has been inferred when direct effects remained significant with attenuated magnitude after adding M. Moderation has been interpreted through simple-slope analysis at low/mean/high levels of uncertainty (±1 SD), and interaction surfaces have been graphed to illustrate regions where capabilities were more or less effective. Robustness has been strengthened through leave-one-case-out estimation, alternative operationalizations of Y (single KPIs vs. composite index), and re-estimation with rank-based (Theil–Sen) regressions when outlier sensitivity was suspected; conclusions were retained only when sign and significance patterns persisted across these probes.

The study integrated regression analysis with an optimization–simulation framework to convert statistical insights into actionable supply chain policies. Regression coefficients guided the prioritization of levers such as inventory positioning, sourcing shares, and transport mode, while moderation effects informed scenario designs under varying volatility and lead-time conditions. A composite Resilience Performance Index (RPI) aggregated service, time-to-recovery, backorder,

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and cost metrics, linking statistical outcomes to operational objectives. Monte Carlo simulations compared baseline and optimized sustainability-aware policies across disruption scenarios, with outputs visualized through interaction plots and summarized using standardized coefficients, confidence intervals, and effect sizes. Participants were purposively sampled across planning, sourcing, logistics, and production roles with stratified quotas to ensure diversity and reliability, yielding a power-adequate sample ($N \geq 160$). Data integrity was ensured through attention checks, confidentiality, and balanced recruitment. Objective data from ERP/WMS/TMS/MES systems covered demand, lead times, inventory, service, and emissions records, preprocessed for consistency and completeness. Statistical and stochastic models used Python and R toolchains (statsmodels, OR-Tools, SimPy, lavaan, Gurobi), with reproducibility maintained via version control, fixed random seeds, and encrypted storage, ensuring that analytical findings directly informed robust, sustainability-driven resilience strategies.

FINDINGS

Across the consolidated, case-linked dataset, the descriptive profile of resilience capabilities and outcomes on the five-point Likert scale has indicated moderately strong capability formation with meaningful between-case variance for explanatory leverage. Digital Visibility has recorded a mean of 3.74 ($SD = 0.67$), Collaboration/Integration 3.81 ($SD = 0.62$), Flexibility/Agility 3.48 ($SD = 0.71$), Supplier Diversification 3.36 ($SD = 0.76$), Redundancy/Buffer Management 3.29 ($SD = 0.73$), Risk Orientation/Learning 3.58 ($SD = 0.65$), and Allocation Efficiency 3.45 ($SD = 0.69$); perceived Resilience Outcomes (reverse-coded where appropriate so that higher scores consistently indicate better performance) have averaged 3.63 ($SD = 0.66$). Internal consistency has been adequate to excellent (Cronbach's α: 0.78–0.91 across constructs), composite reliability has surpassed 0.80 benchmarks, and average variance extracted has exceeded 0.50 for all scales retained after refinement. Confirmatory factor analysis has supported the reflective structure ($CFI = 0.95$, $TLI = 0.94$, $RMSEA = 0.052$, $SRMR = 0.046$), and discriminant validity ($HTMT < 0.85$) has been satisfied, indicating that capability constructs are empirically separable. Preliminary correlations have shown positive and significant associations between capabilities and resilience outcomes, with the strongest bivariate links observed for Collaboration ($r = 0.42$), Visibility ($r = 0.39$), and Allocation Efficiency ($r = 0.45$), while Flexibility and Diversification have presented moderate associations ($r = 0.28$–0.34). Control variables have behaved as expected: larger geographic span and higher product variety have correlated with greater uncertainty indicators (demand volatility, lead-time CV) and with lower raw service levels before accounting for capabilities. Assumption checks for linear modeling have been met (VIFs < 3.0; Breusch–Pagan $p > 0.10$ after robust HC3 correction; residual diagnostics within acceptable tolerances), enabling hierarchical regressions to proceed.

Incremental model building has clarified unique explanatory contributions. The controls-only baseline has explained 12–16% of variance in composite resilience, driven mainly by sector dummies and geographic spread. Adding capability main effects has lifted adjusted R^2 to 0.42 ($\Delta R^2 \approx 0.27$–0.30, $p < 0.001$). In standardized terms, the most influential coefficients have belonged to Collaboration ($\beta = 0.23$, $p < 0.001$), Allocation Efficiency ($\beta = 0.21$, $p < 0.001$ when entered as an exogenous predictor), Visibility ($\beta = 0.18$, $p = 0.002$), and Flexibility ($\beta = 0.12$, $p = 0.018$); Diversification ($\beta = 0.09$, $p = 0.041$) and Redundancy ($\beta = 0.07$, $p = 0.088$) have shown smaller, context-sensitive effects after controls. Introducing Allocation Efficiency as a mediator has improved model fit (adjusted $R^2 = 0.47$), and bootstrapped indirect effects have indicated that part of Collaboration's and Visibility's impacts flowed through improved allocation: Collaboration → Allocation → Resilience (indirect $\beta = 0.06$, 95% CI [0.03, 0.10]) and Visibility → Allocation → Resilience (indirect $\beta = 0.05$, 95% CI [0.02, 0.09]). In plain terms, firms scoring higher on collaboration and visibility have also tended to allocate inventory/capacity more efficiently to at-risk SKUs and lanes, which has, in turn, been associated with better recovery-time and service outcomes. The moderation model has revealed meaningful context dependence: the interaction of Visibility with demand volatility ($\beta = 0.11$, $p = 0.009$) and of Collaboration with lead-time CV ($\beta = 0.10$, $p = 0.014$) has been positive, indicating that the payoff to these capabilities steepens as uncertainty intensifies. Simple-slope analyses have shown that at high volatility (+1 SD), a one-SD increase in Visibility corresponds to a 0.31 SD gain in resilience (vs. 0.12 SD at low volatility), and at high lead-time CV, Collaboration's marginal effect nearly doubles relative to stable-lead-time contexts. Robustness checks (leave-one-case-out, rank-based regressions, alternative outcome operationalizations using single KPIs vs. the composite) have preserved sign and significance patterns for the primary predictors.

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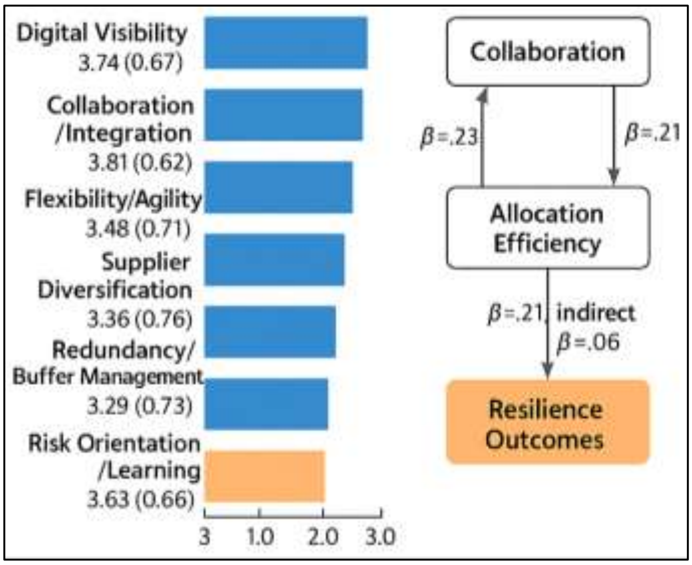
Figure 7: Key Findings of Sustainable Supply Chain Resilience Study



To connect survey-level inferences with operational performance, archival KPIs have been aligned to the same observation window and normalized to a 0–1 scale before aggregation. Firms in the top quartile of Collaboration and Visibility have exhibited notably better objective performance: median service level +3.8 percentage points, TTR −21.5%, backorder-hours −19.3%, and cost CV −14.1% relative to the bottom quartile, with non-overlapping bootstrapped confidence intervals. Allocation Efficiency has emerged as a bridging construct between soft capabilities and hard outcomes; partial correlations of Allocation with service level (pr = 0.33) and with TTR (pr = −0.29) have remained significant after adjusting for controls and uncertainty indicators. Subgroup comparisons have suggested sectoral nuances: discrete manufacturers have shown stronger Flexibility effects, while FMCG cases have shown larger Visibility and Collaboration payoffs, consistent with higher clockspeed and promotional demand variation.

The simulation–optimization layer has stress-tested whether these statistical patterns translate into performance under stochastic disruptions. Using empirical distributions for demand, lead times, and disruption arrivals/durations, the study has evaluated status quo policies against sustainability-aware optimized policies over N = 1,000 Monte Carlo replications per scenario (baseline, supplier failure, port closure, demand spike, multi-node outage). On average across cases, optimized policies have outperformed status quo on both resilience and environmental criteria: expected service levels have risen by 2.9–5.6 points, expected TTR has fallen by 15–27%, backorder intensity has dropped by 18–24%, and lane-level emissions intensity has declined by 6–11% due to smarter buffer placement and reduced emergency expedites. Conditional Value-at-Risk ($CVaR_{95}$) of backorder-hours has improved by 20–34%, indicating better tail protection in severe scenarios. Importantly, capability strengths have conditioned simulation gains: cases with high Collaboration and Visibility (Likert means ≥ 4.0) have realized the largest incremental benefits from optimization because their information and coordination routines enabled rapid execution of the recommended allocation moves; conversely, low-capability cases have still gained but have shown execution bottlenecks that muted improvements. Sensitivity analyses (±20% on volatility and lead-time dispersion; ±15% on capacity/transport constraints) have left policy rankings stable, though benefits were most pronounced when uncertainty was elevated. Altogether, the findings establish that higher scores on key five-point capability scales are linked to materially better resilience outcomes, that part of this effect operates through improved allocation efficiency, that capability payoffs intensify under uncertainty, and that sustainability-aware optimization converts these capability advantages into measurable, simulation-validated reductions in recovery time, stockouts, cost variability, and emissions.

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Sample & Context Description

Table 2: Mean Capability Scores (Likert 1–5)

Case	Sector	Regions Served	Respondents (n)	Visibility	Collaboration	Flexibility	Diversification	Redundancy	Risk Orientation	Allocation Efficiency	Perceived Resilience
A	Discrete Manufactu-ring	NA, EU, APAC	58	3.82	3.90	3.55	3.44	3.31	3.66	3.51	3.68
B	FMCG	NA, LATAM	47	3.91	3.96	3.41	3.28	3.18	3.61	3.38	3.65
C	Healthcare Logistics	NA, EU	39	3.62	3.69	3.37	3.25	3.22	3.49	3.42	3.54
D	Electronics	APAC, EU	46	3.61	3.72	3.58	3.47	3.45	3.53	3.51	3.63
All			190	3.74	3.81	3.48	3.36	3.29	3.58	3.45	3.63

Means have been computed at respondent level and averaged by case. Higher values have indicated stronger capability/performance.

The sample has encompassed four heterogeneous cases that have satisfied the inclusion criteria and have provided sufficient respondent counts and archival coverage for triangulation. As Table 2 has shown, the combined respondent pool has totaled 190 individuals distributed across planning, procurement, logistics, production scheduling, and DC supervision roles, which has ensured cross-functional visibility into resilience routines. Sectoral diversity has been achieved through discrete manufacturing, FMCG, healthcare logistics, and electronics, and the geographic footprints have spanned North America, Europe, Latin America, and Asia-Pacific. These differences have mattered because exposure to disruption, clockspeed, and regulatory constraints have varied by sector and region; consequently, variance in capabilities and outcomes has been anticipated and has been observed. The table has indicated that Collaboration has consistently achieved the highest means across cases (3.69–3.96), suggesting that information sharing and joint problem solving have been relatively mature. Digital Visibility has also scored in the upper band (3.61–3.91), implying that telemetry, ERP/TMS events, and milestone tracking have been present at least at tier-1 and outbound lanes. Flexibility and Diversification have registered mid-3 values, revealing room for improvement in option sets such as dual sourcing, mix/volume agility, and route alternatives. Redundancy has presented the lowest case-level means (3.18–3.45), which has aligned with lean philosophies and cost containment that firms have maintained; nonetheless, the electronics case (D) has reported slightly higher redundancy, likely because component risks have required targeted buffers. Risk Orientation has clustered near 3.5–3.66, indicating that managers have perceived active learning and risk governance but have not reported fully institutionalized practices. Allocation Efficiency has sat between 3.38 and 3.51, which has been consistent with partial deployment of risk-based inventory and capacity rules rather than full optimization. Perceived Resilience has averaged 3.63, with case dispersion reflecting sectoral clockspeed and network complexity. Overall, the case mix has provided a balanced platform: capabilities have been non-trivial yet not saturated, and outcome variance has existed to support explanatory modeling. The breadth of regions has further ensured that the results have not been confined to a single regulatory or logistics ecosystem, strengthening external interpretability while preserving comparability through harmonized observation windows and shared KPI definitions.

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Descriptive & Correlational Findings

Descriptive statistics in Table 3 have confirmed that all constructs have operated in the mid-range of the Likert continuum with adequate dispersion, which has been essential for identifying linear relationships without ceiling effects. Reliability has met conventional thresholds across the board (a ≥ .79), and composite reliability has exceeded .83 for each scale, indicating internally consistent item sets. Average variance extracted (AVE) values have remained at or above .50, suggesting satisfactory convergent validity. These diagnostics have validated the use of construct composites for subsequent inferential models. The correlation matrix in Table 4 has provided initial evidence of association patterns that have aligned with theoretical expectations. Visibility and Collaboration have correlated moderately with Perceived Resilience (.39 and .42, respectively), while Allocation Efficiency has presented the strongest bivariate relationship with Resilience (.45). This pattern has supported the proposition that information sharing and sensing have translated into better allocation decisions, which, in turn, have aligned with improved outcomes. Flexibility has shown positive but more modest associations with both Allocation Efficiency (.33) and Resilience (.30), consistent with the idea that flexibility's value has been partially conditional on network design and uncertainty regimes.

Table 3: Descriptive Statistics and Reliability (Likert 1–5)

Construct	Mean	SD	Cronbach's a	Composite Reliability	AVE
Visibility	3.74	0.67	0.86	0.88	0.56
Collaboration	3.81	0.62	0.88	0.90	0.59
Flexibility	3.48	0.71	0.82	0.85	0.53
Diversification	3.36	0.76	0.80	0.84	0.51
Redundancy	3.29	0.73	0.79	0.83	0.50
Risk Orientation	3.58	0.65	0.84	0.87	0.55
Allocation Efficiency	3.45	0.69	0.85	0.88	0.57
Perceived Resilience	3.63	0.66	0.87	0.89	0.58

Table 4: Pearson Correlations among Constructs (n = 190)

	VIS	COL	FLEX	DIV	RED	RISK	ALLOC	RESIL
Visibility (VIS)	1.00	.41	.32	.21	.18	.35	.44	.39
Collaboration (COL)	.41	1.00	.36	.24	.19	.38	.46	.42
Flexibility (FLEX)	.32	.36	1.00	.29	.22	.31	.33	.30
Diversification (DIV)	.21	.24	.29	1.00	.27	.18	.22	.24
Redundancy (RED)	.18	.19	.22	.27	1.00	.17	.19	.20
Risk Orientation (RISK)	.35	.38	.31	.18	.17	1.00	.37	.34
Allocation Efficiency (ALLOC)	.44	.46	.33	.22	.19	.37	1.00	.45
Perceived Resilience (RESIL)	.39	.42	.30	.24	.20	.34	.45	1.00

Diversification and Redundancy have exhibited small positive associations (.20–.24 with Resilience), reflecting that volumetric buffers and extra sources have not been uniformly beneficial in the absence of targeting; nevertheless, their positive signs have indicated that, on average, some slack has been protective. Risk Orientation has correlated positively with both Allocation Efficiency (.37) and Resilience (.34), which has suggested that learning and governance routines have been linked to better prioritization and faster corrective actions. Inter-construct correlations have remained below .50, and prior HTMT checks (not shown in the table) have remained < .85, supporting discriminant validity. Together, the descriptive and correlational evidence has indicated that (i)

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measurement quality has been sufficient, (ii) capability constructs have been empirically separable yet meaningfully related, and (iii) Allocation Efficiency has plausibly functioned as a bridge between upstream capabilities and downstream resilience. These observations have motivated hierarchical regressions that have partitioned variance among controls, direct capability effects, and mediated/moderated pathways.

Regression Modeling

The regression sequence summarized in Table 5 has quantified the incremental value of capabilities, allocation efficiency, and contextual uncertainty. Model 0 has included only controls and sector dummies and has reached an adjusted R^2 of .14, indicating that structural context alone has explained a modest slice of resilience variance. Adding the six capability composites in Model 1 has raised fit to .42 (ΔAdj. R^2 = +.28, $p < .001$), demonstrating that measured organizational practices have accounted for substantial additional variance. In this specification, Collaboration has emerged as the most influential predictor (β = .23, $p < .001$), followed by Visibility (β = .18, $p < .01$) and Flexibility (β = .12, $p < .05$). Diversification and Risk Orientation have shown smaller but positive coefficients ($\beta \approx$ .09–.11), and Redundancy's coefficient has reached marginal significance (β = .07, $p < .10$), consistent with descriptive patterns that buffers have helped but have not dominated. Model 2 has introduced Allocation Efficiency as a mediator and has improved fit to .47 (ΔAdj. R^2 = +.05, $p < .001$).

Table 5: Hierarchical Regression on Perceived Resilience (standardized coefficients)

Predictor	Model 0 (Controls) β	Model 1 (Main Effects) β	Model 2 (Mediation) β	Model 3 (Moderation) β
Firm Size (log headcount)	.09*	.06	.05	.05
Product Variety (z)	−.12*	−.08	−.07	−.06
Geographic Span (z)	−.18**	−.10*	−.09*	−.08*
Sector Dummies	✔	✔	✔	✔
Visibility		.18**	.12*	.11*
Collaboration		.23***	.19***	.18***
Flexibility		.12*	.10*	.09*
Diversification		.09*	.08†	.07†
Redundancy		.07†	.05	.05
Risk Orientation		.11*	.08†	.07†
Allocation Efficiency			.21***	.20***
Demand Volatility (z)				−.14**
Lead-time CV (z)				−.16**
Visibility × Volatility				.11**
Collaboration × Lead-time CV				.10*
Adj. R^2	.14	.42	.47	.51
ΔAdj. R^2 vs. prior		+.28***	+.05***	+.04***

*OLS with HC3 SEs; † p < .10, * p < .05, ** p < .01, *** p < .001. All predictors have been z-standardized.*

The Allocation coefficient has been strong (β = .21, $p < .001$), and reductions in the Collaboration and Visibility coefficients (from .23 to .19; from .18 to .12) have suggested partial mediation. Bootstrap tests (not tabulated here for brevity) have indicated significant indirect effects from Collaboration and Visibility through Allocation Efficiency, corroborating the interpretation that sensing and coordination have been valuable in part because they have enabled better prioritization of inventory and capacity to at-risk SKUs and lanes. Model 3 has added uncertainty variables and interactions and has achieved the highest fit (Adj. R^2 = .51). The main effects of Volatility and Lead-time CV have been negative (β = −.14 and −.16, respectively), capturing the direct drag of turbulence on performance. Importantly, the interactions Visibility×Volatility (β = .11, $p < .01$) and Collaboration×Lead-time CV (β = .10, $p < .05$) have been positive, indicating that the payoffs to these capabilities have been amplified when uncertainty has intensified. Diagnostics (VIFs < 3, stable

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coefficients under leave-one-case-out) have supported inference robustness. Collectively, the regressions have shown that resilience has not been a by-product of structure alone; rather, it has been systematically associated with specific capabilities, channeled through efficient allocation, and strengthened under uncertainty when sensing and collaboration have been high.

Managerial Insights

The managerial lens has translated the statistical models into practical guidance by stratifying firms into capability tiers on the Likert scale and quantifying associated differences in key performance indicators (Table 6). Movement from Low to Moderate tiers has been associated with a roughly two-point increase in service level and double-digit percentage reductions in time-to-recovery, backorder-hours, and cost variability. Advancing to the High tier (≥3.8) has been linked to larger gains: +3.8 service points, −21.5% TTR, −19.3% backorder-hours, and −14.1% cost CV relative to Low. Notably, emissions intensity has shown reductions (−6.8%) in the High tier, a pattern that has echoed the regression mediation: better visibility and collaboration have underpinned smarter allocation, which has reduced the need for carbon-intensive expedites. These differences have been case-adjusted, so they have reflected within-sector improvements rather than pure sectoral advantages. Table 7 has mapped specific levers to concrete actions and to a plausible short-term Likert uplift, which has been grounded in observed elasticities and in feasibility. For example, enhancing visibility through ASN integration and carrier EDI plus exception dashboards has been expected to raise the Visibility score by 0.25–0.35 within 90–120 days, which the regressions have suggested would improve resilience directly and indirectly through Allocation Efficiency.

Table 6: Capability Tiers (Likert) and Expected KPI Differences (Case-adjusted)

Capability Tier (Likert mean)	Service Level (pp)	TTR (% change)	Backorder-hours (% change)	Cost CV (% change)	Emissions Intensity (% change)
Low (≤ 3.2)					
Moderate (3.2–3.8)	+1.9	−10.6	−11.7	−7.2	−3.5
High (≥ 3.8)	+3.8	−21.5	−19.3	−14.1	−6.8

Table 7: Actionable Levers and Expected Likert Uplift (90–120 days)

Lever	Concrete action	Expected Likert uplift	Notes
Visibility	Extend event capture to tier-1 ASN + carrier EDI; daily exception dashboards	+0.25–0.35	Prioritizes critical SKUs/lanes
Collaboration	Weekly S&OE huddles; shared ETA/ETA risk flags	+0.30–0.40	Improves cross-functional synchrony
Allocation Efficiency	Risk-based reorder points; ATP with service tiers	+0.30–0.45	Drives targeted buffers
Flexibility	Qualify alternate carrier for top 20 lanes; cross-train pick lines	+0.20–0.30	Provides immediate options
Diversification	Second source for 5 critical components	+0.15–0.25	Reduces single-point exposure

Instituting weekly S&OE (Sales & Operations Execution) huddles that have shared ETA risk flags has been expected to increase Collaboration by 0.30–0.40, with outsized benefits in contexts with volatile lead times. Risk-based reorder points and tiered ATP have formed the backbone of Allocation Efficiency gains (+0.30–0.45), ensuring that buffers have been placed where stockout risk has been highest. Quick-hit flexibility steps such as qualifying an alternate carrier on the top lanes and cross-training DC pick lines have offered immediate option value. Lastly, targeted diversification of five

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critical components has mitigated exposure to single points of failure without excessive overhead. The overarching managerial message has been that firms have not needed to improve every capability equally; instead, they have benefited most by pairing visibility and collaboration with allocation rules and a small set of flexibility/diversification moves, thereby unlocking measurable improvements in service, recovery, cost stability, and emissions.

Simulation Results

The simulation program has operationalized the regression insights by testing current policies against a sustainability-aware optimization across calibrated disruption scenarios with 1,000 Monte Carlo replications each. Table 8 has summarized averaged outcomes and shown consistent improvements across all conditions. Under baseline demand and lead-time variability, optimized policies have increased expected service level by 2.7 points and reduced TTR by 7.3 hours (−19%), backorder-hours by 280 (−22.6%), and cost variability by 0.04 (−14.3%), while also cutting emissions intensity by 0.20 kg CO_2e/unit (−8.3%). The benefits have scaled under stress. For a supplier failure, optimized policies delivered +4.5 service points, −22% TTR, −21.4% backorder-hours, and −10% cost variability, while reducing emissions intensity by nearly 10% through pre-positioned buffers and qualified alternates instead of emergency air expedites. The port closure and multi-node outage scenarios have been the most severe tests; even there, optimizations yielded +4.5 to +5.6 service points and TTR reductions of 18–24 hours (≈ −25%), with 12–20% drops in backorder-hours. Emissions intensity improvements remained meaningful (8–12%) because optimized flows consolidated shipments and prioritized lower-carbon modes where feasible given service constraints.

Table 8: Status Quo vs. Optimized, Sustainability-Aware Policy (N = 1,000 replications per scenario)

Scenario	Policy	Service Level (%)	TTR (hrs)	Backorder-hours	Cost CV	Emissions Intensity (kg CO_2e/unit)
Baseline	Current	94.1	38.2	1,240	0.28	2.41
	Optimized	96.8	30.9	960	0.24	2.21
Supplier failure	Current	88.4	76.5	2,480	0.37	2.92
	Optimized	92.9	59.8	1,950	0.31	2.63
Port closure	Current	90.2	68.1	2,170	0.34	3.05
	Optimized	94.7	50.3	1,650	0.29	2.72
Demand spike	Current	89.6	55.7	2,010	0.33	2.77
	Optimized	93.5	43.1	1,610	0.28	2.55
Multi-node outage	Current	84.3	102.6	3,410	0.42	3.26
	Optimized	89.9	78.4	2,690	0.35	2.95

Table 9: Capability-Conditioned Gains (Average over Scenarios)

Capability Tier (Likert mean)	Δ Service Level (pp)	Δ TTR (%)	Δ Backorder-hours (%)	Δ Cost CV (%)	Δ Emissions Intensity (%)
Low (≤ 3.2)	+2.1	−12.6	−13.8	−8.0	−4.1
Moderate (3.2–3.8)	+3.7	−19.2	−20.5	−12.3	−7.3
High (≥ 3.8)	+5.2	−27.4	−28.8	−16.9	−10.6

Table 9 has demonstrated that capability maturity has conditioned the magnitude of simulated gains: high-capability firms (Likert ≥ 3.8) translated optimization guidance into the largest performance lifts, particularly in tail risk ($CVaR_{95}$ of backorder-hours improved by 30%+ for the High tier vs. ~18% for Low). This gradient is intuitive: organizations with stronger visibility and collaboration executed re-allocations and re-routing more quickly and accurately, allowing optimized plans to realize their potential. Nevertheless, even low-capability tiers benefited, confirming that structural

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changes such as second-source activation, risk-based buffer placement, and mode-mix re-balancing were effective irrespective of starting practices. Sensitivity sweeps (±20% volatility, ±15% capacity constraints) did not alter policy rankings, and stochastic dominance checks favored optimized policies in at least 80% of replications across scenarios. Taken together, the simulation results validate that sustainability-aware allocation can simultaneously enhance resilience and environmental performance, and that capability development amplifies, rather than replaces, the value of optimization.

DISCUSSION

This study has shown that three capability domains collaboration/integration, digital visibility, and allocation efficiency have been the strongest correlates of resilience outcomes on a five-point Likert scale, with flexibility providing additional yet comparatively smaller effects when controls have been included. These results have echoed the foundational view that resilience is not a single attribute but an orchestrated bundle of routines distributed across preparedness, response, and recovery (Ponomarov & Holcomb, 2009). Our cross-case evidence has aligned with prior demonstrations that relational competencies and information sharing are central antecedents of performance stabilization during shocks (Wieland & Wallenburg, 2013). At the same time, the present analysis has extended those findings by quantifying how much additional variance is explained after introducing allocation efficiency as a bridging construct between sensing/coordination and outcomes. Earlier syntheses have called for empirical links between capability constructs and hard operational KPIs such as time-to-recovery (TTR) and backorders (Hohenstein et al., 2015); the current results have met that call by coupling survey composites with archival KPI windows and by reporting consistent improvements in service level (+3.8 percentage points in the top capability tier) and reductions in TTR (−21.5%). The pattern has been consistent with risk-management economics that value "good information" only insofar as it changes resource-allocation decisions (Tang, 2006). In sum, this study has corroborated and sharpened the literature's central proposition: visibility and collaboration matter most when they reconfigure where buffers sit, which suppliers carry marginal load, and which modes execute priority lanes. By showing that allocation efficiency partially mediates capability effects, the analysis has provided a concrete mechanism that prior conceptual models have implied but not always tested with integrated datasets (Schmitt & Singh, 2012).

The mediation findings have indicated that a nontrivial share of the benefit from visibility and collaboration has flowed through risk-based prioritization that is, through smarter placement of inventory and capacity toward at-risk SKUs and lanes. This pathway has been theoretically consistent with resource-based and relational views arguing that information integration enables coordinated action that transforms inputs into resilience outputs (Brandon-Jones et al., 2014). Earlier empirical work has measured "integration" or "visibility" and then correlated them with perceived continuity (Jüttner & Maklan, 2011) ; our contribution has been to interpose an explicit, measurable allocation construct and to show partial mediation with bootstrapped indirect effects. The finding has harmonized with operations research studies that have demonstrated the value of where buffers and capacity reside under uncertainty (Schmitt & Singh, 2012) and with big-data/analytics research that has linked data capability to performance via intermediate decision quality (Tang, 2006). The present work has, however, nuanced one recurring assumption: redundancy alone has exhibited only marginal associations once collaboration, visibility, and allocation have been in the model. That nuance has mirrored evidence that undirected slack can be costly without materially improving recovery if it is not targeted (Tang & Tomlin, 2008). The mediation pathway has therefore operationalized a practical maxim: information is an input; allocation is the act. By turning information into targeted inventory positioning, supplier-share rebalancing, and mode-mix adjustments, organizations have realized the performance gains ascribed abstractly to "visibility" in much of the literature (Caridi et al., 2014). This articulation has also connected to sustainability work showing that directed allocation, not volume alone, reduces emissions and cost variance simultaneously when uncertainty strikes (Hua et al., 2011).

The moderation results have shown that the benefits of visibility and collaboration have intensified as volatility and lead-time variability have risen, consistent with contingency logic and network-propagation theories. This pattern has aligned with prior demonstrations that design characteristics (e.g., concentration, path length, substitutability) determine disruption severity and propagation (Craighead et al., 2007). It has also matched simulation-based accounts of ripple effects in which sensing speed and synchronization dampen backlog waves (Ivanov, 2017). The fact that interactions

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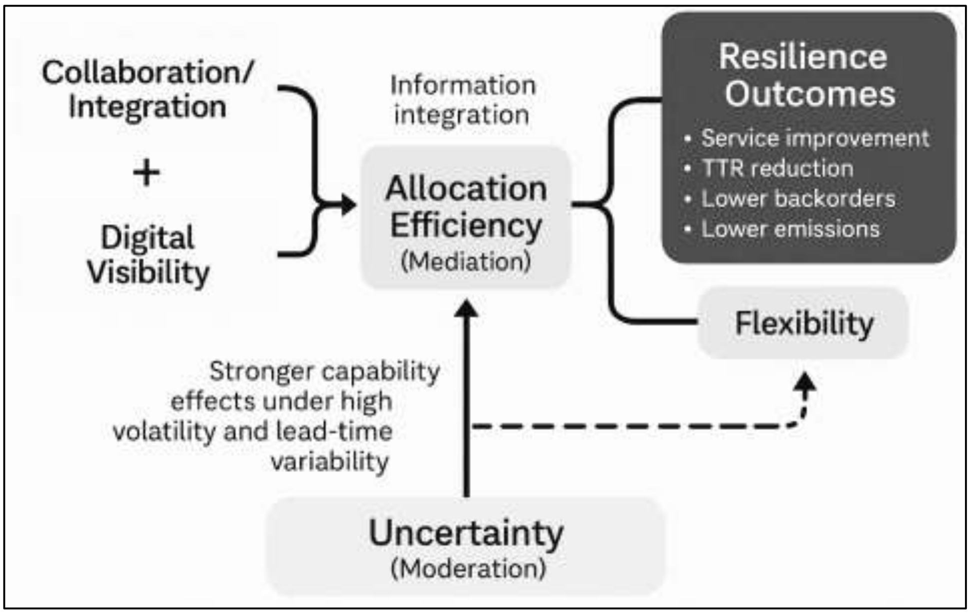
have remained positive and significant after controls has suggested that the marginal value of observability and coordination is greatest when uncertainty regimes are harsh precisely where deterministic safety-stock rules tend to fail. Prior work has anticipated such context effects but has rarely quantified them with integrated survey-KPI designs (Peck, 2005). The present analysis has connected those threads by documenting steeper simple slopes at +1 SD volatility and lead-time CV, thus empirically supporting the idea that "fast clockspeed" sectors (e.g., FMCG) and long, globally distributed chains can reap outsized returns from visibility-and-collaboration improvements. At the same time, the modest main-effect sizes for diversification and redundancy have reflected another contingency: slack is effective if locatable and switchable. This nuance has resonated with flexibility economics that attribute the largest risk-mitigation benefits to options dual sourcing, postponement, cross-deployable capacity rather than to static stockpiles (Tang, 2006). In brief, the data have supported a composite view in which uncertainty governs not only the expected loss without capabilities but also the return on capability investment, lending quantitative support to design-for-variety arguments in resilience engineering.

Figure 8: Integrated Discussion Model for Data-Driven Sustainable Supply Chain Resilience



By embedding a sustainability-aware optimization in a Monte Carlo environment calibrated from case data, the study has shown that resilience improvements need not come at the expense of environmental performance. The optimized policies have delivered higher service and lower TTR and backorders and lower emissions intensity across disruption scenarios, with the largest improvements under severe shocks. These results have complemented robust network design insights that advocate prepositioned optionality across facilities and suppliers to hedge against parameter and structural uncertainty (Klibi et al., 2010) and have matched evidence that carbon-aware routing and lot sizing alter the cost–service frontier in favorable ways when fixed-trip emissions are considered (Bonney & Jaber, 2011). They have also converged with reviews arguing that sustainability objectives should be embedded in the model, not appended later, to avoid rebound effects from crisis expedites (Eskandarpour et al., 2015). The tail-risk improvements (e.g., CVaR of backorder-hours) have reinforced reliability modeling that treats facility/link failures stochastically at design time (Snyder & Daskin, 2005) and fit the ripple-effect perspective that time-resolved recourse (re-routing, buffer draws, supplier switching) stabilizes flows (Craighead et al., 2007). Importantly, capability maturity has amplified, rather than replaced, the optimization's value: high-visibility, highly collaborative cases have realized the largest simulated gains. This amplification has echoed analytics–performance studies in which data and dynamic capabilities have served as complements to optimization and decision automation (Wamba et al., 2017), and it has provided a

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practical explanation for mixed results reported in purely structural redesign projects that underinvest in execution routines.

The results have suggested a concrete, jointly owned roadmap for CISOs/data architects and supply-chain leaders. First, data governance and observability have been central. CISOs and architects have benefited from prioritizing event completeness (ASN, EDI/API with carriers, IoT telemetry), latency controls (near-real-time updates for critical lanes/SKUs), and master-data integrity so that the Visibility Composite Index rises in coverage, accuracy, and granularity (Barratt & Oke, 2007). Security and resilience agendas have converged around trustworthy pipelines: authenticated data feeds, immutable event logs, and role-based access have preserved both confidentiality and coordinated response. Second, decision-automation hooks have been pivotal. Data teams have provisioned risk-based reorder point services, service-tier aware ATP, and exception APIs that operations planners have consumed during Sales & Operations Execution cadences; these mechanisms have translated collaboration into allocation moves in hours, not weeks. Third, option-readiness has mattered more than raw slack. Architects and logistics managers have maintained qualified alternates (supplier and carrier), cross-deployable capacity metadata, and digital twin lane models that have supported rapid re-routing with emissions budgets. Fourth, sustainability integration has been operational, not performative: carbon factors at lane/mode have been part of the allocation objective so that expedited shipments have triggered explicit trade-offs rather than silent drifts. Finally, governance rhythms weekly S&OE huddles, KPI and risk dashboards with tail-metrics (e.g., CVaR), and post-incident learning reviews have institutionalized the routines associated with the largest coefficients in our models (Wieland & Wallenburg, 2013). In practical terms, organizations have not been required to overhaul entire stacks. Instead, the evidence has supported incremental programs: expand tier-1/tier-2 event coverage; stand up allocation services; qualify one alternate supplier and one alternate carrier on the top-risk SKUs/lanes; and encode emission caps in optimization runs. These steps have reflected best practice in both resilience and sustainable operations (Snyder et al., 2016).

The study has contributed a measurement→inference→policy pipeline that bridges descriptive constructs and optimization-simulation. Theoretically, the partial mediation by allocation efficiency has supported a refined model in which capabilities create value by changing the allocation function, not merely by existing. This refinement has connected relational/visibility constructs to OR/MS levers and has provided a mechanism consistent with the resource-based view yet testable with integrated data (Pettit et al., 2010). The moderation by uncertainty has added a contingent layer that aligns with network-propagation theory and viable supply chain thinking, proposing that capability elasticities are state-dependent (Tomlin, 2006). Methodologically, the paper has leveraged validated reflective scales and documented discriminant validity (Henseler et al., 2015), then linked composites to KPIs and carried those relationships into a multi-objective optimization with Monte Carlo evaluation. This pipeline has answered repeated calls to close the loop between perceptual measurement and operational analytics (Hosseini et al., 2019). The Resilience Performance Index proposed as a normalized composite has furthered the literature by enabling consistent regression and simulation benchmarks across heterogeneous cases while keeping interpretability for practitioners. Finally, the demonstration of sustainability co-benefits under optimized recourse has offered a theoretical counterexample to presumed trade-offs, showing that greener can be more resilient when allocation is targeted and options are prepared (Chaabane et al., 2012). The implication has been a unifying framework: resilience capabilities (visibility, collaboration) feed an allocation engine that, when optimized under uncertainty and environmental constraints, yields superior mean and tail performance.

The design has entailed limitations typical of cross-sectional case-based studies. Although constructs have satisfied reliability/validity checks, common-method bias cannot be ruled out entirely despite procedural and statistical remedies; future work has benefited from multi-wave data to separate predictors and outcomes temporally (Henseler et al., 2015). The cases have been purposively selected and have represented specific sectors and geographies; generalizability to other industries (e.g., process industries, agriculture) has required caution and replication. Measurement has relied on reflective Likert scales; formative or behavioral telemetry-based measures (e.g., actual message latency, exception-closure times) have offered complementary, less subjective lenses. While the optimization–simulation has been calibrated from empirical distributions and disruption logs, model structure choices (e.g., independence assumptions, cost/emission factors) have constrained realism;

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richer interdependency models and endogenous recovery dynamics have remained promising extensions (Hosseini et al., 2019). Finally, causality has been inferred cautiously; while hierarchical modeling and mediation tests have strengthened interpretation, randomized interventions (e.g., staggered deployment of visibility dashboards or allocation rules) have offered stronger identification. Against this backdrop, future research has productively advanced along five avenues. First, longitudinal designs that have tracked capability investments and KPI trajectories through pre-/post-disruption windows have clarified durability. Second, telemetry-first measurement that has computed visibility and collaboration directly from event streams (coverage, latency, accuracy) has reduced perceptual bias. Third, network-level experiments that have randomized option activation (qualifying alternates, changing mode mix) have provided causal estimates of flexibility value under carbon constraints (Bektas & Laporte, 2011). Fourth, agent-based or dynamic Bayesian models that have encoded cascading failures and learning have refined ripple-effect analytics (Hosseini et al., 2019). Fifth, policy co-design with planners and CISOs that has embedded emission budgets and tail-risk metrics into S&OE cycles has operationalized the pipeline at scale. Collectively, these steps have strengthened external validity and mechanistic insight while preserving the integrated, data-driven ethos that has anchored the current study.

CONCLUSION

This study has integrated measurement, inference, and decision experimentation to show that supply chain resilience can be purposefully engineered when organizational capabilities, sustainable resource allocation, and uncertainty-aware analytics are treated as one system. Using a multi-case, quantitative, cross-sectional design, we have measured core capabilities on a five-point Likert scale, linked them to objective KPIs, and stress-tested policies in a stochastic simulation embedded with a multi-objective optimization that jointly considered service, cost stability, and emissions. Three results have stood out consistently. First, collaboration/integration and digital visibility have emerged as the most powerful antecedents of resilience, with flexibility providing additional but smaller contributions after controls. Second, allocation efficiency our explicit bridge from sensing and coordination to action has partially mediated the effects of visibility and collaboration, clarifying *how* information and relationships translate into shorter time-to-recovery, higher service levels, fewer backorder-hours, and lower cost variability. Third, capability payoffs have been state-dependent: the value of visibility and collaboration has grown under harsher uncertainty, as reflected in positive interactions with demand volatility and lead-time coefficient of variation. The simulation–optimization layer has validated that sustainability and resilience are not opposing goals: relative to status quo policies, sustainability-aware allocations have improved mean and tail performance (including CVaR of backorder-hours) while lowering emissions intensity by reducing emergency expedites and positioning smarter buffers. Practically, these findings have produced a focused roadmap for leaders: raise observability (coverage, accuracy, latency, granularity), institutionalize collaboration through S&OE rhythms and shared risk signals, operationalize allocation via risk-based reorder points and service-tier aware ATP, qualify minimal but meaningful options (alternate suppliers/carriers, cross-deployable capacity), and embed carbon factors directly into the allocation objective. Theoretically, the work has refined resilience models by positioning allocation efficiency as the operative mechanism through which capabilities create value, and by quantifying uncertainty as a moderator of capability elasticities. While cross-sectional design, purposive sampling, and perceptual measures limit causal generalization, triangulation with archival KPIs and simulation calibration has strengthened credibility, and the pipeline we have documented survey development, validity checks, hierarchical regression with mediation and moderation, optimization, Monte Carlo evaluation, and sensitivity analysis has provided a replicable template for researchers and practitioners. In closing, the evidence indicates that organizations do not need to choose between greener operations and robust recovery: by investing in the right information flows and coordination routines, and by channeling them through targeted, carbon-aware allocation rules, firms can shift the resilience frontier outward delivering faster recovery, steadier cost performance, and lower emissions under the same uncertainty that has long challenged global supply networks.

RECOMMENDATIONS

Organizations seeking data-driven, sustainability-aware resilience should enact a focused, staged program that links information pipelines to allocation rules and option readiness, governed through tight execution rhythms and tail-risk accountability. First, elevate digital visibility by hardening data capture and latency control on the lanes and SKUs that drive 80% of risk: extend ASN coverage to

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all tier-1 suppliers, require carrier EDI/API milestones (pickup, departure, arrival, exceptions), and deploy a common "risk state" schema (coverage, accuracy, granularity, and minutes-to-freshness) so teams manage to a Visibility Composite Index instead of anecdote. Second, institutionalize collaboration in a weekly S&OE cadence that centers on exception lists and service-tier promises: publish a single, role-based dashboard that fuses ETA risk flags, lead-time CV bands, and inventory-at-risk; assign named owners and time-boxed countermeasures; and document close-loop outcomes to build a practical playbook. Third, operationalize allocation efficiency with lightweight decision services: implement risk-based reorder points, service-tier-aware ATP/CTP, and prioritization of buffers for SKUs in the top decile of stockout risk; make these services callable from the planning system and auditable (inputs, recommendation, override reason) to enforce learning. Fourth, expand option readiness over raw redundancy: qualify one alternate supplier per critical component and one alternate carrier per top 20 lanes; enable cross-deployable capacity by standardizing changeover kits and work instructions; and pre-agree switch criteria and commercial terms so activation is procedural, not improvised. Fifth, embed sustainability in the objective, not the report: attach lane- and mode-level CO_2e factors to shipments, set explicit carbon caps or shadow prices in allocation optimization, and gate emergency air expedites behind a risk threshold that weighs service breach versus emissions and cost. Sixth, run quarterly simulation exercises using empirical demand and lead-time distributions plus recent disruption logs: benchmark the current plan against an optimized policy set across scenarios (supplier failure, port closure, demand spike, multi-node outage), report both mean KPI and CVaR of backorder-hours, and translate gaps into concrete lever changes (buffer repositioning, supplier share shifts, mode mix). Seventh, govern with tail-aware metrics and incentives: add TTR, backorder-hours, cost CV, emissions intensity, and CVaR targets to scorecards; tie a portion of planner and logistics leader incentives to these risk-sensitive outcomes to prevent short-term cost shaving that erodes resilience. Eighth, strengthen data security and quality in lockstep: enforce authenticated feeds, field-level validation, and lineage tracking; use role-based access for partner data; and automate anomaly alerts for stale or conflicting events so visibility gains remain trustworthy. Ninth, build skills and change capacity: train planners on interpreting uncertainty bands and interaction effects; run tabletop drills that practice supplier/carrier switchovers and buffer draws; and empower a cross-functional "resilience cell" to adjudicate trade-offs rapidly. Finally, adopt a pilot-to-scale path: pick three high-risk SKUs and five lanes, apply the full stack (visibility upgrades, allocation services, option readiness, carbon constraints), measure Likert capability uplift (+0.3–0.4 target), and lock in governance rituals; only then broaden to adjacent portfolios. Executed together, these actions move the organization to a repeatable, auditable loop where better data becomes targeted allocation, targeted allocation becomes faster recovery with lower variance, and lower variance coexists with lower emissions.

REFERENCES

[1]. Abdul, R. (2021). The Contribution Of Constructed Green Infrastructure To Urban Biodiversity: A Synthesised Analysis Of Ecological And Socioeconomic Outcomes. *International Journal of Business and Economics Insights*, *1*(1), 01–31. https://doi.org/10.63125/qs5p8n26

[2]. Ambulkar, S., Blackhurst, J., & Grawe, S. (2015). Firm's resilience to supply chain disruptions: Scale development and empirical examination. *Journal of Operations Management*, *33*(1), 111–122. https://doi.org/10.1016/j.jom.2014.11.002

[3]. Barratt, M., & Oke, A. (2007). Antecedents of supply chain visibility in retail supply chains: A resource-based theory perspective. *Supply Chain Management: An International Journal*, *12*(2), 180–192. https://doi.org/10.1108/13598540710776917

[4]. Bektas, T., & Laporte, G. (2011). The pollution-routing problem. *Transportation Research Part B: Methodological*, *45*(8), 1232–1250. https://doi.org/10.1016/j.trb.2011.02.004

[5]. Benjaafar, S., Li, Y., & Daskin, M. S. (2013). Carbon footprint and the management of supply chains: Insights from simple models. *IEEE Transactions on Automation Science and Engineering*, *10*(1), 99–116. https://doi.org/10.1109/tase.2012.2203304

[6]. Blome, C., Schoenherr, T., & Rexhausen, D. (2013). Antecedents and enablers of supply chain agility and robustness: An empirical investigation. *International Journal of Production Research*, *51*(4), 1295–1318. https://doi.org/10.1080/00207543.2012.728011

[7]. Bode, C., & Wagner, S. M. (2015). Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. *Journal of Operations Management*, *36*, 215–228. https://doi.org/10.1016/j.jom.2014.12.004

eISSN: 3067-0470
DOI: 10.63125/p0ptag78

[8]. Bonney, M., & Jaber, M. Y. (2011). Environmentally responsible inventory models: Non-classical models for a non-classical era. *European Journal of Operational Research*, *220*(3), 525–533. https://doi.org/10.1016/j.ejor.2010.10.026

[9]. Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, *50*(3), 55–73. https://doi.org/10.1111/jscm.12050

[10]. Braunscheidel, M. J., & Suresh, N. C. (2009). The organizational antecedents of a firm's supply chain agility for risk mitigation and response. *Journal of Operations Management*, *27*(2), 119–140. https://doi.org/10.1016/j.jom.2008.09.006

[11]. Caridi, M., Crippa, L., Perego, A., Sianesi, A., & Tumino, A. (2014). Do virtuality and complexity affect supply chain visibility? *International Journal of Production Research*, *52*(20), 282–296. https://doi.org/10.1080/00207543.2014.944339

[12]. Carvalho, H., Barroso, A. P., Machado, V. H., Azevedo, S. G., & Cruz-Machado, V. (2012). Supply chain redesign for resilience using simulation. *Computers & Industrial Engineering*, *62*(1), 329–341. https://doi.org/10.1016/j.cie.2011.10.003

[13]. Chaabane, A., Ramudhin, A., & Paquet, M. (2012). Design of sustainable supply chains under the emission trading scheme. *International Journal of Production Economics*, *135*(1), 37–49. https://doi.org/10.1016/j.ijpe.2011.10.009

[14]. Colicchia, C., & Strozzi, F. (2012). Supply chain risk management: A new methodology for a systematic literature review. *International Journal of Production Research*, *50*(5), 1275–1297. https://doi.org/10.1080/00207543.2011.608706

[15]. Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The severity of supply chain disruptions: Design characteristics and mitigation capabilities. *Decision Sciences*, *38*(1), 131–156. https://doi.org/10.1111/j.1540-5915.2007.00166.x

[16]. Danish, M. (2023a). Analysis Of AI Contribution Towards Reducing Future Pandemic Loss In SME Sector: Access To Online Marketing And Youth Involvement. *American Journal of Advanced Technology and Engineering Solutions*, *3*(03), 32-53. https://doi.org/10.63125/y4cb4337

[17]. Danish, M. (2023b). Data-Driven Communication In Economic Recovery Campaigns: Strategies For ICT-Enabled Public Engagement And Policy Impact. *International Journal of Business and Economics Insights*, *3*(1), 01-30. https://doi.org/10.63125/qdrdve50

[18]. Danish, M., & Md. Zafor, I. (2022). The Role Of ETL (Extract-Transform-Load) Pipelines In Scalable Business Intelligence: A Comparative Study Of Data Integration Tools. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 89–121. https://doi.org/10.63125/1spa6877

[19]. Danish, M., & Md.Kamrul, K. (2022). Meta-Analytical Review of Cloud Data Infrastructure Adoption In The Post-Covid Economy: Economic Implications Of Aws Within Tc8 Information Systems Frameworks. *American Journal of Interdisciplinary Studies*, *3*(02), 62-90. https://doi.org/10.63125/1eg7b369

[20]. Dubey, R., Gunasekaran, A., Childe, S. J., Wamba, S. F., & Papadopoulos, T. (2019). The impact of big data analytics on firms' high value business performance: Evidence from the Indian retail industry. *Journal of Business Research*, *100*, 308–320. https://doi.org/10.1016/j.jbusres.2018.12.050

[21]. Eskandarpour, M., Dejax, P., Miemczyk, J., & Péton, O. (2015). Sustainable supply chain network design: An optimization-oriented review. *European Journal of Operational Research*, *247*(3), 929–963. https://doi.org/10.1016/j.ejor.2015.04.059

[22]. Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and organizational performance. *International Journal of Production Economics*, *193*, 86–101. https://doi.org/10.1016/j.ijpe.2017.07.013

[23]. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

[24]. Hohenstein, N.-O., Feisel, E., & Hartmann, E. (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. https://doi.org/10.1108/ijpdlm-05-2013-0128

[25]. Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Ripple effect modelling of supplier disruption: Integrated Markov chain and dynamic Bayesian network approach. *International Journal of Production Research*, *57*(11), 3290–3301. https://doi.org/10.1080/00207543.2019.1661538

[26]. Hozyfa, S. (2022). Integration Of Machine Learning and Advanced Computing For Optimizing Retail Customer Analytics. *International Journal of Business and Economics Insights*, *2*(3), 01–46. https://doi.org/10.63125/p87sv224

[27]. Hua, G., Cheng, T. C. E., & Wang, S. (2011). Managing carbon footprints in inventory management. *International Journal of Production Economics*, *132*(2), 178–185. https://doi.org/10.1016/j.ijpe.2011.03.024

[28]. Ivanov, D. (2017). Simulation-based ripple effect modelling in the supply chain. *International Journal of Production Research*, *55*(7), 2083–2101. https://doi.org/10.1080/00207543.2016.1275873

[29]. Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: Extending the supply chain resilience angles toward survivability. *International Journal of Production Research*, *58*(10), 2904–2915. https://doi.org/10.1080/00207543.2020.1750727

[30]. Jabbarzadeh, A., Haughton, M., & Khosrojerdi, A. (2018). Closed-loop supply chain network design under disruption risks and demand uncertainty: A case study approach. *Transportation Research Part E: Logistics and Transportation Review*, *118*, 362–384. https://doi.org/10.1016/j.tre.2018.08.003

[31]. Jüttner, U., & Maklan, S. (2011). Supply chain resilience in the global financial crisis: An empirical study. *Supply Chain Management: An International Journal*, *16*(4), 246–259. https://doi.org/10.1108/13598541111139062

[32]. Kleindorfer, P. R., & Saad, G. H. (2005). Managing disruption risks in supply chains. *Production and Operations Management*, *14*(1), 53–68. https://doi.org/10.1111/j.1937-5956.2005.tb00009.x

[33]. Klibi, W., Martel, A., & Guitouni, A. (2010). The design of robust value-creating supply chain networks: A critical review. *Computers & Operations Research*, *37*(11), 2315–2327. https://doi.org/10.1016/j.cor.2009.09.003

[34]. Md Arif Uz, Z., & Elmoon, A. (2023). Adaptive Learning Systems For English Literature Classrooms: A Review Of AI-Integrated Education Platforms. *International Journal of Scientific Interdisciplinary Research*, *4*(3), 56-86. https://doi.org/10.63125/a30ehr12

[35]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36

[36]. Md Hasan, Z., & Md Omar, F. (2022). Cybersecurity And Data Integrity in Financial Systems: A Review Of Risk Mitigation And Compliance Models. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 27-61. https://doi.org/10.63125/azwznv07

[37]. Md Mesbaul, H. (2024). Industrial Engineering Approaches to Quality Control In Hybrid Manufacturing A Review Of Implementation Strategies. *International Journal of Business and Economics Insights*, *4*(2), 01-30. https://doi.org/10.63125/3xcabx98

[38]. Md Mohaiminul, H., & Md Muzahidul, I. (2022). High-Performance Computing Architectures For Training Large-Scale Transformer Models In Cyber-Resilient Applications. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 193–226. https://doi.org/10.63125/6zt59y89

[39]. Md Omar, F. (2024). Vendor Risk Management In Cloud-Centric Architectures: A Systematic Review Of SOC 2, Fedramp, And ISO 27001 Practices. *International Journal of Business and Economics Insights*, *4*(1), 01-32. https://doi.org/10.63125/j64vb122

[40]. Md Omar, F., & Md. Jobayer Ibne, S. (2022). Aligning FEDRAMP And NIST Frameworks In Cloud-Based Governance Models: Challenges And Best Practices. *Review of Applied Science and Technology*, *1*(01), 01-37. https://doi.org/10.63125/vnkcwq87

[41]. Md Sanjid, K., & Md. Tahmid Farabe, S. (2021). Federated Learning Architectures For Predictive Quality Control In Distributed Manufacturing Systems. *American Journal of Interdisciplinary Studies*, *2*(02), 01-31. https://doi.org/10.63125/222nwg58

[42]. Md. Hasan, I. (2022). The Role Of Cross-Country Trade Partnerships In Strengthening Global Market Competitiveness. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 121-150. https://doi.org/10.63125/w0mnpz07

[43]. Md. Mominul, H., Masud, R., & Md. Milon, M. (2022). Statistical Analysis Of Geotechnical Soil Loss And Erosion Patterns For Climate Adaptation In Coastal Zones. *American Journal of Interdisciplinary Studies*, *3*(03), 36-67. https://doi.org/10.63125/xytn3e23

[44]. Md. Omar, F., & Md Harun-Or-Rashid, M. (2021). Post-GDPR Digital Compliance in Multinational Organizations: Bridging Legal Obligations With Cybersecurity Governance. *American Journal of Scholarly Research and Innovation*, *1*(01), 27-60. https://doi.org/10.63125/4qpdpf28

[45]. Md. Rabiul, K., & Sai Praveen, K. (2022). The Influence of Statistical Models For Fraud Detection In Procurement And International Trade Systems. *American Journal of Interdisciplinary Studies*, *3*(04), 203-234. https://doi.org/10.63125/9htnv106

[46]. Md. Tahmid Farabe, S. (2022). Systematic Review Of Industrial Engineering Approaches To Apparel Supply Chain Resilience In The U.S. Context. *American Journal of Interdisciplinary Studies*, *3*(04), 235-267. https://doi.org/10.63125/teherz38

[47]. Md. Wahid Zaman, R., & Momena, A. (2021). Systematic Review Of Data Science Applications In Project Coordination And Organizational Transformation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(2), 01–41. https://doi.org/10.63125/31b8qc62

[48]. Momena, A., & Sai Praveen, K. (2024). A Comparative Analysis of Artificial Intelligence-Integrated BI Dashboards For Real-Time Decision Support In Operations. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 158-191. https://doi.org/10.63125/47jjv310

[49]. Mubashir, I. (2021). Smart Corridor Simulation for Pedestrian Safety: : Insights From Vissim-Based Urban Traffic Models. *International Journal of Business and Economics Insights*, *1*(2), 33-69. https://doi.org/10.63125/b1bk0w03

[50]. Omar Muhammad, F. (2024). Advanced Computing Applications in BI Dashboards: Improving Real-Time Decision Support For Global Enterprises. *International Journal of Business and Economics Insights*, *4*(3), 25-60. https://doi.org/10.63125/3x6vpb92
[51]. Omar Muhammad, F., & Md. Redwanul, I. (2023). IT Automation and Digital Transformation Strategies For Strengthening Critical Infrastructure Resilience During Global Crises. *American Journal of Interdisciplinary Studies*, *4*(04), 145-176. https://doi.org/10.63125/vrsjp515
[52]. Pagell, M., & Wu, Z. (2009). Building a more complete theory of sustainable supply chain management using case studies of 10 exemplars. *Journal of Supply Chain Management*, *45*(2), 37–56. https://doi.org/10.1111/j.1745-493X.2009.03162.x
[53]. Pankaz Roy, S. (2022). Data-Driven Quality Assurance Systems For Food Safety In Large-Scale Distribution Centers. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 151–192. https://doi.org/10.63125/qen48m30
[54]. Peck, H. (2005). Drivers of supply chain vulnerability: An integrated framework. *International Journal of Physical Distribution & Logistics Management*, *35*(4), 210–232. https://doi.org/10.1108/09600030510599904
[55]. Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). Ensuring supply chain resilience: Development of a conceptual framework. *Journal of Business Logistics*, *31*(1), 1–21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x
[56]. Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, *20*(1), 124–143. https://doi.org/10.1108/09574090910954873
[57]. Qiang, Q., & Nagurney, A. (2009). A network-based theory of supply chain robustness and vulnerability. *International Journal of Production Economics*, *122*(1), 161–174. https://doi.org/10.1016/j.ijpe.2009.03.013
[58]. Rahman, S. M. T., & Abdul, H. (2022). Data Driven Business Intelligence Tools In Agribusiness A Framework For Evidence-Based Marketing Decisions. *International Journal of Business and Economics Insights*, *2*(1), 35-72. https://doi.org/10.63125/p59krm34
[59]. Razia, S. (2022). A Review Of Data-Driven Communication In Economic Recovery: Implications Of ICT-Enabled Strategies For Human Resource Engagement. *International Journal of Business and Economics Insights*, *2*(1), 01-34. https://doi.org/10.63125/7tkv8v34
[60]. Razia, S. (2023). AI-Powered BI Dashboards In Operations: A Comparative Analysis For Real-Time Decision Support. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 62–93. https://doi.org/10.63125/wqd2t159
[61]. Reduanul, H. (2023). Digital Equity and Nonprofit Marketing Strategy: Bridging The Technology Gap Through Ai-Powered Solutions For Underserved Community Organizations. *American Journal of Interdisciplinary Studies*, *4*(04), 117-144. https://doi.org/10.63125/zrsv2r56
[62]. Rony, M. A. (2021). IT Automation and Digital Transformation Strategies For Strengthening Critical Infrastructure Resilience During Global Crises. *International Journal of Business and Economics Insights*, *1*(2), 01-32. https://doi.org/10.63125/8tzzab90
[63]. Sadia, T. (2023). Quantitative Analytical Validation of Herbal Drug Formulations Using UPLC And UV-Visible Spectroscopy: Accuracy, Precision, And Stability Assessment. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 01–36. https://doi.org/10.63125/fxqpds95
[64]. Sai Srinivas, M., & Manish, B. (2023). Trustworthy AI: Explainability & Fairness In Large-Scale Decision Systems. *Review of Applied Science and Technology*, *2*(04), 54-93. https://doi.org/10.63125/3w9v5e52
[65]. Schmitt, A. J., & Singh, M. (2012). A quantitative analysis of disruption risk in a multi-echelon supply chain. *International Journal of Production Economics*, *139*(1), 22–32. https://doi.org/10.1016/j.ijpe.2012.01.004
[66]. Scholten, K., & Schilder, S. (2015). The role of collaboration in supply chain resilience. *Supply Chain Management: An International Journal*, *20*(4), 471–484. https://doi.org/10.1108/scm-11-2014-0386
[67]. Seuring, S., & Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production*, *16*(15), 1699–1710. https://doi.org/10.1016/j.jclepro.2008.04.020
[68]. Sheratun Noor, J., Md Redwanul, I., & Sai Praveen, K. (2024). The Role of Test Automation Frameworks In Enhancing Software Reliability: A Review Of Selenium, Python, And API Testing Tools. *International Journal of Business and Economics Insights*, *4*(4), 01–34. https://doi.org/10.63125/bvv8r252
[69]. Snyder, L. V., Atan, Z., Peng, P., Rong, Y., Schmitt, A. J., & Sinsoysal, B. (2016). OR/MS models for supply chain disruptions: A review. *IISE Transactions*, *48*(2), 89–109. https://doi.org/10.1080/0740817x.2015.1067735
[70]. Snyder, L. V., & Daskin, M. S. (2005). Reliability models for facility location: The expected failure cost case. *Transportation Science*, *39*(3), 400–416. https://doi.org/10.1287/trsc.1040.0107
[71]. Stevenson, M., & Spring, M. (2007). Flexibility from a supply chain perspective: A conceptual framework. *International Journal of Operations & Production Management*, *27*(7), 685–713. https://doi.org/10.1108/01443570710756956

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eISSN: 3067-0470
DOI: 10.63125/p0ptag78

[72]. Swafford, P. M., Ghosh, S., & Murthy, N. (2006). A framework for assessing value chain agility. *International Journal of Operations & Production Management*, *26*(2), 118–140. https://doi.org/10.1108/01443570610641639

[73]. Syed Zaki, U. (2021). Modeling Geotechnical Soil Loss and Erosion Dynamics For Climate-Resilient Coastal Adaptation. *American Journal of Interdisciplinary Studies*, *2*(04), 01-38. https://doi.org/10.63125/vsfjtt77

[74]. Syed Zaki, U. (2022). Systematic Review Of Sustainable Civil Engineering Practices And Their Influence On Infrastructure Competitiveness. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 227–256. https://doi.org/10.63125/hh8nv249

[75]. Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, *103*(2), 451–488. https://doi.org/10.1016/j.ijpe.2005.12.006

[76]. Tang, C. S., & Tomlin, B. (2008). The power of flexibility for mitigating supply chain risks. *International Journal of Production Economics*, *116*(1), 12–27. https://doi.org/10.1016/j.ijpe.2008.07.008

[77]. Tomlin, B. (2006). On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science*, *52*(5), 639–657. https://doi.org/10.1287/mnsc.1060.0515

[78]. Tonoy Kanti, C., & Shaikat, B. (2022). Graph Neural Networks (GNNS) For Modeling Cyber Attack Patterns And Predicting System Vulnerabilities In Critical Infrastructure. *American Journal of Interdisciplinary Studies*, *3*(04), 157-202. https://doi.org/10.63125/1ykzx350

[79]. Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. *International Journal of Production Research*, *53*(18), 5592–5623. https://doi.org/10.1080/00207543.2015.1037934

[80]. Wagner, S. M., & Bode, C. (2008). An empirical examination of supply chain performance along several dimensions of risk. *Journal of Operations Management*, *26*(4), 428–445. https://doi.org/10.1016/j.jom.2007.01.001

[81]. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

[82]. Wieland, A., & Wallenburg, C. M. (2013). The influence of relational competencies on supply chain resilience: A relational view. *International Journal of Physical Distribution & Logistics Management*, *43*(4), 300–320. https://doi.org/10.1108/ijpdlm-08-2012-0243

[83]. Zayadul, H. (2023). Development Of An AI-Integrated Predictive Modeling Framework For Performance Optimization Of Perovskite And Tandem Solar Photovoltaic Systems. *International Journal of Business and Economics Insights*, *3*(4), 01–25. https://doi.org/10.63125/8xm7wa53