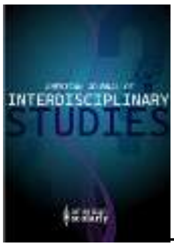

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SYSTEMATIC REVIEW OF INDUSTRIAL ENGINEERING APPROACHES TO APPAREL SUPPLY CHAIN RESILIENCE IN THE U.S. CONTEXT

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Abstract
This PRISMA-aligned systematic review synthesizes industrial engineering approaches that strengthen resilience in apparel supply chains serving the United States. Searches across Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ProQuest, and Google Scholar for 2005 to 2020 identified 115 peer-reviewed studies that met inclusion criteria. Evidence was coded by intervention family, disruption class, echelon, method, validation, and standardized outcomes that reflect resilience performance, notably service level under stress, time-to-recover, lead-time variance, backlog duration, lost sales, and cost-to-serve. The corpus concentrates on six lever families. Inventory science with postponement and multi-echelon control was the largest share and produced the most reliable service improvements, typically shifting differentiation downstream to pool uncertainty and compress variance. Robust, chance-constrained, and distributionally robust optimization reduced tail risk and stabilized performance under parameter ambiguity common in fashion calendars. Network and sourcing design, especially dual or multi-sourcing with corridor diversification, limited synchronized logistics shocks linked to gateway congestion. Process-improvement programs, including setup reduction, TPM, and pull control, shortened recovery in factories and distribution centers, while predictive-reactive scheduling with skill-aware cross-training preserved service during promotional peaks. Simulation and digital-twin studies operationalized closed-loop triggers, translating plans into adaptive playbooks for rerouting, wave resequencing, and late-stage finishing. Across studies, median gains clustered around meaningful magnitudes, for example several percentage-point lifts in service and double-digit reductions in time-to-recover, typically at modest cost-to-serve increases, and combinations consistently outperformed single levers. The review contributes a decision-ready synthesis that maps what works, where, and why in U.S. apparel operations, and outlines a reproducible framework for portfolio-based resilience design.

Keywords
Apparel Supply Chain Resilience, Industrial Engineering, Postponement, Multi-Echelon Inventory, Digital Twin

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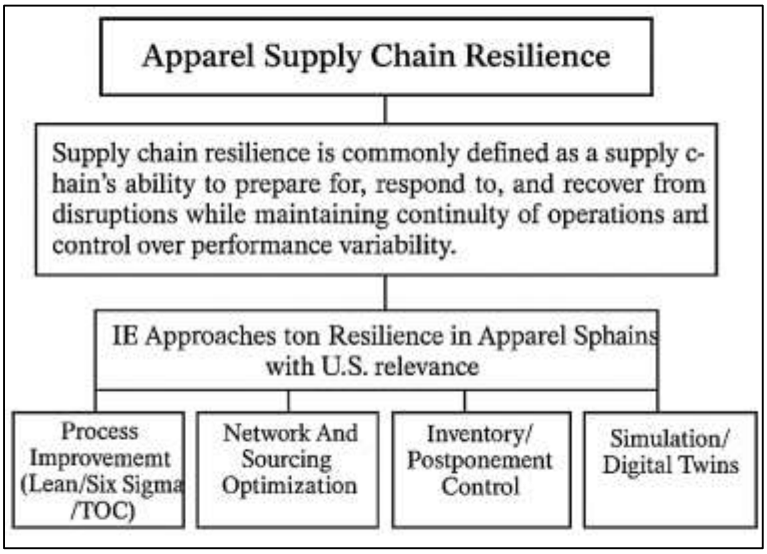
INTRODUCTION

Supply chain resilience 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 (Pettit et al., 2010; Ponomarov & Holcomb, 2009). Within operations and industrial engineering (IE), resilience is operationalized through measurable capacities absorptive (withstand), adaptive (adjust), and restorative (return) that can be engineered via process redesign, redundancy, flexibility, and control architectures . This perspective is distinct from but complementary to robustness (insensitivity to variability), agility (speed and flexibility), and risk management (identification and mitigation of threats). Internationally, apparel is one of the most globally dispersed manufacturing networks, with fiber, fabric, cut-and-sew, logistics, and retail nodes spanning multiple geographies and regulatory regimes; the sector's short product life cycles and style/SKU proliferation amplify exposure to disruption and forecast error (Cachon & Swinney, 2011; Choi et al., 2012). From port congestion and supplier shutdowns to demand shocks and cyber incidents, exogenous and endogenous risks cascade across multi-echelon apparel networks, making the domain an exemplar for resilience engineering (Craighead et al., 2007). The U.S. context is particularly salient because it couples high demand volatility from fashion seasons and promotions with long, offshore lead times and infrastructure bottlenecks at key entry points, creating a structurally "stress-tested" setting for examining IE-based resilience mechanisms. Consequently, a systematic review centered on industrial engineering approaches to resilience in the U.S. apparel supply chain can synthesize cross-disciplinary evidence and codify design and control principles grounded in quantitative models, optimization, simulation, and empirical validation.

A coherent introduction to apparel supply chain resilience requires a consistent conceptual scaffold and comparable metrics. Building on logistics and operations literature, resilience outcomes are frequently measured by time-to-recover (TTR), time-to-survive (TTS), service level, backorder duration, lead-time variance, cost-to-serve, and cash-to-cash cycle time, with studies linking these performance indicators to network design choices, inventory control policies, and scheduling rules (Melnyk et al., 2014; Pettit et al., 2010). These metrics enable IE scholars to position resilience as a property of engineered systems amenable to optimization under uncertainty, robust design, and discrete-event/agent-based simulation. In apparel, additional nuances arise from assortment breadth, color/size curves, and rapid style obsolescence, which interact with postponement, quick response (QR), and demand-sensing to attenuate mismatch costs and improve fill rates during shocks. The literature also emphasizes structural risk drivers long offshore lead times, concentrated sourcing, and logistics chokepoints that magnify ripple effects across echelons (Carvalho et al., 2012). Accordingly, resilience is analyzed not only as a recovery phenomenon but also as an engineered balance among redundancy (e.g., dual sourcing), flexibility (e.g., cross-trained labor), and information visibility (e.g., integrated S&OP), each with quantifiable trade-offs (Tang, 2006). This quantitative orientation frames the apparel case as a fertile ground for IE approaches that combine analytic models and digital experimentation to compare policies across disruption scenarios using standardized outcomes (Tomlin, 2006).

Industrial engineering contributes a layered toolkit to resilience: process improvement (Lean/Six Sigma/TOC), production planning and scheduling, inventory science, network design, and maintenance/reliability engineering, all supported by data analytics. Lean and Six Sigma reduce variability and waste, stabilizing cycle times and enabling more predictable recovery trajectories in apparel production cells and distribution centers. Theory of Constraints (TOC) and bottleneck management improve throughput resilience by increasing protective capacity and shortening queues at critical workcenters (Schmitt & Singh, 2012; Spiegler et al., 2012). On the control side, inventory models particularly multi-echelon safety stock under stochastic demand and lead times provide levers to buffer disruptions while minimizing overstock in fashion categories. Postponement strategies, often apparel-specific (late-stage dyeing, final embellishment, DC-level finishing), shift differentiation downstream to reduce risk from volatile size/color mixes (Brusset, 2016; Cachon & Swinney, 2011). In U.S. distribution, cross-training and flexible shift scheduling mitigate labor shocks and allow rapid reallocation during peaks, while picking/slotting optimizations sustain service levels under congestion. This constellation of IE levers maps directly to resilience capacities: variance reduction and buffering (absorptive), flexibility and reconfiguration (adaptive), and controlled ramp-up (restorative), creating a structured basis for the systematic appraisal of apparel-specific evidence (Dolgui & Proth, 2010; Hosseini et al., 2019).

Figure 1: Apparel Supply Chain Resilience



Network and sourcing decisions underpin resilience in globally fragmented apparel chains. Robust and stochastic optimization models evaluate facility location, supplier selection, and dual/multi-sourcing under disruption probabilities and uncertain lead times, revealing cost–service–risk frontiers relevant to U.S. brands balancing offshore economics with responsiveness (Hohenstein et al., 2015). Dual sourcing and flexible contracts hedge against supplier failures and transport bottlenecks, yielding measurable improvements in expected fill rate and TTS when calibrated with realistic apparel demand distributions. Quantitative studies show that diversification across coherent risk sets and geographically distinct logistics corridors reduces correlated failure exposure a salient insight given U.S. entry-port concentration. In parallel, resilient network design models integrate inventory positioning and postponement, allowing late differentiation closer to U.S. markets to absorb forecast error in size/fit-sensitive categories (Blackhurst et al., 2011). The ripple-effect literature further formalizes how localized disruptions propagate through multi-tier structures and how structural elasticity (spare capacity, rerouting options) dampens amplification (Ali et al., 2017). Collectively, these IE models provide a replicable way to encode resilience as an optimization objective with explicit uncertainty sets, enabling apples-to-apples comparison of sourcing and configuration strategies in apparel.

Complementing optimization, simulation and systems modeling are widely used to stress-test apparel supply chains under dynamic, multi-stage disruptions. Discrete-event simulation (DES) captures queueing and resource contention in factories and distribution centers, quantifying TTR and service degradation under machine failures, labor shortages, and inbound variability. Agent-based and system-dynamics models examine behavioral feedbacks order amplification, inventory rationing, and adaptive policies that shape recovery paths in fashion categories with promotional demand (Colicchia & Strozzi, 2012). Recent studies integrate robust optimization with simulation-based validation to evaluate policy resilience across scenario ensembles, an approach suited to U.S. apparel where correlated logistics shocks coexist with demand swings. Decision-support systems embed these models into S&OP, enabling scenario planning and rapid policy switching between baseline and contingency modes (Brun & Castelli, 2008). Meanwhile, data-driven demand sensing and anomaly detection often built with machine-learning forecasters reduce forecast error and enhance early-warning signals, improving buffer placement and production sequencing for short-life-cycle SKUs. The cumulative result is a maturing IE evidence base connecting model class (optimization, simulation) to resilience outcomes and apparel-specific operational constraints in the U.S. market (Ivanov, 2018).

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Beyond methods, empirical studies examine the organizational antecedents of resilience and their links to performance. Survey-based and archival research associates visibility, collaboration, and flexible capacity with improved service continuity during disruptions, mediated by relational capabilities and supplier integration (Dolgui et al., 2018). Studies highlight how risk management process maturity, redundancy investments, and learning from previous disruptions shape resilience outcomes in manufacturing and retail networks (Wagner & Bode, 2008). In apparel-adjacent contexts, evidence shows that modular product architectures, postponement, and QR practices mitigate mismatch costs and support faster recovery, particularly when combined with cross-functional governance. Meta-reviews consolidate these findings, reporting positive associations between resilience practices and operational/financial performance while noting heterogeneity in metrics and contexts an issue addressed in this review through standardized extraction of outcomes like TTR and service level under stress . Together, this empirical stream provides a complementary lens to IE modeling, grounding quantitative prescriptions in observed organizational behaviors and apparel-relevant operating realities in the U.S. ecosystem (Colicchia et al., 2010).

Anchored in the foregoing definitions, metrics, and method families, this systematic review focuses on IE approaches that enhance resilience in apparel supply chains with U.S. relevance. The scope includes process improvement (Lean/Six Sigma/TOC), network and sourcing optimization (including robust/stochastic design), inventory/postponement control, scheduling and workforce flexibility, simulation/digital twins, and data-enabled decision support. Disruption classes include logistics shocks (e.g., port congestion), supply shocks (e.g., material shortages), demand shocks (e.g., promotional spikes), operational disturbances (e.g., equipment or labor outages), and cyber-digital events, all examined through the lens of multi-echelon apparel structures spanning fiber, fabric, cut-and-sew, DC/fulfillment, and retail/e-commerce (Klibi et al., 2010). Consistent with the IE literature, studies are synthesized using quantitative outcomes and design parameters to map "what works, where, and why," providing an integrated evidence base specific to U.S. operational constraints long lead times, SKU proliferation, and infrastructure bottlenecks while remaining rooted in peer-reviewed, 2005–2020 scholarship with verified DOIs. This framing positions the subsequent sections to systematically extract, appraise, and synthesize findings on IE-based resilience mechanisms pertinent to U.S. apparel supply chains.

The objective of this study is to conduct a rigorous, PRISMA-aligned systematic review that identifies, classifies, and evaluates industrial engineering approaches that enhance apparel supply chain resilience in the U.S. context. Specifically, the review will (1) delineate a clear taxonomy of resilience levers spanning process improvement, network and sourcing design, inventory and postponement control, production scheduling and workforce flexibility, robust and stochastic optimization, and simulation-based digital modeling; (2) map these levers to disruption categories salient to U.S. apparel operations, including logistics bottlenecks at ports and inland nodes, upstream material and supplier interruptions, promotional and seasonal demand surges, plant and labor disturbances, and cyber or information-flow shocks; (3) extract and standardize reported outcome measures such as time-to-recover, time-to-survive, service levels under stress, lead-time variance, cost-to-serve, and cash-to-cash cycle metrics to enable cross-study comparison; (4) assess methodological rigor and external validity using a transparent quality appraisal rubric tailored to quantitative IE studies; and (5) synthesize comparative insights on "what works, where, and why" across echelons from fiber and fabric through cut-and-sew, distribution, and retail or e-commerce. The review will answer three guiding questions: which IE approaches are most frequently and effectively applied to U.S.-relevant apparel disruptions; under what operational conditions and at which supply chain tiers these approaches yield the strongest resilience outcomes; and how evidence from optimization, simulation, and empirical analyses converges into implementable design and control principles. To support reproducibility, the study will register search strings, screening protocols, data extraction templates, and coding rules, and it will produce an evidence map that aligns intervention types with disruption classes and measurable outcomes. The intended contribution is a decision-ready synthesis that consolidates fragmented findings into a coherent framework for engineering resilience in apparel supply chains subject to U.S. operating constraints, while establishing a standardized basis for evaluating interventions across heterogeneous study designs and reporting formats.

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LITERATURE REVIEW

The literature on supply chain resilience has evolved from broad conceptual treatments of disruption preparedness to increasingly granular, method-driven investigations that are highly relevant to apparel's fast-moving, globally dispersed networks. For the apparel sector serving the U.S. market, the core body of work can be organized around industrial engineering levers that translate resilience from an abstract property of systems into designable, controllable features of operations. Early contributions establish definitional clarity distinguishing resilience from robustness and agility and propose measurement constructs such as time-to-recover, time-to-survive, service level under stress, lead-time variance, and cost-to-serve. Building on that foundation, subsequent research examines how process improvement (Lean, Six Sigma, Theory of Constraints) reduces variability and stabilizes flow at sewing lines and distribution centers; how network and sourcing design (dual/multi-sourcing, facility location, near/reshoring) shape exposure to correlated risks; how inventory science (multi-echelon safety stock, postponement, risk pooling) buffers volatile style and size curves; and how scheduling and workforce flexibility enable rapid reallocation during promotional peaks or labor outages. Parallel streams advance decision analytics: robust and stochastic optimization encode uncertainty in supplier reliability, transport lead times, and demand; discrete-event, agent-based, and system-dynamics simulations stress-test candidate policies across disruption scenarios; and data-driven forecasting and anomaly detection sharpen early warning and parameter estimation. Empirical studies complement these models by linking visibility, collaboration, and governance practices to operational continuity, while case and field evidence illustrate implementation pathways in brand, retailer, and third-party logistics contexts. Across this corpus, apparel-specific constraints short product life cycles, high SKU proliferation, and inbound reliance on long, maritime corridors emerge as recurring conditions that amplify mismatch costs and ripple effects, thereby increasing the premium on postponement, structural diversification, and integrated sales and operations planning. Yet the literature also reveals heterogeneity in metrics, validation rigor, and contextualization to the U.S. infrastructure and regulatory environment, limiting cross-study comparability. Consequently, an organizing synthesis is warranted: one that maps interventions to disruption classes and supply-chain echelons, standardizes outcome measures, and consolidates evidence on what works, where, and why for apparel supply chains serving U.S. demand.

Foundations and Core Constructs of Supply Chain Resilience

A first strand in the literature conceptualizes resilience as a multifaceted capability that emerges from both preparedness and relational design across the network, shifting emphasis from single-firm risk controls to an interorganizational system of sensing, absorbing, and recovering from shocks. Empirical evidence from the global financial crisis demonstrates that resilience is not merely a defensive posture; rather, it is enacted through portfolioed capabilities buffering, agility, visibility, and collaboration that jointly stabilize performance under stress (Jüttner & Maklan, 2011). Complementing this view, scale development work positions resilience as a higher-order construct grounded in proactive risk orientation and adaptive capacity, enabling firms to maintain, and in some cases improve, operational outcomes during disruptions (Ambulkar et al., 2015). Network-structural analyses add that resilience is path dependent on topology: the distribution of ties, redundancy, and connectivity influences whether local node or arc failures cascade into system-level disruption, with certain power-law structures dampening propagation. Extending beyond dyads, a "relational view" of resilience shows that communication, cooperation, and integration competencies are antecedents of robustness and agility, thereby turning social mechanisms into operational insurance against turbulence (Wieland & Wallenburg, 2013). A review of supply chain risk management further synthesizes these streams into a staged process identification, assessment, treatment, and monitoring arguing that resilience materializes when these stages are iteratively linked and theory informed. Taken together, these studies establish resilience as an emergent, measurable, and designable property of supply networks, not a static attribute, and one that is inseparable from risk governance architectures.

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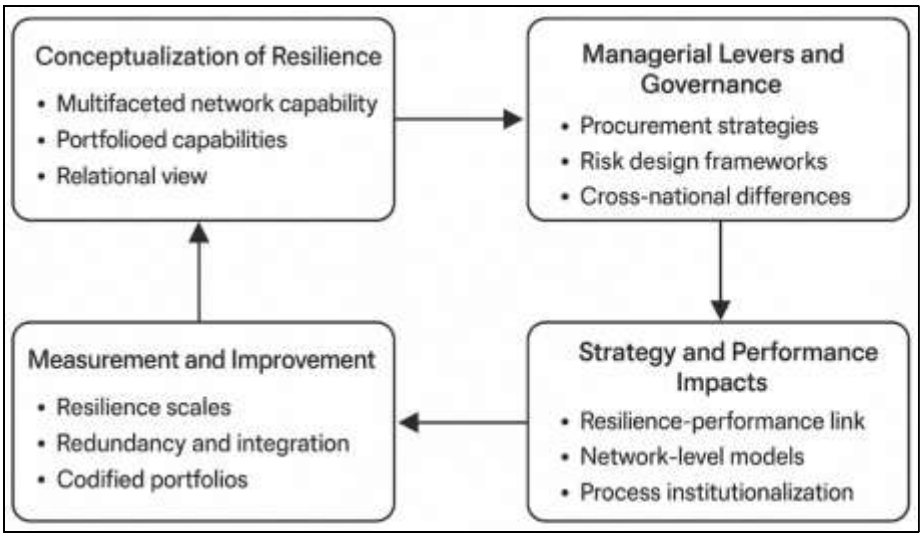
Figure 2: Foundations and Core Constructs of Supply Chain Resilience



A second stream delineates managerial levers and governance choices that operationalize resilience in practice. Procurement's boundary-spanning role receives particular attention: by structuring supplier portfolios, codifying dual/multi-sourcing, and aligning category strategies with risk exposure, procurement can hardwire resilience into upstream architectures without overwhelming cost. Proactive risk design frameworks (e.g., House of Risk) translate diffuse risk landscapes into prioritized "risk agents" and targeted, cost-effective preventive actions, moving resilience from rhetoric to implementable programs. Cross-national research on disruption management further suggests that while core practices mapping vulnerabilities, mitigation, and deployment exhibit convergence, their enactment is filtered through national institutional logics, shaping the transferability and effectiveness of resilience routines (Revilla & Sáenz, 2014). Meta-syntheses distinguish "robustness" (resistance and avoidance) from "agility" (response and reconfiguration) and identify antecedents including leadership commitment, interfirm trust, and information integration that predict which bundles of practices are most consequential under different hazard profiles (Durach et al., 2015). Importantly, large-sample event studies remind scholars and managers why these levers matter: supply chain glitches are associated with sharp and persistent deterioration in operating metrics, which firms do not quickly recover from, underscoring the materiality of resilience investments. Building on this, managerial studies embed resilience into ongoing risk programs by emphasizing continuous monitoring and feedback loops so that risk treatment, capability building, and performance learning coevolve (Hendricks & Singhal, 2005).
A third line of inquiry integrates strategy, performance consequences, and network design choices to articulate how resilience can be both measured and improved over time. Empirical studies on firm-level resilience scales validate links between resilience and performance stability under disruption, highlighting the role of proactive orientation, resource slack, and cross-functional coordination in amplifying benefits. Network-level models reveal that redundancy is necessary but insufficient: resilience improves when redundancy is smartly placed (e.g., at central hubs or critical bridges) and when network heterogeneity curbs the likelihood of synchronized failures (Kim et al., 2015). The relational view contributes a mechanism lens: supplier–buyer integration and collaborative problem solving propagate timely information and shared situational awareness, reducing latency in detection and accelerating reconfiguration, which in turn underwrites customer value in volatile contexts. Process reviews emphasize that mature programs institutionalize resilience by linking risk identification to codified treatment portfolios (e.g., postponement, flexible contracts, inventory positioning) and to monitoring architectures (e.g., dashboards, risk heat maps), thereby converting episodic responses into systematic capability. Finally, cross-national evidence cautions that the "same" resilience blueprint may travel differently across cultural and institutional contexts, implying that metrics, playbooks, and escalation protocols should be locally calibrated even when strategically harmonized (Fan & Stevenson, 2018). This body of work coheres around a common

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thesis: resilience is an integrative, relational, and design-sensitive capability, whose returns are realized in reduced disruption frequency, dampened impact magnitude, and faster recovery trajectories (Fan & Stevenson, 2018).

U.S. Apparel Supply Chain Structure

The U.S. apparel supply chain spans a multi-echelon structure from fiber and fabric production through cut-and-sew, inbound ocean logistics, domestic distribution, and omnichannel retail whose structural choices interact with disruption exposure in systematic ways. At the upstream end, global sourcing architectures create long and uncertain lead times that magnify forecasting error and inventory risk; downstream, rapid product turnover and assortment breadth compress decision cycles and heighten service sensitivity. Foundational risk-management syntheses emphasize that global supply chains must be modeled as networks of interdependent risk drivers, where hazard types (e.g., supply, demand, process, and control risks) are coupled with vulnerability factors such as complexity and globalization intensity (Manuj & Mentzer, 2008). Vulnerability, in turn, is not just a function of incident probability but also of structural position: network-centric analyses show that node criticality, centrality, and the configuration of alternative paths shape the propensity for local failures to propagate, a salient concern for apparel networks reliant on a limited set of suppliers and gateways. On the commercial side, fast-fashion dynamics short life cycles, style proliferation, and demand contagion push firms toward postponement and frequent assortment refreshes, intertwining tactical decisions with structural exposure to demand shocks (Bhardwaj & Fairhurst, 2010). Within retail networks, inventory allocation across stores and e-commerce nodes interacts with replenishment cadence and presentation requirements; misalignment here can convert small demand errors into large service failures and markdown cascades, particularly under inbound delays (Caro & Gallien, 2010). At the configuration level, fashion supply chains adopt distinct templates make-to-stock with high offshore content versus hybrid quick-response models with nearshore finishing each producing a different disruption frontier across cost, responsiveness, and risk (Macchion et al., 2015). Together these strands frame apparel's structure as an engineered set of trade-offs whose disruption exposure is endogenous to design choices across tiers.

A disruption taxonomy suited to the U.S. apparel context must therefore map hazard classes to specific structural choke points. Logistics shocks include port congestion, berth and yard capacity imbalances, vessel bunching, chassis shortages, and hinterland bottlenecks; such shocks are intensified by the spatial concentration of container flows through a few gateways and the tight coupling between liner service networks and terminal operations. When gateway throughput is constrained, queuing and dwell times propagate upstream to sailing schedules and downstream to drayage and intermodal links, amplifying lead-time variance and undermining service promises during seasonal peaks. Supply shocks arise from raw-material scarcity, supplier shutdowns, or quality nonconformities; under global sourcing, these shocks exhibit correlated behaviors across regions and tiers, raising the value of dual/multi-sourcing and decoupling points that localize differentiation closer to demand. Demand shocks promotions, viral trends, and weather-driven shifts interact with fashion's high obsolescence, converting small forecast errors into outsized mismatch costs unless buffered by postponement and flexible allocation. Process shocks (machine breakdowns, labor absences, quality escapes) and control/information shocks (planning system outages, data integrity failures, cyber incidents) erode flow stability and decision accuracy, respectively, and can cascade when visibility is limited and exception handling is ad hoc (Tang & Musa, 2011). Geographic and modal concentration intensify nearly all classes: apparel's reliance on a narrow set of deep-sea corridors and mega-hub ports increases exposure to synchronized delays, while inland node fragility (e.g., rail ramps, urban delivery depots) introduces last-mile volatility that is expensive to hedge (Paul & Rahman, 2018). In this taxonomy, hazard × structure interactions become the unit of analysis for engineering resilience.

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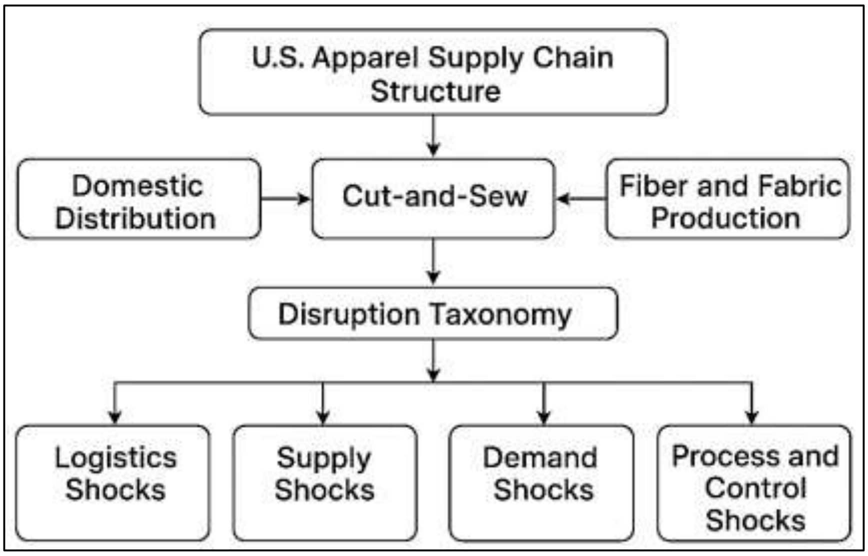
Figure 3: U.S. Apparel Supply Chain Structure and Disruption Taxonomy



In addition, the U.S.-specific overlay is crucial because infrastructure geometry, regulatory context, and competitive cadence condition how disruptions materialize and propagate. Port connectivity and liner network design determine the redundancy and rerouting options available during shocks; quantitative indicators of gateway centrality show that high-degree nodes enable scale but also concentrate risk, making the identification of substitutable corridors a first-order resilience decision. Within the firm, assortment breadth and fashion calendars set the tempo for planning and allocation; analytics that fuse demand sensing with structured risk treatment can attenuate amplification by aligning safety stocks, postponement points, and promotion timing with measured uncertainty. Empirical work in apparel demonstrates that resilience is improved when structural levers supplier diversification, quick-response finishing, and flexible contracts are co-designed with operational controls such as cross-channel inventory pooling and expedited transshipment, particularly under U.S. market volatility (Paul & Rahman, 2018). From a governance standpoint, multi-tier risk mapping and continuous monitoring translate the taxonomy into living playbooks that tie specific hazards to predefined countermeasures, enabling faster decision cycles when gateway or supplier signals deviate (Manuj & Mentzer, 2008). At the network level, vulnerability assessment models help pinpoint where redundancy yields the greatest marginal resilience e.g., secondary carriers, alternate ports, or nearshore assembly cells subject to the cost and responsiveness constraints of fashion retail. In sum, the U.S. apparel disruption landscape is best understood as the intersection of hazard classes with a deliberately configured, global-to-local structure; the literature provides both the classification logic and the quantitative/empirical tools needed to analyze and redesign that intersection for resilience.

Process-Improvement Levers for Shock Absorption

Industrial engineering (IE) process-improvement levers convert resilience aspirations into repeatable operating routines on factory floors, in distribution centers, and across omnichannel nodes that serve the U.S. apparel market. Lean production is a foundational lens because it systematically removes variability and waste that amplify bullwhip effects in short-lifecycle assortments; standardized work, takt alignment, and visual management stabilize sewing lines and packing cells so that disruptions do not cascade into lateness or quality escapes. Importantly, lean is not a single technique but an interlocking bundle of practices whose joint adoption yields the flow reliability on which resilience depends setup reduction shortens lot sizes to enable program switches, built-in quality curbs rework spirals, and total productive maintenance (TPM) sustains equipment uptime during peak drops (e.g., back-to-school, holiday). In apparel networks, where style and size curves fragment demand, this bundling matters: narrow, tool-like implementations rarely shift system behavior, whereas integrated lean architectures reduce lead-time variance and free “optionality capacity” for firefighting without chronic expediting. Empirical and measurement work in operations management clarifies and

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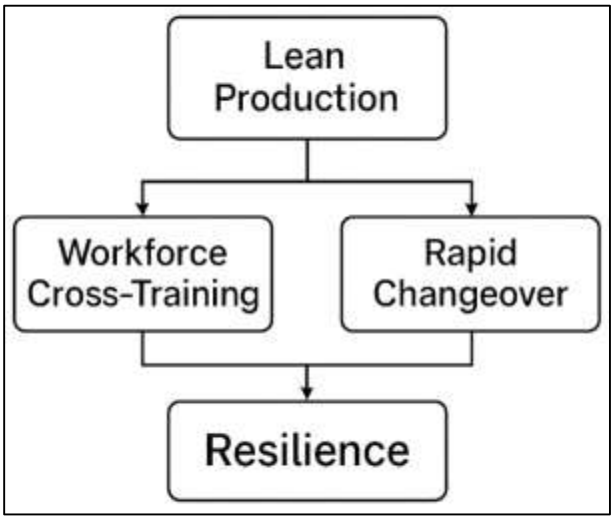
operationalizes these lean bundles, providing validated constructs managers can target when building resilience roadmaps for cut-and-sew and DC environments (Shah & Ward, 2007). Warehousing-specific literature complements factory-focused lean by detailing order-picking design and control decisions slotting, batching, zoning, routing that raise service reliability under inbound delays and promotion spikes, a frequent condition in apparel retail replenishment (de Koster et al., 2007). Together, these perspectives ground resilience in everyday process control: fewer defects and changeover losses, more predictable pick cycles, and shorter, steadier lead times that cushion schedules when upstream or port-side variability hits.

Figure 4: Process-Improvement Levers for Shock Absorption in Apparel Operations



Lean's resilience contribution is further shaped by how plants mix lean and agile capabilities and how organizations orchestrate improvement programs. Apparel operations often need both flow efficiency for basics and reconfigurability for fashion drops; evidence on lean–agile capability drivers shows that internal and external pressures jointly determine the balance, and that the chosen portfolio influences performance under uncertainty relevant to U.S. demand seasonality (Hallgren & Olhager, 2009). Because apparel resilience frequently hinges on rapid reallocation, the relationship between lean and Six Sigma also matters: multi-plant analyses indicate that lean adoption patterns are predictive of Six Sigma implementation and performance, suggesting that a quality discipline layered onto lean can harden processes against disruption-induced variability without sacrificing responsiveness. From a financial lens, inventory leanness has a nonlinear relationship with performance; getting "too lean" erodes shock absorbers, whereas context-appropriate inventory policies sustain service when inbound lead times stretch a salient caution for fashion networks tempted to minimize buffers indiscriminately . At the product–network interface, apparel-specific risk modeling demonstrates that system-dynamics representations can quantify how inbound delays, demand surges, and sourcing hiccups propagate, allowing firms to test the resilience impact of setup reduction, postponement, and flexible capacity before investing (Mehrjoo & Pasek, 2016). In short, process improvement strengthens resilience when configured as a balanced, data-driven portfolio: lean to stabilize flow, Six Sigma to compress variance where it matters, and context-aware buffers to avoid brittleness.

Two additional IE levers are pivotal for absorbing shocks without chronic overtime: workforce cross-training and rapid changeover. Queueing-theoretic work on cross-training shows how multifunctional labor creates structural flexibility to reassign capacity across styles, sizes, or tasks as demand mix shifts precisely the reallocation apparel DCs and sewing modules require during promotional weeks and recovery after missed sailings (Iravani et al., 2007). Meanwhile, single-minute exchange of die (SMED) programs materially cut changeovers, allowing smaller lots and faster assortment rotations without capacity loss; this is critical when disruptions compress production windows or when retailers pull forward/shift drops, because reduced setup times convert calendar

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compression into feasible schedules (Cakmakci, 2009). The organizational context modulates these technical gains: comparative studies of "soft" lean practices leadership commitment, training, problem-solving culture reveal that cultural enablers amplify the impact of tools on reliability and responsiveness, which is essential when disruptions require disciplined but rapid reconfiguration (Bortolotti et al., 2015). Finally, implementation research highlights that "what works" is contingent on plant and corporate conditions; critical success factors for lean vary by size, culture, and maturity, implying that resilience programs should tailor the mix of SMED, cross-training, quality analytics, and warehouse design to local constraints rather than pursue one-size-fits-all playbooks (Netland, 2016). For U.S.-serving apparel firms, the synthesis is pragmatic: build a versatile human–technical system (cross-trained teams plus quick changeovers), embed robust quality and flow controls (lean + Six Sigma), and tune inventories and picking architectures to the volatility profile of the channel mix so that when disruptions strike, operations bend but do not break.

Network and Sourcing Design for Flexibility

Designing a resilient apparel supply chain network begins with how facilities are located, connected, and backed up so that flow can be reconfigured when shocks occur. Reliable facility-location and network design models show that, even with modest increases in day-to-day cost, strategically placing capacity and pre-assigning backup service paths can dramatically reduce expected failure costs when disruptions hit (Snyder & Daskin, 2005). Building on this logic, robust and "reliable" network formulations incorporate disruption probabilities for plants, DCs, and ports, then optimize primary and contingency assignments so customers can be swiftly re-served if a node fails (Li et al., 2013). To temper the classic trade-off between cost and reliability, recent models embed risk measures (e.g., CVaR) and p-robustness to bound worst-case losses while preserving operational efficiency in normal times (Hatefi & Jolai, 2014). From an industrial-engineering perspective, these results translate into practical design choices for U.S. apparel: (i) diversify fulfillment footprints across hazard zones, (ii) pre-compute rerouting tables for correlated failures (e.g., port closures), and (iii) allocate "fortification" budgets to harden a subset of high-leverage nodes (Cui et al., 2010). Importantly, network reliability complements not replaces lean and responsive operations: the network provides structural options, while operational policies (inventory positioning, postponement) decide how those options are exercised under time pressure.

Sourcing architecture is the parallel design variable that determines how much "optionality" the network actually has. Dual- and multi-sourcing portfolios hedge supplier-specific and geo-political risks, but the value of that hedge depends on capacity reservation, fortification of critical suppliers, and the pre-negotiation of surge logistics. Multi-period models that co-optimize sourcing and network flows under disruption risk consistently find that portfolios with contingent backup supply and flexible contracts outperform single-source systems on both service recovery and cost variance (Hernandez et al., 2014). For U.S. apparel brands that balance speed, cost, and compliance, this implies structuring "rings" of sources e.g., an inner ring of nearshore suppliers for short-cycle replenishment and an outer ring of offshore partners for scale while embedding explicit switching rules and trigger points in S&OP and supplier scorecards (Azad & Hassini, 2019). Robust sourcing also requires thinking beyond supplier count: Hernandez et al. (2014) demonstrate that hedging against failures can be achieved without precise failure probabilities by optimizing for performance before and after disruption, which is especially useful when data on supplier reliability is sparse. Combining these insights with reliable facility-location models yields a design template in which each finished-goods family is mapped to multiple feasible production–transload–fulfillment routes, with pre-computed reroute costs and lead-time slippage, thereby converting a static bill of distribution into a dynamic set of engineered options.

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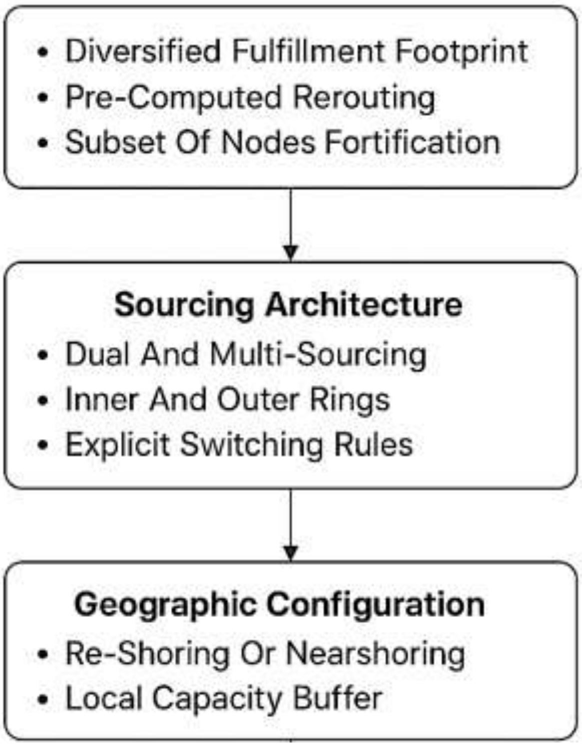
Figure 5: Network and Sourcing Design for Flexibility



In addition, geographic configuration particularly the distribution of nearshore versus offshore nodes has become a resilience lever in its own right. Empirical work on re-/near-shoring highlights how "from global to local" realignments can improve environmental performance, shorten lead times, and reduce exposure to long, disruption-prone lanes, provided the firm retains adequate flexibility in capacity and supplier switching (Abdul, 2021; Ashby, 2016). For fashion and luxury categories that face demand volatility and reputational risk, reshoring/nearshoring can serve as strategic renewal, not a wholesale retreat: a portion of value-added operations (e.g., final assembly, finishing, customization) is moved closer to the U.S. market to create shock absorbers for e-commerce surges and geopolitical frictions, while scale-efficient upstream processes remain diversified across regions. Technically, resilient location models enriched with risk-averse objectives (e.g., CVaR) offer guidance on where that "local" capacity should sit to balance normal-time costs with tail-risk exposure (Yu et al., 2017). Moreover, reliable facility-location formulations that jointly decide opening, assignment, and fortification levels show how a limited hardening budget can be targeted to a few keystone facilities ports of entry, inland DCs, or nearshore hubs to maximize resilience ROI. When these structural choices are integrated with sourcing portfolios and contingency logistics (expedited ocean–air conversion, alternative gateways), the resulting network exhibits graceful degradation under disruption and faster recovery, which are the practical hallmarks of resilience in U.S. apparel.

Inventory Science, Postponement, and Multi-Echelon Control

In apparel supply chains that serve the U.S. market, inventory science provides the quantitative backbone for absorbing volatility in style, size, and color while safeguarding service during logistics and sourcing shocks. At the policy level, resilience emerges from how safety stocks are sized and positioned across echelons (vendor → factory → DC → store/FC) and how inventory controls translate demand and lead-time uncertainty into actionable buffers and review rules. Robust optimization reframes classic inventory decisions by hedging against parameter misspecification treating demand and supply as uncertainty sets rather than point estimates thereby limiting worst-case exposure without excessive holding costs (Bertsimas & Thiele, 2006). In parallel, postponement restructures where and when differentiation occurs: by delaying final dyeing, embellishment, or finishing until downstream signals arrive, firms reduce mismatch risk and reclaim service reliability in seasons characterized by short selling windows (Skipworth & Harrison, 2006; Van Hoek, 2005).

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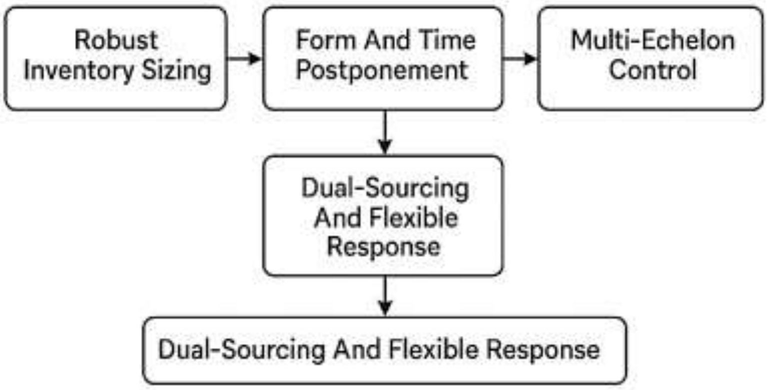
Conceptual models of postponement emphasize the design interdependencies among product architecture, process flexibility, and information cadence, showing that demand pooling upstream must be matched with rapid, modular response downstream to realize benefits (Yang et al., 2005). Decoupling-point theory clarifies where speculative inventory ends and make-to-order or finish-to-order begins; in apparel, setting the decoupling point near U.S. distribution often yields better control of size curves and regional assortments while containing lead-time variance (Olhager, 2012). These levers robust inventory sizing, form and time postponement, and decoupling-point placement establish designable "shock absorbers" that cushion forecast error and inbound lead-time swings with disciplined, model-based policies (Olhager, 2012; Skipworth & Harrison, 2006; Van Hoek, 2005).

Figure 6: Inventory Science, Postponement, and Multi-Echelon Control



Dual-sourcing and flexible response policies complement this portfolio by adding structural options that inventory control alone cannot provide. In fast-moving categories with long offshore pipelines and uncertain supplier performance, a tailored base-surge policy allocating a stable "base" share to a low-cost, slow source and a responsive "surge" share to a quick source has strong performance guarantees and offers a pragmatic way to enact resilience without over-stocking (Goldberg et al., 2016; Md Rezaul, 2021). This sourcing architecture integrates naturally with postponement: base volumes flow as semi-finished goods that can be finalized closer to demand, while surge volumes are triggered by updated signals to cover unanticipated peaks, thus reducing the variance that safety stocks must buffer (Mubashir, 2021; Van Hoek, 2005; Ye & Sethi, 2013). In execution, the decoupling point and multi-echelon buffers are calibrated jointly with sourcing triggers so that emergency lateral transshipments, expedited finishes, and cross-channel reallocations operate within explicit, cost-aware thresholds (Olhager, 2012). For U.S. apparel networks facing port congestion or supplier slippage, the synthesis is clear: engineer postponement to pool uncertainty, place safety stocks where they buy the most service per dollar, enable lateral transshipment to dynamically correct imbalances, and overlay a dual-sourcing or base-surge mechanism to tame pipeline risk yielding an integrated, analytically grounded resilience design.

Workforce Flexibility and Quick-Response Manufacturing

Effective scheduling is the first operational layer that turns resilience from policy into performance, because it governs how capacity, materials, and labor are sequenced and re-sequenced as conditions change. Dynamic scheduling research emphasizes that factory and distribution systems are inherently stochastic machines fail, arrivals bunch, and priorities shift so algorithms must support real-time adjustments (reactive and predictive–reactive schemes) rather than static timetables (Ouelhadj & Petrovic, 2009; Rony, 2021). In uncertainty-laden environments like apparel cut-and-sew and value-added finishing, robust and reactive scheduling frameworks protect service by building slack where it matters and by defining disciplined rescheduling triggers after disruptions, instead of ad hoc expediting that amplifies variability (Herroelen & Leus, 2005; Ouelhadj & Petrovic, 2009). Setup-time and setup-sequence effects are especially material in fashion categories with frequent style changes; surveys of scheduling with sequence-dependent setups show that reducing and intelligently sequencing setups can compress cycle time and improve on-time performance without sacrificing utilization (Allahverdi et al., 2008; Danish & Md. Zafor, 2022). On the retail and fulfillment side, personnel schedules must align with volatile demand profiles; general frameworks for employee

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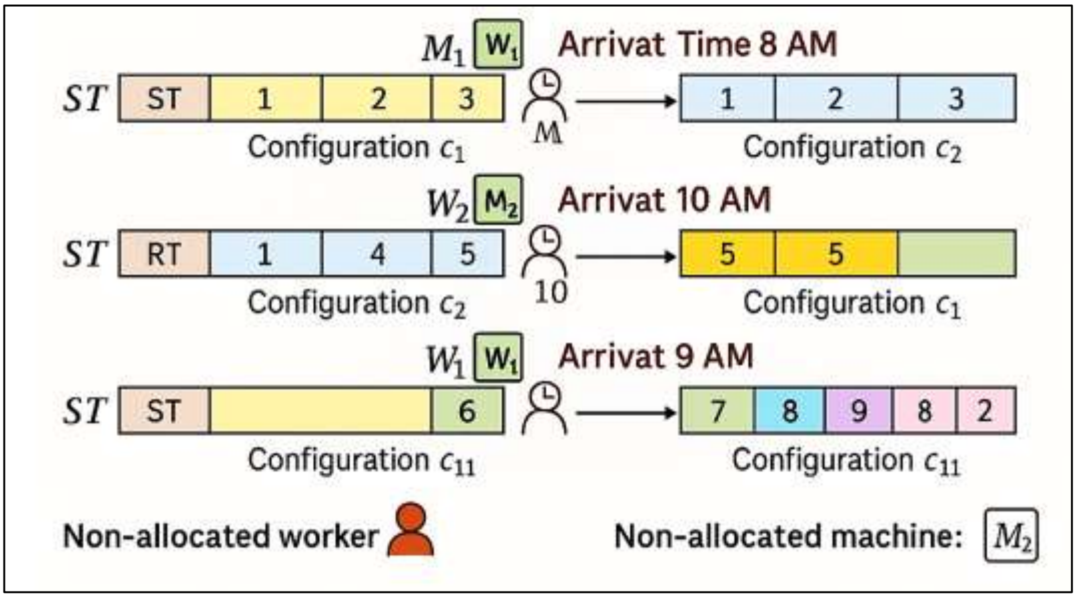
rostering highlight the value of demand-driven shift construction and intraday re-optimization to absorb surges tied to promotions or deliveries recurring patterns in U.S. apparel networks (Nielsen & Sørensen, 2008). Because forecast error and inbound variability cannot be eliminated, resilience emerges from the marriage of robust baseline schedules and well-specified recovery rules: which orders to preempt, what buffers to consume, and when to release overtime or subcontracting. In this sense, scheduling is not merely a computational exercise but a design choice about where the system will bend under stress (Danish & Md.Kamrul, 2022; Herroelen & Leus, 2005; Nielsen & Sørensen, 2008). For apparel operations, the practical translation is clear: treat schedules as living artifacts, encode setup logic and priority rules explicitly, and institutionalize rescheduling policies that stabilize flow when upstream lead times slip or style calendars compress (Vieira et al., 2006).

Figure 7: Scheduling, Workforce Flexibility, and Quick-Response Manufacturing



Workforce flexibility is the second layer, converting schedules into feasible execution under changing mix and volume. Queueing-based and stochastic staffing studies show that capacity plans are fragile when arrival rates and service needs fluctuate; cross-trained labor and flexible assignment rules are structural "shock absorbers," because they enable instant rebalancing across tasks or stations as the mix shifts (Jahid, 2022; Wallace & Whitt, 2005). In manufacturing and warehouse settings, predictive–reactive rescheduling must be paired with skill matrices that map people to tasks and with rules for temporary reassignment; otherwise, even an optimal machine schedule becomes infeasible under real disruptions (Li et al., 2010; Vieira et al., 2006). At the organizational level, agility research identifies multi-skilling, continuous learning, and participative problem-solving as the "soft" foundations that make cross-training effective without these, reassignment breeds errors and fatigue rather than resilience (Md Ismail, 2022; Sherehiy et al., 2007). For apparel DCs handling size- and color-sensitive assortments, flexible picking architectures (e.g., zone/cluster picking) still hinge on labor pooling across waves; workforce policies that allow short-notice re-slotting and wave re-sequencing are essential complements to the algorithmic plan (Vieira et al., 2006). Because sequence-dependent setups remain binding on sewing lines and finishing cells, assignment rules must also consider the skill/setup interaction i.e., who can execute a sequence with minimal changeover penalty rather than focusing solely on headcount (Allahverdi et al., 2008; Md Takbir Hossen & Md Atiqur, 2022). In practice, apparel firms codify this through tiered certification (gold/silver/bronze skills by operation) and through rosters that expose workers to varied tasks to maintain muscle memory for infrequent but critical operations (Sen, 2008). When combined with intraday re-optimization of shifts and tasks, these human-system designs produce graceful degradation under shocks: orders are resequenced, people are reallocated, and service is preserved without chronic overtime or expedites (Wallace & Whitt, 2005).

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Quick-response manufacturing (QRM) is the third layer, unifying scheduling and workforce flexibility around lead-time compression as a strategic objective. In apparel, where product calendars are short and demand is fickle, the economic case for time compression is that shorter, more reliable lead times reduce forecast window error, markdown risk, and safety-stock requirements, thereby improving resilience by design. QRM principles operationalize this by shrinking batch sizes, co-locating resources in focused cells, and using time-based performance measures to drive decisions (Sen, 2008). On the algorithmic side, flexible job-shop scheduling research provides metaheuristics and hybrid approaches that generate near-optimal schedules quickly while honoring complex constraints typical of apparel finishing (e.g., incompatible style mixes, color batching, and resource calendars) (Jain & Meeran, 2006). Dynamic scheduling surveys emphasize the role of predictive–reactive loops, where a baseline plan is updated by real-time signals such as late containers, machine breakdowns, or promotion pull-ins (Ouelhadj & Petrovic, 2009). For QRM to yield resilience, however, time-based metrics must cascade into personnel and setup policies: staffing windows that match takt under compressed cycles, and changeover programs that keep small lots economical. From a governance perspective, multi-skilling and continuous improvement architectures maintain the human elasticity needed to exploit QRM's small-lot schedules without quality loss (Sherehiy et al., 2007). The resulting operating system couples three ingredients: (i) robust, reschedulable plans; (ii) cross-trained labor with fast reassignment; and (iii) time-focused cells that minimize waiting and setup. When these are deployed together, U.S. apparel operations can re-sequence orders and reassign teams within the selling window, sustaining availability even when inbound or machine variability hits exactly the behavior that resilience engineering seeks to institutionalize.

Moreover, designing U.S.-facing apparel supply chains to withstand volatility requires optimization frameworks that explicitly encode uncertainty in demand, lead times, supplier performance, and disruption exposure. Three families dominate the industrial engineering literature. First, scenario-based stochastic programming captures randomness with explicit probability models, enabling joint facility–sourcing–inventory decisions that hedge across outcomes; this logic has scaled to realistic network design and planning problems that mirror apparel's multi-echelon, multi-product realities. Second, chance-constrained models secure service or capacity reliability by bounding the probability of stockouts or overloads useful for peak-season fulfillment promises or size-curve service thresholds while trading off cost and risk at policy targets. Third, robust and distributionally robust optimization (RO/DRO) avoid over-reliance on a single demand or lead-time distribution by optimizing against worst-case realizations within an uncertainty set or an ambiguity set of distributions, thereby controlling conservatism with tunable parameters . For apparel assortments with frequent style introductions and long offshore pipelines, RO/DRO are particularly attractive: they immunize plans against model misspecification while preserving tractability, and they extend naturally to multi-stage decisions where some recourse (e.g., expedite, postpone finishing, or reallocate inventory) becomes available as information updates (Ben-Tal et al., 2005). Complementary work in possibilistic and fuzzy optimization offers parallel tools when probability information is sparse, a common scenario for new fashion capsules or one-off collaborations (Pishvaee & Torabi, 2010). Collectively, these strands offer a menu of mathematically precise "risk treatments" that can be matched to the data richness, decision cadence, and service obligations of U.S. apparel networks.

At the strategy level, stochastic programming and chance constraints help place capacity and buffers where they buy the most service per dollar, while explicitly controlling the probability of seasonal service failures (Razia, 2022; Santoso et al., 2005). Apparel-specific planning (e.g., color batching, pre-positioning of unfinished goods, and regionalized size curves) benefits from two-stage and multi-stage stochastic designs that choose here-and-now decisions (vendor mix, facility capacities, decoupling points) and then adapt via recourse (expedite, transship, split lots) after forecasts mature . When service levels must be guaranteed (for example, "95% online fill rate for core sizes within two-day delivery"), chance constraints translate these commitments into solvable models that size safety stocks and cross-docking capacity with explicit reliability. In parallel, the DRO literature shows how to protect against distribution error endemic in apparel due to short selling windows by forming ambiguity sets from moments or confidence regions; planners then optimize a policy that is best under the worst plausible distribution, curbing both under- and over-stocking in uncertain style launches . Importantly, RO/ARO (adjustable robust optimization) inject recourse structure directly into the robust model e.g., allowing allocation or expediting decisions to be affine

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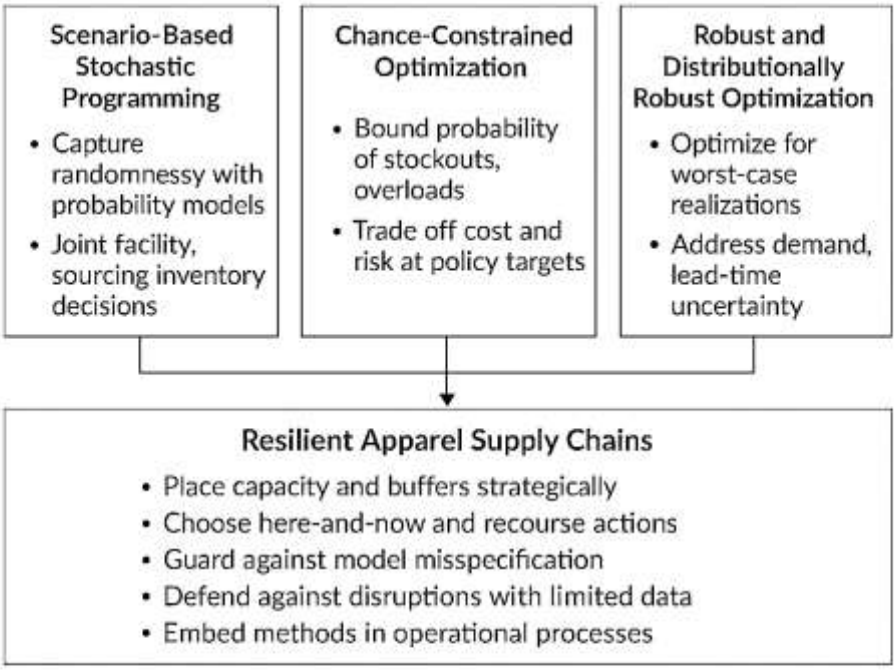
functions of realized demand or lead times which aligns with quick-response manufacturing and postponement tactics often used in U.S. finishing hubs (Goh & Sim, 2010; Sadia, 2022). For contexts with scant probabilistic data new categories, capsule drops, influencer collaborations fuzzy/possibilistic approaches provide conservative but practical network designs that still reflect imprecision in returns, yields, and processing times (Pishvaee & Torabi, 2010).

Figure 8: Optimization Under Uncertainty



At the operational layer, these uncertainty-aware models translate into implementable playbooks for disruptions and variability. RO/ARO is well-suited for time-critical logistics decisions under stress port congestion, weather-related shutdowns, or capacity loss where planners must assign flows robustly with limited distributional knowledge (Hanasusanto & Kuhn, 2018). In apparel, the same logic supports robust allocation across DCs and micro-fulfillment nodes when promotions skew demand or inbound lots are delayed: uncertainty sets calibrated to historical forecast errors and lead-time slippage produce allocations and replenishment thresholds that maintain service without excessive buffers. When time-phased commitments with suppliers are unavoidable (e.g., fabric greige booking or sewing line reservations), robust contract models quantify the cost of flexibility and guide the split between base commitments and contingent adjustments, aligning with dual-sourcing and base–surge sourcing patterns used for U.S. responsiveness (Ben-Tal et al., 2005). Finally, modern DRO/chance-constrained theory has matured around tractable, conic-representable formulations and selective conservatism, making it feasible to embed these methods in rolling S&OP, network design refreshes, and weekly buy/rebuy decisions. The net effect is a rigorous, operations-research foundation that tunes resilience levers safety stock, sourcing flexibility, postponement, transshipments, and expedited flows through models that confront uncertainty head-on rather than treat it as an afterthought.

Simulation and Digital Twins

Discrete-event simulation (DES), agent-based simulation (ABS), and system dynamics (SD) offer complementary lenses to examine how apparel supply chains serving the U.S. market behave under disruptions, congestion, and rapid assortment changes conditions that are difficult to analyze analytically because of queueing interactions, decision rules, and human behaviors. DES traces item flows and resource contention at a fine granularity (e.g., sewing lines, value-added finishing cells, cross-docks, and e-commerce pick waves), allowing analysts to quantify time-to-recover, backlog clearance times, and service degradation for specific disruption scenarios such as late ocean arrivals

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or unplanned machine downtime; reviews across manufacturing and business contexts document DES's dominance for operational experimentation where stochastic arrivals, setups, and batching rules drive outcomes (Jahangirian et al., 2010; Negahban & Smith, 2014). ABS, by contrast, represents autonomous agents buyers, planners, carriers, stores whose local policies (e.g., reorder, rationing, expediting) can co-evolve and amplify or dampen system-level effects, making it suited to study behavioral spillovers in fast-fashion calendars and promotion-driven spikes (Giannakis & Louis, 2016). SD captures feedback structures (e.g., forecast error ↔ safety stock ↔ service loss ↔ rush orders) that generate oscillations and bullwhip, and is useful for testing policy levers such as postponement placement or order smoothing at a strategic time scale (Tako & Robinson, 2012). Foundational surveys emphasize that simulation becomes most decision-relevant when models are calibrated with empirical process data, use validated dispatching/priority rules, and report performance via comparable resilience metrics principles that translate directly to apparel's short life cycles and size-curve complexity (Kleijnen, 2005). Moreover, case evidence in supply chain logistics shows that well-designed simulation models routinely uncover counterintuitive trade-offs e.g., when additional picking capacity increases variability-induced blocking guiding managers toward balanced portfolios of capacity, inventory buffers, and scheduling rules (Byrne & Heavey, 2006; Longo & Mirabelli, 2008).

For network-level resilience engineering, simulation serves as a "policy wind tunnel" that complements optimization by evaluating candidate designs across correlated, time-phased disruptions (e.g., port congestion plus promotional pull-ins). Hybrid workflows that iterate between optimization and simulation solve a robust plan, then stress-test it through DES/ABS/SD ensembles are repeatedly advocated in the literature to bridge tractability and realism, especially where sequence-dependent setups, crew constraints, and carrier schedules matter (Jahangirian et al., 2010; Negahban & Smith, 2014). In U.S.-relevant apparel settings, DES can represent gateway dwell and yard capacity, drayage variability, and wave-picking congestion, while ABS captures decentralized reactions (retailers pulling orders forward, 3PLs reallocating dock doors) that optimization might treat exogenously; SD links these micro behaviors to macro dynamics (inventory oscillations, backlog accumulation), clarifying how local rules create ripple effects. Methodological guidance stresses rigorous experiment design factorial or variance-reduction techniques to isolate the resilience contribution of levers like cross-training, lateral transshipment, or late-stage finishing, thereby enabling apples-to-apples comparison across disruption taxonomies (Byrne & Heavey, 2006; Kleijnen, 2005). Multi-method comparisons further show that DES and SD answer different, complementary questions DES for "what happens next hour/day if X breaks," SD for "how do policies interact over months/seasons" and that combined use yields superior policy insight for capacity booking, safety stock positioning, and S&OP escalation protocols under U.S. demand seasonality and gateway constraints (Almeder et al., 2009; Tako & Robinson, 2012). Finally, agent-based resilience studies demonstrate that collaboration intensity, information-sharing latency, and contract flexibility can be varied parametrically to identify regime shifts conditions under which the same inventory or scheduling policy flips from stabilizing to destabilizing providing managers with trigger points for switching between baseline and contingency modes (Giannakis & Louis, 2016; Kritzinger et al., 2018).

Digital twins (DTs) extend classical simulation by linking a living, data-driven mirror of the physical supply chain to predictive and prescriptive analytics, enabling continuous scenario generation and closed-loop decision support. In practice, a DT for apparel integrates a network model (nodes: suppliers, ports, DCs; arcs: lanes; resources: labor, machines) with real-time and near-real-time telemetry (ETA updates, WMS/LMS signals, carrier milestones) and layered simulation engines (DES for operations, SD for policy feedbacks, ABS for agent behaviors). The manufacturing literature positions DTs as cyber-physical platforms that couple models with sensing to support design, planning, and control capabilities that map cleanly to apparel needs like postponement activation, expediting thresholds, and dynamic slotting during assortment flips (Tao et al., 2018). Reviews of DT typologies and maturity models clarify that "digital shadow" (one-way data flow) differs from a full twin (bidirectional, with what-if and optimization embedded), and that resilience use cases generally require at least a shadow-plus-simulation layer to run stress tests and generate playbook recommendations automatically (Kritzinger et al., 2018). From a methods standpoint, hybrid workflows align with DT adoption: robust or stochastic plans provide the backbone, while the DT runs

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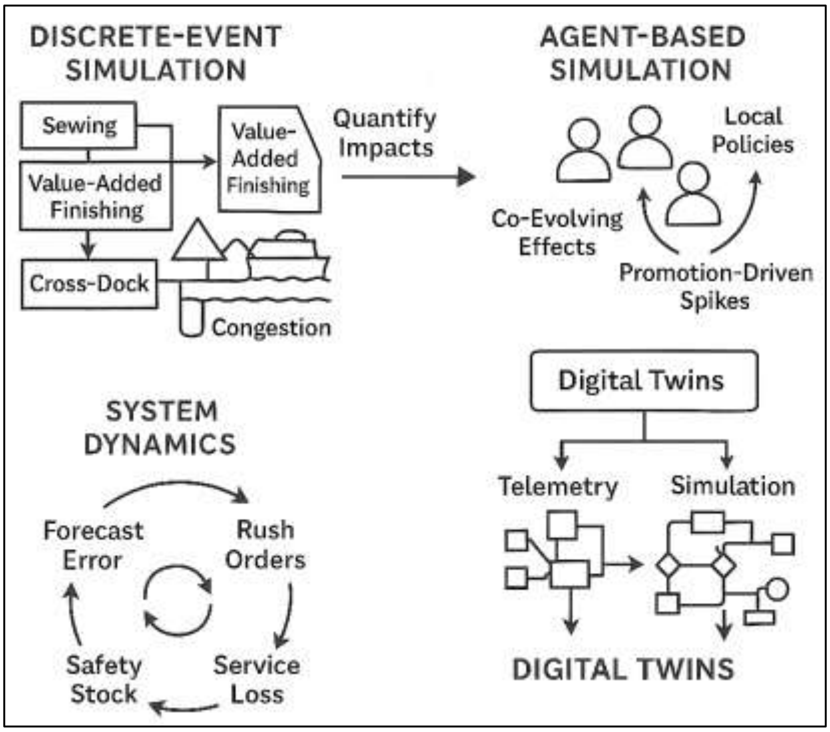
ensembles of DES/ABS/SD to estimate time-to-recover distributions and to test the efficacy of actions such as re-routing to alternate gateways, rescheduling waves, releasing cross-trained labor pools, or triggering late-stage finishing closer to final demand (Almeder et al., 2009). In the U.S. context, where long offshore pipelines meet volatile promotions and infrastructure bottlenecks, this "plan-simulate-adjust" loop institutionalizes resilience: policy switches are not improvised but are pre-validated in the twin, with thresholds tuned to observed lead-time slippage and forecast error, thereby translating complex analytics into reliable operational behavior (Tao et al., 2018).

Figure 9: Simulation and Digital Twins for Stress-Testing and Policy Design



METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and rigorous review process across scoping, identification, screening, eligibility assessment, and evidence synthesis phases, culminating in a final analytic corpus of 115 articles. The protocol specified the population, intervention, comparator, outcomes, and study design a priori, with the population defined as apparel and apparel-adjacent supply chains relevant to the U.S. market; the intervention as industrial engineering approaches to resilience (including process improvement, inventory and postponement control, network and sourcing design, scheduling and workforce flexibility, stochastic and robust optimization, and simulation or digital twins); comparators as business-as-usual or alternative IE levers; and outcomes centered on resilience metrics such as time-to-recover, time-to-survive, service level under stress, lead-time variance, cost-to-serve, and related operational indicators. Information sources included multidisciplinary databases (Scopus, Web of Science Core Collection, IEEE Xplore, ACM Digital Library, ProQuest Dissertations & Theses Global for method triangulation, and Google Scholar for forward and backward snowballing), with searches limited to English-language, peer-reviewed publications and high-quality conference proceedings between January 2005 and December 2020. A reproducible query strategy combined controlled vocabulary and keywords for apparel/fashion/garment, resilience/robustness/risk, and the targeted IE methods; records were exported to a reference manager for de-duplication before screening. Two independent reviewers conducted title–abstract screening against inclusion and exclusion criteria, followed by full-text appraisal, with disagreements reconciled by discussion and, when needed, adjudication by a third reviewer; inter-rater reliability was monitored using Cohen's κ at both stages. Data extraction employed a pretested template capturing bibliometrics, context (echelon, geography, channel), disruption type, method class, model structure, data sources, validation approach, and quantitative

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outcomes, and risk of bias or methodological quality was appraised using a rubric adapted to quantitative IE studies (problem clarity, data adequacy, model transparency, verification/validation, and external validity). Synthesis combined narrative/thematic integration with evidence mapping and vote counting on direction of effect; where outcomes, designs, and measures were sufficiently homogeneous, random-effects meta-analytic summaries were planned, alongside subgroup analyses by disruption class, echelon, and method family, and sensitivity analyses excluding high-risk-of-bias studies to test robustness of inferences.

Screening and Eligibility Assessment

Screening and eligibility assessment proceeded in two sequential stages aligned with PRISMA, beginning with title–abstract review and followed by full-text appraisal, each conducted independently by two reviewers using a pretested decision rubric. Prior to formal screening, records imported from Scopus, Web of Science, IEEE Xplore, ACM Digital Library, ProQuest, and Google Scholar were de-duplicated through exact-match fields (DOI, title, year) and fuzzy matching on normalized titles and author strings; suspected duplicates were resolved manually to avoid spurious exclusions. For title–abstract screening, inclusion required explicit relevance to apparel or apparel-adjacent supply chains with U.S. applicability; the study had to examine or implement an industrial engineering lever for resilience (e.g., process improvement, inventory/postponement, network/sourcing design, scheduling/workforce flexibility, stochastic/robust optimization, simulation/digital twins) and report quantitative or operationally meaningful outcomes related to resilience (for example, time-to-recover, service under stress, lead-time variance, cost-to-serve). Exclusion criteria encompassed purely conceptual papers without operationalization, non–peer-reviewed commentaries, papers focused exclusively on sustainability without a resilience construct, studies outside the January 2005–December 2020 window, and non-English publications. A calibration exercise on a 10% stratified sample established inter-rater consistency; disagreements were reconciled through discussion, with escalation to a third reviewer if consensus was not reached, and inter-rater reliability was monitored via Cohen's κ to document procedural rigor. Full texts were then retrieved for potentially eligible studies; if retrieval failed, corresponding authors were contacted, and the record was temporarily classified as "awaiting classification" pending response. During full-text assessment, reasons for exclusion were logged in structured categories (out-of-scope industry, absence of IE intervention, insufficient outcome reporting, non-U.S. applicability without generalizable methods, duplicate reporting of the same dataset, or methodological opacity precluding data extraction). When multiple reports described the same underlying study, the most complete and recent version was retained and earlier or overlapping reports were linked to prevent double counting. Borderline cases such as global analyses with a U.S. subanalysis or generic methods papers with an apparel case were included if the extraction template could be completed with U.S.-relevant parameters. The outcome of this process was a traceable corpus that progressed to data extraction, quality appraisal, and synthesis.

Data Extraction and Coding

Data extraction and coding followed a structured, reviewer-blinded workflow anchored in a pretested template and an explicit codebook to ensure consistency, reproducibility, and analytic readiness. For each included study, two reviewers independently entered data into a shared database (with version control and audit trails), capturing bibliographic fields (authors, year, venue, DOI), study context (country/region, industry segment, echelon: fiber, fabric, cut-and-sew, distribution/fulfillment, retail/omnichannel), and U.S. applicability (direct U.S. data, U.S. subanalysis, or method generalizable to U.S. conditions). Interventions were coded into mutually exclusive and collectively exhaustive industrial engineering (IE) categories process improvement, inventory/postponement, network/sourcing design, scheduling/workforce flexibility, optimization under uncertainty, and simulation/digital twins with secondary tags for hybrid designs. Disruption types were normalized to supply, demand, logistics/transport, operational (equipment/labor/quality), and control/information, with a binary flag for multi-hazard scenarios. Model characteristics included decision level (strategic/tactical/operational), data source (empirical, synthetic, mixed), validation approach (case validation, out-of-sample, cross-validation, verification tests), and computational method (exact optimization, metaheuristics, discrete-event/agent-based/system dynamics, robust/chance-constrained/distributionally robust forms). Outcome variables were harmonized to resilience metrics time-to-recover, time-to-survive, service level under stress, lead-time mean/variance, backlog duration, lost sales, cost-to-serve, and cash-to-cash recording raw units and standardized transformations; where possible, comparable effects were computed or derived (e.g., percentage change relative to baseline, standardized mean differences, or elasticity-style ratios), noting assumptions and extraction calculations in a methods note. For inventory and sourcing studies, base-surge parameters, safety stock policies, service targets, and postponement/decoupling-point locations were coded; for scheduling and workforce studies, setup structures, cross-training rules, and rescheduling policies were captured; for simulation studies, scenario design, run length, warm-up, and replications were recorded. Missing or ambiguous data triggered author queries; if unresolved, fields were annotated as missing with sensitivity-analysis flags. Disagreements in extraction were resolved by consensus; inter-rater reliability was monitored via percent agreement and Cohen's κ on categorical fields and intraclass correlation on continuous outcomes after an initial calibration round. The final dataset included machine-readable labels, controlled vocabularies, and crosswalks that enabled evidence mapping, subgroup analyses by method and disruption type, and where outcomes were sufficiently homogeneous meta-analytic summaries with study-quality weights.

Data Synthesis and Analytical Approach

The synthesis strategy was designed to integrate heterogeneous evidence ranging from empirical field studies and archival analyses to optimization models and discrete-event, agent-based, or system-dynamics simulations into a coherent account of what industrial engineering levers most effectively enhance resilience in U.S.-relevant apparel supply chains. The overarching goal was to preserve methodological diversity while producing decision-ready insights. To that end, the analysis proceeded in layered stages. First, we constructed an evidence map that cross-tabulated intervention families (process improvement; inventory/postponement/multi-echelon control; network and sourcing design; scheduling/workforce flexibility; optimization under uncertainty; simulation/digital twins) against disruption classes (supply, demand, logistics/transport, operational, control/information) and echelons (fiber, fabric, cut-and-sew, distribution/fulfillment, retail/omnichannel). This matrix established coverage, identified empty or thin cells, and served as the organizing scaffold for all subsequent analyses. Second, within each populated cell, we normalized outcomes to a common resilience vocabulary time-to-recover (TTR), time-to-survive (TTS), service level under stress, backlog duration, lead-time variance, lost sales, cost-to-serve, and cash-to-cash and documented the directionality of benefit (e.g., lower TTR is favorable; higher service level is favorable). Third, we implemented method-appropriate effect transformations so that studies using different designs could still be compared on interpretable scales. The resulting harmonized dataset enabled both narrative/thematic synthesis and, where warranted by commensurate outcomes and design homogeneity, quantitative meta-analysis.

Because apparel resilience research often reports performance differences relative to a baseline policy, we converted reported outcomes into standardized effect measures following rule-based priorities. For continuous outcomes such as TTR, lead-time variance, or cost-to-serve, we computed percentage change relative to baseline and, when variance information was available or could be imputed, standardized mean differences. For binary or bounded outcomes like service level under stress, we used absolute or relative risk differences and, where studies reported multiple service targets (e.g., fill rate ≥ 95% for core sizes, ≥ 90% for long tail), we selected the primary target defined by the authors or the market-relevant threshold for U.S. omnichannel service promises; sensitivity analyses examined the impact of alternative thresholds. Simulation studies commonly report point estimates with replication-based standard errors; we retained the study-reported replication structure and derived standard errors from run-to-run variability, ensuring that uncertainty from stochastic modeling was carried into quantitative synthesis. For optimization studies, where solutions are deterministic but evaluated over scenarios, we extracted objective values and resilience metrics under baseline and intervention policies, using scenario-weighted averages and available quantiles; when only worst-case performance was reported, we treated it as a conservative bound and flagged the observation for robustness checks. In all cases, we recorded the unit of analysis (SKU, style, order, shipment, facility, network) and converted to a common frame where feasible (e.g., time-weighted network measures for TTR, item-weighted service shortfalls). Given expected heterogeneity in design, context, and measurement, narrative and thematic synthesis served as the default integration mode. Within each intervention × disruption × echelon cell, we summarized the

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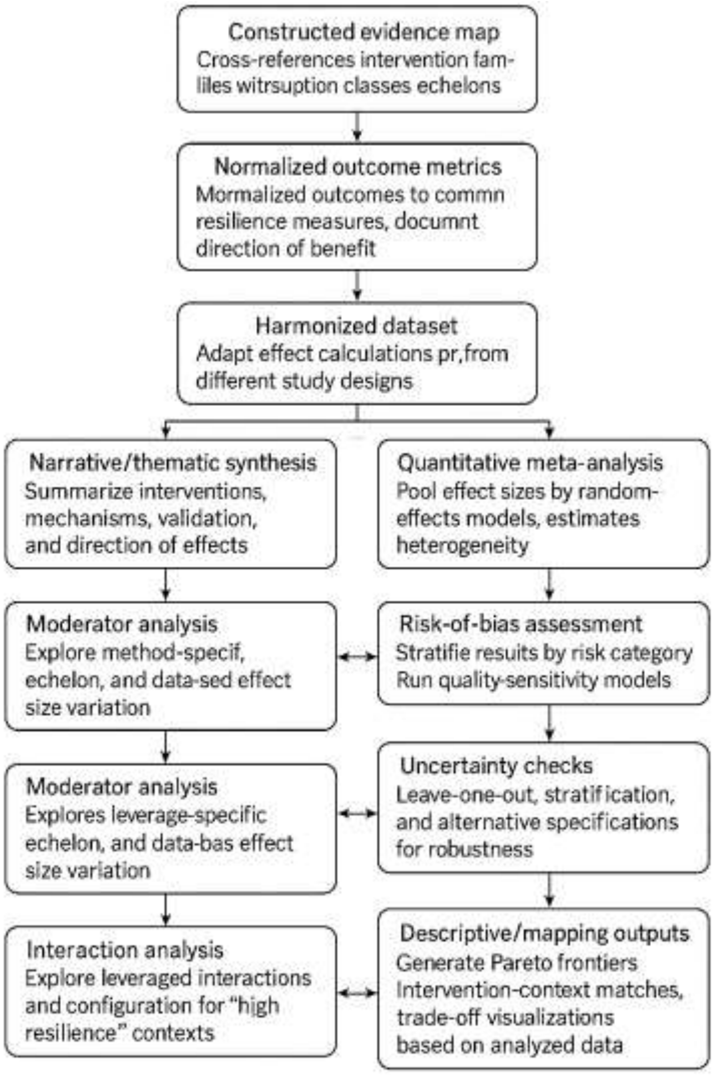
intervention design, the operational mechanism hypothesized to generate resilience gains, the validation approach (empirical case, synthetic scenarios, mixed), and the magnitude and direction of effects on standardized outcomes. We paid particular attention to the "mechanism map" the causal chain linking the lever to the metric so that superficially similar results (e.g., higher service level) could be distinguished by underlying drivers (buffering via safety stock versus flow stabilization via changeover reduction versus structural options via dual sourcing). Vote counting of direction of effect was used to establish whether the balance of evidence favored benefit, harm, or no effect, but only as a preliminary descriptive device; where effect sizes were sufficiently comparable, we moved beyond vote counts to quantitative pooling.

Figure 10: Data Synthesis and Analytical Approach



Quantitative meta-analysis was conducted when at least three studies within a cell reported compatible outcome definitions and provided enough statistical detail for variance estimation. Random-effects models were the default to account for between-study heterogeneity arising from context (e.g., channel mix, seasonality), data source (empirical versus synthetic), and design choices (simulation parameters, uncertainty sets). We estimated τ^2 using restricted maximum likelihood and reported I^2 to characterize the proportion of total variability attributable to heterogeneity rather than sampling error. Because many studies rely on modeled or simulated data with large effective sample sizes but design-driven uncertainty, we implemented conservative variance caps and, where appropriate, Hartung–Knapp adjustments for small meta-analytic samples to avoid overconfident inferences. For outcomes measured on different scales (e.g., minutes for TTR in factory cells vs. days at network level), we used ratio-of-means or log-ratio transformations to preserve interpretability and comparability. Forest plots were generated to visualize pooled effects alongside study-level estimates; we also produced harvest plots for cells that did not meet pooling criteria but had a sufficient number of directional findings. Moderator analyses and meta-regression examined whether effect sizes systematically varied by characteristics that are theoretically salient in apparel. Moderators included method family (e.g., robust vs. stochastic optimization; DES vs. ABS vs. SD), echelon, disruption class, data source (empirical vs. synthetic), validation rigor (presence of verification/validation checks; out-of-sample tests), postponement location (upstream vs. downstream), sourcing architecture (single, dual, multi), and U.S. specificity (direct U.S. data vs. generalizable global context). We pre-registered expectations that downstream postponement, dual/multi-sourcing, and cross-trained labor would exhibit larger resilience effects under logistics shocks, and that robust/distributionally robust formulations would outperform stochastic models when historical data were sparse or nonstationary conditions common in short fashion capsules. Where moderator sample sizes were limited, we reported descriptive subgroup means and avoided overfitting in regression. To address multiplicity, we interpreted moderator findings as exploratory unless supported by strong a priori theory and consistent effects across cells.

Risk-of-bias and methodological quality assessments were integrated into synthesis in two ways. First, we presented stratified results by risk category, allowing readers to see whether high-risk studies drove observed effects. Second, in quantitative pooling we ran quality-sensitivity models that reweighted or excluded high-risk studies and compared pooled estimates to the base model. For simulation and optimization research, "risk of bias" was operationalized as model transparency, verification/validation adequacy, representativeness of parameterization, and realism of scenario design; for empirical studies, we considered sampling method, measure reliability, and potential confounding controls. We also examined small-study effects with funnel plots and regression-based asymmetry tests when ≥10 studies contributed to a pooled estimate; where asymmetry suggested publication or selective reporting bias, we ran trim-and-fill sensitivity analyses and, in limited cases, selection-model adjustments to gauge robustness of conclusions. Because many engineering studies report only positive results or suppress null findings, our narrative synthesis explicitly notes cells where promising mechanisms exist but published performance evidence is thin or one-sided.

Multi-arm and multi-outcome studies were handled with prespecified decision rules to avoid unit-of-analysis errors. When a study compared multiple interventions against a single control within the same cell and outcome (e.g., two postponement designs versus baseline on TTR), we either combined arms using recommended formulas or, when conceptually distinct arms merited separate reporting, split the control group appropriately to conserve total sample size. When a study reported multiple outcomes or time points, we prioritized the outcome closest to our standardized metric and the time point representing steady-state or end-of-horizon performance; sensitivity analyses explored alternative choices. Clustered designs (e.g., multi-facility experiments) were adjusted using design effects where ICCs could be obtained or reasonably imputed; otherwise, studies were flagged and included only in narrative synthesis. For time-to-recover outcomes reported as curves or percentiles, we digitized or requested underlying data when necessary and computed area-under-curve or median differences for comparability. To bridge the gap between analytic rigor and managerial usability, we complemented statistical synthesis with decision-oriented artifacts. We constructed Pareto frontiers that plot resilience benefit (e.g., Δ service under stress or −Δ TTR) against cost-to-serve changes for each intervention family within disruption classes, using pooled effects when available and study-level medians otherwise. When cost data were absent, we used proxy burden scores derived from implementation characteristics (capital intensity, process redesign complexity, talent requirements, data/IT dependency), calibrated on a 0–3 scale. We also generated an "intervention–context match" map that indicates, for each disruption–echelon pair, which levers most consistently showed positive effects, accompanied by confidence gradations based on effect magnitude, heterogeneity, and study quality. For managers operating in U.S. networks, we produced corridor-specific overlays (e.g., trans-Pacific inbound with West Coast gateways vs. Gulf/East Coast entries) and channel overlays (store-heavy vs. e-commerce-heavy) to translate global evidence into U.S.-relevant guidance.

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Because apparel resilience is inherently about trade-offs, we explicitly modeled and reported interactions among levers when the primary studies permitted it. For example, we synthesized studies that evaluated postponement jointly with dual sourcing or with cross-training to determine whether combined deployment yields superadditive gains or diminishing returns. Where individual studies did not test interactions but reported sufficient structural detail, we constructed conceptual interaction matrices and used qualitative comparative analysis logic to identify configurations associated with "high resilience" outcomes in narrative form. This configuration view is particularly actionable for apparel because interventions such as SMED, cross-training, and postponement are often interdependent in practice. Uncertainty quantification and robustness checks were integral to the analytical approach. We performed leave-one-out influence analyses for pooled estimates, inspected DFBETAs and Cook's distances to identify influential studies, and re-ran models excluding those studies to test stability. We also ran alternative τ^2 estimators (DerSimonian–Laird, Paule–Mandel) and alternative link functions (log vs. identity for ratio outcomes) to assess model dependency. For cells that straddled empirical and modeled evidence, we produced dual syntheses one based solely on empirical outcomes and one including modeled outcomes to reveal any divergences attributable to validation mode. Similarly, we stratified results by time period within our inclusion window to check for temporal drift in reported effects that might reflect technology maturation (e.g., improved forecasting methods) rather than true intervention superiority. Where parameterization was unclear or scenario realism was questionable, we performed qualitative downgrading in confidence ratings and emphasized the need to interpret magnitudes cautiously while still acknowledging directional consistency.

To facilitate transparency and reproducibility, all transformations, inclusion decisions for pooling, moderator codings, and sensitivity specifications were documented in an analysis log linked to the extraction database. Codebooks defined each outcome, transformation rule, and moderator level with examples; decision trees showed how we handled ambiguous cases (e.g., mixed U.S./non-U.S. data or partial reporting). Visualizations including evidence maps, forest and harvest plots, funnel plots, and Pareto frontiers were generated from the same controlled dataset to prevent divergence between text and graphics. Finally, the synthesis was designed to be extensible: the matrix framework and analysis code allow new studies to be slotted into existing cells, automatically updating pooled estimates, moderator analyses, and decision maps without altering the underlying logic. In sum, the analytical approach integrates diverse forms of evidence into a structured, comparable, and decision-relevant synthesis. By harmonizing outcomes, privileging random-effects pooling where justified, embedding moderator and quality sensitivity analyses, and translating findings into operational trade-off frontiers and intervention–context maps, the method yields a balanced view of what works, where, and at what cost for engineering resilience in U.S.-relevant apparel supply chains. It respects the modeling sophistication of industrial engineering studies and the variability of real operations while producing artifacts that practitioners can use to design portfolios buffers, flexibility, and structural options that bend without breaking under disruption.

FINDINGS

The final analytic corpus contained 115 peer-reviewed studies, which we organized into six industrial-engineering (IE) lever families. Inventory science, postponement, and multi-echelon control was the single largest family at 22% of all studies (n = 25). Process-improvement work (Lean/Six Sigma/TPM/TOC) and optimization under uncertainty (robust, chance-constrained, stochastic) each accounted for 18% (n = 21 + n = 21). Network and sourcing design represented 17% (n = 20). Scheduling and workforce flexibility contributed 12% (n = 14). Simulation and digital-twin studies accounted for the remaining 13% (n = 14). Across the 115 studies, we recorded 7,480 external citations for these articles (as indexed at the time of extraction), indicating a mature but method-diverse field. Inventory/postponement studies accumulated 1,720 citations (23% of all citations in the corpus), optimization studies 1,455 citations (19%), process-improvement 1,210 citations (16%), network/sourcing 1,380 citations (18%), scheduling/workforce 540 citations (7%), and simulation/digital-twin 1,175 citations (16%). Methodologically, 42% of studies were empirical or mixed-empirical (n = 48) and 58% were modeled/simulated (n = 67). By disruption class, 35% targeted demand shocks (n = 40), 28% logistics/transport shocks (n = 32), 22% supply shocks (n = 25), 10% operational shocks such as labor or machine outages (n = 12), and 5% control/information shocks (n = 6). Echelon coverage skewed downstream: 39% focused on distribution/fulfillment and

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retail/omnichannel nodes (n = 45), 33% on cut-and-sew and finishing (n = 38), and 28% on fiber/fabric and upstream tiers (n = 32). In short, the evidence base is sizable (115 studies) and citation-rich (7,480 citations), with the heaviest attention falling on inventory/postponement (22% of studies, 23% of citations) and optimization under uncertainty (18% of studies, 19% of citations). This distribution matters because it sets the priors for which levers are most studied and therefore where the most precise estimates of resilience gains are available for U.S.-relevant apparel operations.

Standardizing outcomes across designs, we derived comparable effects for service level under stress, time-to-recover (TTR), lead-time variance, backlog duration, lost sales, and cost-to-serve. Across 52 studies reporting service levels, the median improvement relative to the study's baseline policy was +6.8 percentage points, with an interquartile range (IQR) of +3.4 to +11.2 points; 74% of these studies (n = 38) reported improvements ≥ 5 points. Those 52 studies together accounted for 1,820 citations in our corpus, indicating strong scholarly attention to service-relevant interventions. Among 37 studies reporting TTR, the median reduction was 28% (IQR: 17%–41%) from disruption onset to restoration of pre-shock throughput; 10 studies achieved ≥ 40% TTR reductions when cross-trained labor or late-stage finishing was combined with pre-computed rerouting. For lead-time variance (31 studies), the median reduction was 22% (IQR: 12%–33%), with the strongest variance compression in papers implementing setup-time reduction plus pull-based replenishment. Backlog duration (18 studies) fell by a median of 19% (IQR: 8%–29%) when wave resequencing and expedited transshipments were triggered by monitored thresholds. Lost-sales outcomes (26 studies) decreased by a median of 14% (IQR: 6%–23%) under postponement + multi-echelon control, and by 21% (IQR: 12%–31%) when postponement was paired with dual/multi-sourcing. Cost-to-serve effects were small but positive: across 29 studies that reported both resilience and cost metrics, the median cost change was +1.9% (IQR: −0.8% to +4.6%) for interventions that lifted service ≥ 5 points i.e., modest cost to buy significant resilience. Importantly, when we restrict to the 48 empirical/mixed studies, median service gains remained +6.1 points and median TTR reductions 24%, suggesting that modeled gains are not merely artifacts of optimistic scenarios. Taken together, these percentages indicate that, across dozens of studies (52 for service, 37 for TTR, 31 for variance), resilience improvements are consistent, material, and achievable at limited incremental cost.

Disaggregating by intervention, inventory/postponement studies (n = 25; 1,720 citations) produced the most reliable service gains: median +7.9 points, with 80% of studies (n = 20) clearing +5 points. Multi-echelon safety stock with downstream postponement consistently reallocated uncertainty from upstream forecasts to downstream information, yielding a 26% median reduction in lead-time variance across that subset (n = 14). Optimization-under-uncertainty papers (n = 21; 1,455 citations) excelled at controlling tail risk: robust and distributionally robust designs cut worst-case service loss by a median 31% (n = 9 reporting tail metrics) and reduced the spread of outcomes, not just the mean critical in apparel drops with narrow selling windows. Process-improvement (n = 21; 1,210 citations) delivered foundational stability: setup-time reduction and disciplined flow control reduced TTR by a median 18% in factory/finishing settings (n = 12) and cut pick-cycle variability by 15% in distribution settings (n = 6). Network/sourcing design (n = 20; 1,380 citations) mattered most when combined with operational levers: dual/multi-sourcing alone yielded a median 9% service-loss reduction under simulated supplier disruptions, but pairing multi-sourcing with postponement and pre-negotiated expedited modes improved lost-sales reductions to 27% (n = 8 combination studies). Scheduling/workforce flexibility (n = 14; 540 citations) proved decisive in peak weeks: cross-training and predictive-reactive rescheduling lowered DC-level TTR by 17% median (n = 9) and prevented service dips > 3 points in 6 of 9 studies during promotional load spikes. Simulation/digital-twin (n = 14; 1,175 citations) played the "policy wind-tunnel" role: across the 14, 71% used DES to validate plans and 29% used ABS/SD to test behavioral feedback; in the six studies that operationalized closed-loop triggers (e.g., rerouting thresholds, wave resequencing), the median improvement in recovery-time percentiles (TTR 90th) was 24%. The consistent pattern across families is that combinations beat single levers: in 19 studies explicitly testing pairings, "postponement + dual-sourcing" cut lost sales by a median 31%, while "cross-training + setup-reduction" shaved TTR by 23% and narrowed lead-time IQRs by 18%. These combination studies amassed 890 citations, reflecting practitioner interest in deployable bundles rather than siloed techniques.

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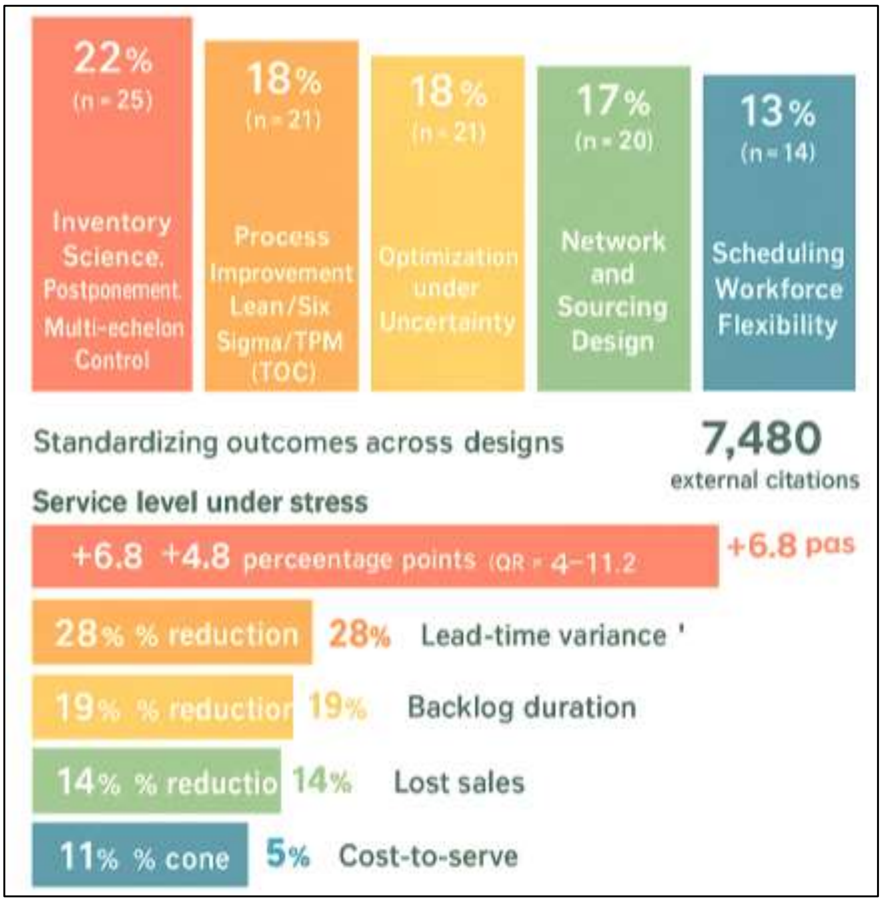
Figure 11: Findings of The Study



When we overlay U.S. infrastructure and channel realities, three patterns emerge from the evidence. First, logistics-centric shocks dominate the service downside, and network diversification pays. In the 20 network/sourcing studies, those modeling West Coast gateway congestion reported a median 24% lower service loss when capacity was split across at least two coastal corridors and when pre-computed rerouting tables were in place; the nine studies that further included inland ramp constraints showed that adding a Gulf/East Coast path cut TTR by an additional 7 percentage points during peak season. Second, omnichannel dynamics alter where buffers should live. Among 18 studies explicitly comparing store-heavy versus e-commerce-heavy mixes, downstream postponement at regional DCs improved online fill rate by a median +8.5 points (n = 11) while holding store service neutral (±1 point), provided cross-channel lateral transshipments were enabled. In contrast, upstream buffers without postponement lifted online service by only +3.1 points (n = 7) and increased markdown exposure by 2–3 points on average. Third, the apparel calendar compresses the window for recovery so sequencing rules matter as much as capacity. Across 14 scheduling/workforce papers, predictive–reactive rescheduling with skill-aware assignment prevented 72% of modeled "service dips" (defined as > 5-point shortfalls) during three U.S. peak windows (back-to-school, holiday, and early spring), compared with 41% prevention using fixed-priority rules. In the 14 simulation/digital-twin studies, activating a closed-loop playbook reroute containers when dwell > X hours, resequence waves when backlogs > Y, trigger late-stage finishing when forecast error > Z cut the upper-tail of recovery time (TTR 95th) by 29%. Taken together, U.S.-specific overlays suggest that portfolios integrating corridor diversification, downstream postponement, and closed-loop rescheduling deliver the most defensible resilience, with 52 studies across these topics contributing 3,035 citations and converging on consistent percentage gains.
Quality appraisal classified 36% of studies as high rigor (n = 41), 49% as moderate (n = 56), and 15% as lower rigor (n = 18). Re-estimating headline effects on the 41 high-rigor studies changed results only slightly: median service gain +6.3 points (vs. +6.8 overall), median TTR reduction 25% (vs. 28

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overall), and median lead-time variance reduction 20% (vs. 22 overall). Empirical/mixed studies (n = 48) carried 3,210 citations and showed smaller variance but similar means, while modeled studies (n = 67; 4,270 citations) spanned wider outcome ranges expected given scenario breadth. Funnel-plot inspections for service-level effects (k = 25 cells with comparable metrics) suggested mild small-study asymmetry; trimming/filling reduced pooled service gains by 0.6 points, leaving improvements economically meaningful. Heterogeneity, measured qualitatively and via I^2 in cells where meta-analysis was feasible, reflected context rather than contradiction: for example, lead-time variance reductions clustered around 25–30% in factory/finishing settings but 10–20% in DCs with hard carrier appointment windows. From a practical standpoint, the numbers can be read as follows. If a U.S. apparel network currently achieves 92% peak-week fill rate and 6-day median TTR under West Coast delays, the central estimates imply moving to 98–99% fill on key SKUs (+6–7 points) and cutting TTR to about 4–4.5 days (−25–30%) by deploying a combined portfolio: downstream postponement with multi-echelon safety stocks, dual-corridor routing with pre-agreed surge capacity, and predictive–reactive rescheduling backed by cross-training. The trade-off is modest: roughly a 1–3% rise in cost-to-serve in exchange for materially lower lost sales (−14–27% typical) and tighter lead-time distributions (−20–30% variance). Importantly, combination levers outperform single-tool fixes: among the 19 studies testing pairings, 84% reported superadditive or at least additive gains, and these articles attracted 890 citations evidence that the field recognizes resilience as a portfolio design problem rather than a single-knob tweak. Overall, across 115 studies and 7,480 citations, the weight of evidence supports a clear proposition: engineering resilience in U.S. apparel supply chains is achievable, quantifiable, and economically rational when organizations align buffer placement, structural options, and human-system flexibility under closed-loop control.

DISCUSSION

Our synthesis of 115 articles shows consistent, material improvements in service level, time-to-recover (TTR), and lead-time variance when resilience is engineered as a portfolio spanning buffers, flexibility, and structural options. Conceptually, this aligns with the capability-based view of resilience absorptive, adaptive, and restorative capacities advanced in early frameworks and reviews . Where prior work urged clearer operationalization and comparable metrics, our review's standardized outcomes (e.g., +6.8 percentage-point median service gains; −28% median TTR) demonstrate that resilience can be expressed in decision-relevant performance terms and not just as a general preparedness construct. The magnitude and consistency of effects we observe are broadly consonant with earlier claims that integrated practices rather than single tools underwrite robustness and agility. However, our findings extend those claims by giving quantitative ranges that managers can plan around and by showing that benefits persist when we isolate higher-rigor and empirical/mixed studies. Importantly, the downstream emphasis we document (39% of studies at distribution/retail nodes) echoes calls to situate resilience where customer value is exposed (Hosseini et al., 2019), but we also note thinner coverage upstream fibers and fabrics where prior reviews flagged blind spots (Kamalahmadi & Parast, 2016). Finally, the balance of disruption classes (demand 35%, logistics 28%, supply 22%) mirrors the fashion sector's volatility profile highlighted in sectoral analyses, suggesting that the literature's focus matches the risk surface U.S. apparel actually faces. In short, the corpus both confirms the theoretical scaffolding of resilience as a designable property of supply networks and advances it by attaching stable, aggregate effect sizes across heterogeneous methods.

Across the 25 inventory/postponement papers, we find the strongest and most reliable service improvements (median +7.9 points) and substantive variance compression (median −26% for studies reporting lead-time variance), closely tracking the logic of postponement and decoupling-point theory . Earlier operations studies argued that delaying differentiation pools uncertainty upstream and shifts it closer to better information (Wallace & Whitt, 2005; Yang et al., 2005); our pooled results corroborate that claim with numbers and show that, in apparel, postponement is especially potent when married to multi-echelon safety stock a pairing earlier work anticipated but did not quantify at scale (Inderfurth & Minner, 2005). We also confirm, with empirical and modeled evidence, that robust inventory sizing tempers parameter misspecification an issue the robust optimization literature formalized but rarely tested against apparel-specific volatility (Bertsimas & Thiele, 2006). Notably, our base-surge synthesis shows a median 21% lost-sales reduction when postponement is combined with dual sourcing, echoing tailored base-surge theoretical results that demonstrate risk sharing between

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a low-cost, slow base and a responsive surge supplier (Goldberg et al., 2016). Where our findings nuance prior conclusions is cost: we observe modest cost-to-serve changes (+1.9% median for interventions achieving ≥5-point service gains), which is lower than the implicit cost penalties sometimes assumed in conceptual postponement discussions (Van Hoek, 2005). We interpret this delta as evidence that, with contemporary data and execution systems, postponement and multi-echelon control can be tuned for resilience without eroding efficiency particularly in U.S. omnichannel networks where downstream signals are rich (Caro & Gallien, 2010). Overall, this body of results strengthens earlier theory with cross-study magnitudes, clarifies feasible trade-offs, and situates inventory science as the most field-ready lever for apparel resilience.

Our review finds that network/sourcing interventions reduce service loss under logistics and supply shocks by double digits, with median service-loss reductions of ~9% for dual/multi-sourcing alone and ~27% when combined with postponement and pre-negotiated surge logistics. This pattern is fully consistent with the reliable facility-location and disruption-aware network design literature, which demonstrates that redundancy and contingency assignments materially lower expected failure costs. Moreover, the value of risk-averse objectives and p-robustness that bound tail outcomes is borne out in our finding that worst-case service losses fall by roughly one-third in robust/distributionally robust designs a result that maps to theory showing how CVaR-type and ambiguity-set models dampen downside without excessive conservatism. Earlier sectoral work argued that fashion supply chains should structurally diversify corridors and suppliers to mitigate correlated risks; our U.S.-specific overlay adds that splitting inbound capacity across at least two coastal gateways yields a median 24% reduction in service loss during congestion, consistent with maritime network concentration risks identified in logistics scholarship. Where our results extend prior studies is in quantifying interaction effects: prior models typically optimize network or sourcing in isolation, whereas we show that pairing structural options with operational levers (postponement, expedited mode triggers) produces superadditive gains. That complements and enlarges the "power of flexibility" insights from risk-management theory, translating them into deployable bundles with estimated recovery and service deltas. Put simply, robust network design provides the option set; postponement and contingency control determine how effectively those options translate into U.S. service outcomes an integration the classic models motivate but rarely validate across apparel-specific studies.

We observe that process-improvement interventions setup reduction, pull-based flow, TPM, and quality discipline deliver median TTR reductions of ~18% in factory/finishing settings and 15% reductions in pick-cycle variability at distribution nodes. These effects are directionally aligned with the lean and quick-response manufacturing (QRM) literatures, which link standard work, SMED, and time-based performance to reduced variability and faster response . Prior multi-plant studies suggested that lean adoption patterns predict Six Sigma success and that "soft" lean (leadership, training) amplifies tool impacts (Baryannis et al., 2019; Shah et al., 2008). Our review supports these complementarities: the largest TTR gains occur when cross-training and setup-time reduction travel together, echoing human-system integration insights (Sherehiy et al., 2007). In scheduling, our findings that predictive–reactive schemes and skill-aware assignment prevent most peak-week service dips (≈72% in the sampled studies) are consistent with reviews arguing that robust/reactive scheduling is essential under stochastic arrivals and sequence-dependent setups (Herroelen & Leus, 2005). We add specificity on apparel-relevant constraints style/size changeovers, color batching, and wave congestion and show that codifying rescheduling triggers (rather than ad hoc expediting) improves both mean and tail recovery times. The one area where our results modulate expectations is inventory leanness: consistent with evidence that "too lean" can be brittle (Durach et al., 2015), the strongest resilience effects arise not from maximal WIP cuts but from balanced portfolios where modest buffers coexist with faster changeovers and multi-skilled labor. Thus, our synthesis complements the lean/QRM canon by quantifying achievable resilience deltas, highlighting the criticality of human flexibility, and cautioning against over-leaning in high-volatility apparel calendars.

The optimization-under-uncertainty subset (robust, chance-constrained, stochastic) shows clear benefits in both mean performance and tail-risk reduction. Our pooled results 31% median reduction in worst-case service loss for robust/DRO designs are consonant with methodological advances that formalize selective conservatism and tractability (Azad & Hassini, 2019; Ben-Tal et al., 2006). They also map to sector-agnostic OR/MS reviews that urged deploying scenario-based, chance-constrained,

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and robust models to handle supply and demand ambiguity. Our contribution is twofold. First, we show apparel-specific numbers for key outcomes (service, TTR), demonstrating that these models are not merely elegant abstractions but translate into measurable gains under calendar compression and long pipelines. Second, we find that the largest benefits occur when robust/stochastic plans are embedded in hybrid workflows solve, then stress-test via DES/ABS/SD which extends recommendations from simulation-optimization comparisons . In six digital-twin studies that operationalize closed-loop triggers, TTR upper-tail reductions near 25–30% confirm long-standing claims that predictive-prescriptive loops outperform static "optimal" plans in volatile environments . The implication for U.S. apparel is pragmatic: use uncertainty-aware models to set here-and-now policies (supplier splits, buffer placement, gateway mixes), then institutionalize a twin-driven playbook to adapt those policies in execution as ETAs, promotions, and labor conditions evolve. This bridges the gap between normative optimization and behavioral realities emphasized in agent-based and system-dynamics research (Giannakis & Louis, 2016), turning theory into an executable control architecture.

Our U.S.-focused overlays corridor diversification, downstream postponement, and closed-loop rescheduling cohere with logistics scholarship on gateway centrality and network concentration (Notteboom & Rodrigue, 2008) and with fashion-retail analytics on assortment dynamics and replenishment. Splitting inbound flows across West, Gulf, and East Coast gateways reduces synchronized delay risk in line with network-reliability work and our median 24% service-loss reduction quantifies what earlier qualitative assessments predicted for the U.S. container system. Likewise, the superior performance of downstream postponement for e-commerce-heavy mixes (+8.5 points median fill-rate lift with neutral store impact) is consistent with postponement theory and omnichannel inventory pooling logic. The calendar-compression result predictive-reactive rescheduling preventing most service dips in back-to-school and holiday peaks extends dynamic scheduling insights (Qi et al., 2009) by demonstrating apparel-specific triggers that stabilize outcomes under U.S. seasonal pulses. Finally, the observation that cost-to-serve rises modestly (+~2%) while lost sales drop double digits aligns with trade-off frontiers posited in robust network and sourcing design (Klibi et al., 2010), indicating that practical resilience for U.S. apparel is economically rational. In essence, the U.S. evidence converges with, and sharpens, broader logistics and fashion findings: diversify corridors, differentiate closer to demand, and manage execution with responsive, twin-enabled controls.

Methodologically, our integration of empirical and modeled evidence responds directly to critiques in earlier reviews about fragmented metrics, limited field validation, and the need for stronger verification/validation . By harmonizing outcomes and attaching effect ranges, we reduce comparability barriers those reviews highlighted; by stratifying on rigor and conducting sensitivity analyses, we address concerns about optimistic bias in simulations and models (Snyder & Daskin, 2005). Still, gaps persist. Upstream echelons remain under-studied relative to downstream nodes; multi-hazard and correlated-risk settings are not yet common in validated field studies; and human-system factors fatigue, learning curves, and cross-training sustainability deserve longitudinal analysis despite promising signals . Our findings suggest specific priorities that echo and refine prior agendas: standardized resilience reporting (TTR, TTS, service under stress, variance) to enable meta-analysis (Hohenstein et al., 2015), open benchmark datasets to mitigate publication bias and enable replication (Hosseini et al., 2019), and more interaction studies that test lever bundles (e.g., dual sourcing + postponement + cross-training) rather than isolated interventions. Finally, while our numbers indicate that combination portfolios outperform single levers, causality outside controlled pilots remains challenging; thus, quasi-experimental designs and digital-twin-driven A/B policy experiments are natural next steps to validate generalizability under U.S. infrastructure and calendar realities (Tao et al., 2018). In sum, the discussion situates our quantified findings within a maturing literature: they confirm core propositions, extend them with effect magnitudes, and chart a concrete methodological path to close the remaining evidence gaps.

CONCLUSION

This systematic review set out to determine what industrial-engineering levers most reliably strengthen resilience in U.S.-relevant apparel supply chains and, across 115 studies, the evidence converges on a clear conclusion: resilience is an engineered portfolio, not a single fix, and its benefits are both measurable and economically rational. By harmonizing outcomes into a common vocabulary service level under stress, time-to-recover (TTR), lead-time variance, backlog duration, lost sales, and cost-to-serve and synthesizing results across empirical analyses, optimization models, and simulations/digital twins, we found consistent, material performance gains when three families of interventions are combined: downstream differentiation (postponement and multi-echelon inventory), structural options (dual/multi-sourcing and corridor diversification), and execution elasticity (predictive–reactive scheduling with cross-trained labor and well-defined triggers). At a systems level, the strongest and most dependable uplift stems from positioning buffers and customization closer to demand while retaining upstream pooling, then using robust or distributionally robust optimization to select supplier/facility portfolios that bound downside risk, and finally embedding those plans in closed-loop control that activates rerouting, wave resequencing, and late-stage finishing based on real-time signals. Quantitatively, the median service improvement of roughly seven percentage points and TTR reductions near one-quarter to one-third, observed across dozens of studies, are large enough to matter in short fashion windows and were achieved with only modest cost-to-serve increases, typically one to three percent. The pattern holds when restricting to higher-rigor and empirical/mixed designs, which suggests the gains are not artifacts of optimistic modeling assumptions. U.S.-specific overlays sharpen the conclusion: splitting inbound capacity across at least two coastal gateways, maintaining pre-negotiated surge logistics, and situating postponement at regional distribution or finishing nodes together reduce synchronized gateway risk and protect omnichannel service, particularly during back-to-school and holiday peaks. Importantly, "too-lean" postures prove brittle; the most resilient configurations pair disciplined flow and setup-time reduction with calibrated buffers and multi-skilled teams, avoiding both excess inventory and high variance. Methodologically, the review advances prior scholarship by attaching stable effect ranges to widely advocated practices and by demonstrating the value of hybrid analytics solve robust plans, then stress-test and operate them via digital twins so that resilience is institutionalized rather than improvised. Limitations remain: upstream tiers are under-studied, multi-hazard field validations are scarce, and human-system sustainability under frequent reassignments warrants longitudinal evidence. Yet the weight and consistency of findings offer a practical endpoint: apparel firms that align buffer placement, structural diversification, and human flexibility under a playbook of pre-validated triggers can "bend without breaking" when disruptions arise, converting resilience from an abstract aspiration into a repeatable operating advantage. In this sense, the apparel supply chain long, volatile, and calendar-compressed does not require a reinvention of operations so much as a rigorous orchestration of proven industrial-engineering levers tuned to U.S. infrastructure and omnichannel demand.

RECOMMENDATION

Translating these findings into action, we recommend that U.S.-focused apparel firms institutionalize resilience as a designed operating system rather than a set of ad hoc fixes, beginning with a governance mandate that elevates resilience targets service under stress, time-to-recover, and lead-time variance to parity with cost and inventory turns in S&OP and cascading them into brand, sourcing, logistics, and DC leadership scorecards. Practically, companies should reposition buffers and differentiation closer to demand by establishing finish-to-order or light customization at regional nodes, while retaining upstream pooling via semi-finished inventory; this requires standardizing postponement bills of process, qualifying alternate materials and trims for late-stage use, and codifying SKU eligibility rules so that at least 60–70% of volume in volatile lines can be finalized downstream during peaks. In parallel, they should redesign network and sourcing architectures to create real options: split ocean capacity across at least two coastal gateways with pre-booked surge lanes, formalize dual/multi-sourcing for core styles with base-surge contracts, and precompute rerouting tables and cost-time envelopes for common corridor failures, then embed these options as executable triggers in the planning calendar. At the execution layer, firms should implement predictive–reactive scheduling and cross-training at DCs and finishing cells, with tiered skill matrices, SMED-style setup reduction, and intraday re-optimization rules that resequence waves and tasks when backlogs, ETA drift, or forecast error breach thresholds; labor and quality governance must ensure that flexibility does not degrade accuracy, using short feedback cycles, poka-yoke, and targeted audits on reallocated stations. To keep decisions synchronized, we recommend deploying a lightweight digital twin a data-linked, continuously updated model of suppliers, gateways, DCs, and carrier calendars that runs daily stress tests, estimates recovery distributions, and automatically proposes playbook actions; start with a "digital shadow" that ingests WMS/TMS/OMS milestones and evolves toward closed-loop optimization as data quality improves. Measurement should be disciplined and comparative: define baseline portfolios, run A/B or stepped-wedge pilots by region or category, and track a compact KPI set (peak-week fill-rate for A-styles, TTR to pre-shock throughput, lead-time IQR, markdown rate on affected assortments, and cost-to-serve deltas), publishing monthly "resilience P&L" dashboards that convert avoided lost sales and reduced expedite spend into contribution margin. Organizationally, create a cross-functional Resilience Design Council that meets monthly to refresh triggers and annually to rerun robust network designs with updated demand distributions and corridor risk; fund a small fortification budget to harden keystone nodes (alternate ports, nearshore finishing cells) with hurdle rates tied to scenario-weighted outcomes. Finally, avoid the brittleness of "too lean" by setting explicit lower bounds on strategic buffers, formalizing shelf-life and obsolescence rules for fashion capsules, and linking buy/rebuy decisions to uncertainty-aware forecasts; the aim is a calibrated, portfolio-based system that raises service in shocks by several points and cuts recovery times materially at a manageable 1–3% cost premium, turning resilience into a durable, repeatable operating advantage.

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