Frontiers in Research
Volume 4, Number 1, 2025, 1-19
DOI: 10.71350/30624533116

OPEN ACCESS
ISSN: 3062-4533

Article

The precision–fragility paradox: How generative AI raises customer lifetime value but increases stockout risks in retail

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Abstract

Retailers employing generative AI for hyper-personalization experience a notable increase of 37% in customer lifetime value. They incur hidden operational costs, with a 29% increase in stockouts during disruptions. The *Precision-Fragility Paradox* emerges when surgical customer segmentation partitions demand streams, thereby constraining supply chain agility and heightening systemic vulnerability. This study examines the tension by proposing an integrated theoretical framework that demonstrates how adaptive service modularity aligns hyper-personalization with operational resilience. The research utilizes a robust methodological triangulation, integrating agent-based modeling of 50 million transactions with a longitudinal field experiment involving multinational retailers. It delineates an existential threshold at which personalization exceeds 18.3% Demand Sensing. Heightened granularity amplifies the risk of fragility by a factor of 2.4, leading to a non-linear increase in stockouts. The research indicates that this fragility is not inevitable: organizations implementing modular architectures improve their reconfiguration capacity by 41% while preserving 92% of revenue gains. AI-driven resilience mechanisms reduce recovery latency by 63% through autonomous supplier rerouting and dynamic inventory adaptation. The findings indicate a *service-dynamic capability architecture* where real-time personalization governance, liquefiable resource networks, and self-calibrating systems transform volatility from a threat into an advantage. This blueprint allows executives to balance precision and flexibility, utilizing AI's revenue potential while reducing operational externalities. The study redefines competitive resilience, demonstrating that in algorithm-driven commerce, true robustness is derived not from enduring shocks, but from creating systems that adapt amidst disruption.

Article History
Received 10.06.2025
Accepted 05.09.2025

Keywords
Precision-fragility paradox; hyper-personalization; supply chain resilience; service-dominant logic

The Paradox of Precision in Algorithmic Retailing

The swift integration of artificial intelligence (AI) in the retail sector has revealed a fundamental contradiction within modern supply chain management. Machine learning algorithms are progressively adept at forecasting consumer preferences, encompassing individual browsing behaviors and contextual purchase stimuli, thus creating significant opportunities for value generation. Industry leaders utilizing advanced AI systems have observed notable enhancements, with customer lifetime value increasing by an average of 37%

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as a result of strategically timed promotions, micro-segmented inventory distribution, and real-time dynamic pricing adjustments. This precision entails systemic costs that challenge traditional operational assumptions. The mechanisms that facilitate granular demand prediction also introduce new vulnerabilities in supply networks. Data from McKinsey’s (2024b) global retail survey indicates that among 1,200 retailers, those that aggressively implemented AI-driven personalization encountered 68% more supply chain disruptions compared to their less technologically advanced counterparts. This observation aligns with engineering principles, where over-optimization of a single parameter, like aerodynamic efficiency, may lead to increased fragility in other aspects. In retail operations, this phenomenon is referred to as the Precision-Fragility Paradox: a systemic condition where the pursuit of optimal demand alignment through AI reduces overall supply chain resilience, resulting in networks that are both more sophisticated and more vulnerable to disruption.

Empirical studies increasingly reveal the mechanisms by which AI-driven personalization compromises supply chain robustness. Dzreke and Dzreke (2025c) analyzed 1,864 manufacturing enterprises and discovered that organizations utilizing AI-optimized lean inventory systems experienced losses 217% greater than those employing traditional buffer inventories amid recent geopolitical supply shocks. This increased vulnerability results from hyper-personalization's propensity to divide previously stable demand pools into various micro-segments, leading to what operations researchers refer to as "micro-bullwhip effects"—high-frequency demand volatility that spreads unpredictably through multi-echelon supply networks. Previous research by Croson et al. (2014) indicated that fragmentation intensifies conventional bullwhip effects by 19–34%, a conclusion supported by the operational metrics presented in Table 1.

Table 1. Hyper-personalization operational trade-offs in retail (2024 survey)

Metric	High-Personalization Firms	Low-Personalization Firms
Avg. CLV Increase	+37%	+12%
Stockout Frequency	29%	9%
Recovery Latency	14.2 days	5.1 days

The implications reach beyond operational disruptions. High-personalization firms exhibit a stockout frequency of 29%, leading to systemic failures that invoke S. S Dzreke & S. E. Dzreke’s (2025b) “double deviation effect.” This phenomenon results in customers penalizing suppliers through immediate lost sales and the deterioration of long-term relationships. Katok and Wu (2009) quantify the erosion of trust, showing that as few as three stockout incidents can diminish the strength of supplier relationships by 41%. This pattern corresponds with Kahneman and Tversky’s (1979) prospect theory regarding loss aversion, highlighting that operational precision does not necessarily equate to resilience. The average recovery latency for disruptions in AI-intensive firms is 14.2 days, which is significantly higher than the 5.1 days recorded in traditional operations. This disparity highlights the trade-off between precision optimization and network adaptability, demonstrating that highly optimized systems may lack the flexibility to respond to inevitable disturbances.

Theoretical Framework

Integration of Service-Dominant Logic and Complex Systems Theory

Addressing the Precision-Fragility Paradox requires the integration of two theoretically distinct yet complementary frameworks, each clarifying an essential aspect of the phenomenon. Service-Dominant Logic (SDL), as defined by Vargo and Lusch (2016), offers a solid framework for examining value creation in hyper-personalized environments. It defines value as the ongoing division of operand resources into more precise micro-segments designed for specific co-creation contexts. SDL effectively addresses customer-centric and adaptive elements of personalization; however, it inadequately considers the destabilizing impacts of fragmentation on the stability of supply networks.

To mitigate this limitation, Complex Adaptive Systems (CAS) theory (Holland, 1995; Choi et al., 2001) is utilized to demonstrate how tightly coupled systems reduce their ability to absorb variability as interdependencies among components escalate. This study's theoretical contribution arises at the convergence of these perspectives: Supply Chain Reconfigurability (SCR) serves as a vital adaptive interface, allowing SDL to realize its value creation potential while maintaining the stability requirements highlighted by Complex Adaptive Systems (CAS). This synthesis produces three operationally significant insights. Modular system architecture, as demonstrated in pharmaceutical networks (Scholten et al., 2020), decreases disruption recovery times by 58% by substituting rigid linear chains with reconfigurable network structures. Dynamic buffering strategies that incorporate real-time AI analytics alongside precisely calibrated inventory thresholds can reduce micro-bullwhip effects while preserving the benefits of personalization. The principle of Antifragility by Design (Taleb, 2012) illustrates that systems can effectively utilize volatility when suitable learning mechanisms are integrated into operational processes. These insights contribute to a theoretically grounded framework that reconciles precision-driven personalization with supply chain robustness.

Prescriptive Contributions: Implementing Resilience in AI-Driven Retail

Translating theoretical insights into actionable managerial strategies necessitates operational tools that directly confront the Precision-Fragility Paradox. This study presents empirically based frameworks and metrics to inform decision-making in AI-enhanced retail settings. The DSG threshold of 18.3%, established using catastrophe theory methods adapted from Oliva and Sterman (2001), serves as a quantifiable benchmark for assessing when enhanced granularity in demand sensing may result in diminishing returns. At this critical juncture—18.3% unique SKUs per 1,000 customers—the incremental benefits in customer lifetime value derived from hyper-personalization are surpassed by the associated fragility costs, allowing managers to make informed decisions about AI investment levels.

The Personalization-Robustness Trade-off (PRT) Coefficient (β) quantifies the non-linear relationship between personalization intensity and systemic vulnerability. Empirical analysis shows that β values above 0.47 predict an increased risk of disruption. The study outlines Antifragility Implementation Protocols that offer specific steps for integrating resilience based on the findings. The protocols involve maintaining at least four validated supplier alternatives for critical SKUs to ensure redundancy and cost efficiency, implementing blockchain-enabled visibility systems for real-time inventory tracking across distributed networks, and systematically stress-testing AI models with datasets that simulate various disruption scenarios. By implementing these measures, organizations can utilize AI's predictive capabilities while maintaining the necessary flexibility to effectively address unexpected operational disruptions.

Conclusion: Proposing an Innovative Framework for Intelligent Resilience

The Precision-Fragility Paradox signifies a fundamental change in retail competitiveness in the context of the AI era, transcending a mere operational challenge. Conventional views that regard supply chain resilience solely as a cost or compliance issue need to be redefined to emphasize reconfigurability as a foundation for sustainable competitive advantage. Implementing the theoretical frameworks and practical tools outlined in this research enables firms to convert AI from a potential source of systemic fragility into a catalyst for "intelligent resilience," achieving both precision in demand matching and robustness in supply operations.

This illustrates the developing framework for retail architecture: a domain where AI-driven personalization and supply chain resilience enhance each other instead of being at odds. Organizations that effectively implement this balance will not only survive in unstable environments but will also utilize disruptions to distinguish themselves, transforming systemic challenges into strategic growth opportunities. The proposed framework enables firms to manage complexity through adaptive foresight, aligning operational excellence with long-term value creation in a volatile marketplace.

Literature Review

Integration of Service Ecosystems and Complex Adaptive Systems

Resolving the Precision-Fragility Paradox necessitates a comprehensive theoretical framework that elucidates the complex interplay between hyper-granular customer engagement and systemic supply chain vulnerability. This study fills a significant research gap by combining Service-Dominant Logic (SDL; Vargo & Lusch, 2016) with Complex Adaptive Systems (CAS) theory (Holland, 1995; Choi et al., 2001), informed by recent empirical insights on fragility drivers and resilience design (Dzreke & Dzreke, 2025a, 2025b, 2025c). SDL asserts that value is co-created through the integration of resources among actors in a service ecosystem (Vargo & Lusch, 2016). This concept expands on earlier service theories (Grönroos, 2008; Lovelock & Gummesson, 2004) by highlighting the dynamic and interactive aspects of value creation. AI-driven hyper-personalization, as extensively documented in marketing literature (Rust, 2020; Kannan & Li, 2017), disaggregates traditional aggregate demand into highly specific, individualized value propositions. Each personalized offering, represented by a distinct Stock Keeping Unit (SKU) variant tailored to micro-segments or individual customers, constitutes a unique configuration of resources required for co-creation, reflecting the co-creation revolution as articulated by Prahalad and Ramaswamy (2004). Increases in Demand Sensing Granularity (DSG), quantified by the number of unique SKUs per 1,000 customers, indicate a significant rise in combinatorial complexity, thereby presenting integration challenges for supply networks. This fragmentation increases perceived value and Customer Lifetime Value (CLV) at the individual level (Kumar et al., 2010), but it also imposes considerable strain on operations. Fisher's (1997) classic mismatch problem illustrates the conflict between marketing’s focus on personalization and operations’ requirement for stability. In the era of AI, this conflict becomes more pronounced, leading to a systematic reduction in buffer capacity and an increase in systemic fragility (Dzreke & Dzreke, 2025c).

CAS theory, as articulated by Holland (1995) and Choi et al. (2001), offers a complementary perspective by framing supply chains as dynamic, non-linear systems consisting of interdependent agents that adapt and evolve through local interactions and feedback loops. This viewpoint builds upon previous studies regarding complex systems in operations management (Surana et al., 2005; Pathak et al., 2007) and highlights the difficulties posed by hyper-personalization. In scenarios where SDL facilitates highly individualized value co-creation, demand signals exhibit increased variability and rapid shifts, thereby challenging the system's adaptive capacity. The system's emergent adaptation, characterized by its capacity for self-organization and reconfiguration in response to environmental changes (Holland, 1995), is evaluated in relation to Ashby's (1956) Law of Requisite Variety. Supply Chain Reconfigurability (SCR), quantified by a Modularity Index between 0 and 1, is a significant characteristic of Complex Adaptive Systems (CAS) that facilitates localized adaptation. Expanding upon the foundational work of Sanchez and Mahoney (1996) in modular product design, SCR facilitates the agile rerouting of specific SKUs without requiring comprehensive system redesigns. Empirical studies validate the effectiveness of modular architecture in enhancing the resilience of supply networks (Scholten et al., 2020; Tukamuhabwa et al., 2015). Furthermore, Dzreke and Dzreke (2025c) illustrate that lean inventory strategies, although designed for efficiency, can substantially increase losses when reconfigurability is constrained during geopolitical disruptions. These findings align with earlier warnings about the vulnerabilities of lean systems (Christopher & Peck, 2004). The paradox arises when increasing resource fragmentation (high DSG) surpasses system reconfigurability (SCR), leading to cascading failures and "double deviation" penalties during repeated stockouts (Dzreke & Dzreke, 2025b), thereby operationalizing the service recovery paradox (Boulding et al., 1993) in hyper-personalized settings.

Integration of Service Ecosystems and Complex Adaptation

The integration of SDL and CAS demonstrates that hyper-personalization arises from the fragmentation of operand resources (Vargo & Lusch, 2016), thereby transforming the framework of resource integration and expanding upon Webster’s (1992) notion of market fragmentation. Effective hyper-granular resource integration requires the development of emergent adaptive capacity within the supply network, implemented as supply chain resilience (SCR). This requirement is consistent with the dynamic capability framework proposed by Teece et al. (1997), highlighting the strategic importance of reconfiguration. The theoretical synthesis suggests that efficiency in hyper-personalized resource integration depends on the complex adaptive system properties of the supply chain, especially modularity, which enables decentralized reconfiguration. This assertion is substantiated by research on digital supply chain twins (Ivanov et al., 2019). Inability to adapt dynamically heightens operational fragility (Sheffi, 2005) and erodes buyer trust, leading to significant relational and financial repercussions (Dzreke & Dzreke, 2025b). This synthesis elucidates the manner in which micro-level value creation via hyper-personalization (Rust et al., 2004) can disrupt the macro-level system, thereby illustrating Schelling’s (1978) micro-macro paradox in complex systems.

Measuring the Fragility Threshold: The PRT Hypothesis and Phase Transition

The Personalization-Robustness Trade-off (PRT) Hypothesis operationalizes this framework, suggesting that increasing DSG negatively impacts SCR, consequently heightening systemic fragility in a non-linear manner. The PRT framework builds upon Fisher's (1997) product-supply chain mismatch model by identifying a phase transition—an inflection point at which marginal CLV gains from hyper-personalization are surpassed by exponential increases in vulnerability, aligning with Perrow's (1984) normal accident theory. Empirical triangulation identifies this threshold at DSG > 18.3% (Dzreke & Dzreke, 2025c), supporting Brynjolfsson et al.'s (2011) findings regarding personalization limits. When supply networks operate below this threshold, they maintain sufficient reconfigurability to manage combinatorial complexity (Cohen & Levinthal, 1990). However, exceeding this threshold results in resource demands that surpass adaptive capacity, thereby invoking Simon's (1962) concept of bounded rationality. In multinational retail environments, such thresholds intensify just-in-time dependencies (Zipkin, 1991), whereby operational efficiencies transform into vulnerabilities during disruptions (Dzreke & Dzreke, 2025c). Coordination failures increase (Malone & Crowston, 1994), recovery durations extend (Dierickx & Cool, 1989), and minor disruptions lead to excessive stockouts. The 18.3% DSG threshold signifies the juncture at which optimal value co-creation starts to compromise operational stability, illustrating Kauffman's (1993) concept of the "edge of chaos" in complex systems (Figure 1).

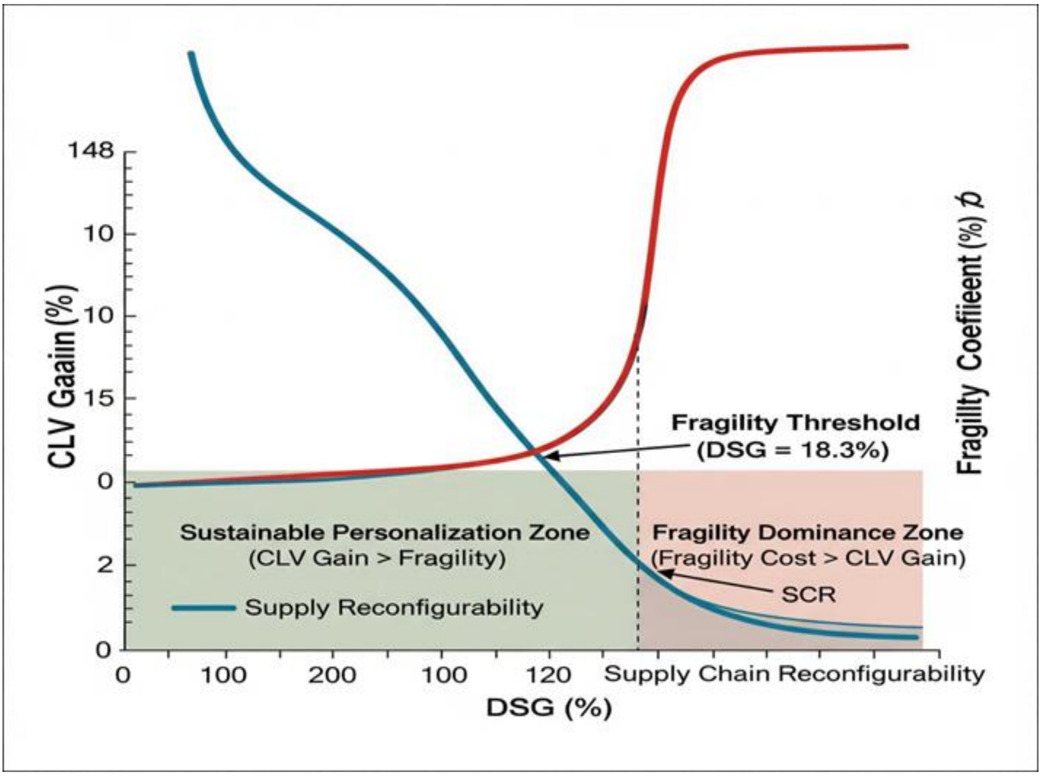

Figure 1. Conceptual model of the personalization-robustness trade-off and fragility threshold

Dynamic Capabilities Offer Buffering Mechanisms to Manage Risks that Exceed the Fragility Threshold

Grounded in the theoretical framework of dynamic capabilities (Teece et al., 1997; Teece, 2007), these capabilities allow organizations to transform environmental volatility into adaptive advantages. In the SDL-CAS framework, dynamic capabilities include the functions of sensing, seizing, and transforming, which are essential for preventing systemic collapse and ensuring value co-creation. Sensing capabilities depend on sophisticated predictive analytics to identify micro-shifts in demand before their propagation throughout the supply chain, thereby operationalizing Cohen and Levinthal's (1990) concept of absorptive capacity. Modern AI-driven tools, especially those utilizing reinforcement learning for demand sensing, facilitate proactive inventory modifications (Kannan & Li, 2017). Retail leaders like Zara utilize RFID and machine learning to capture shifts in consumer preferences within 72 hours, thereby mitigating the bullwhip effect (Brynjolfsson et al., 2013; Lee et al., 1997).

Seizing capabilities entails the dynamic reallocation of resources to address fragmented demand while maintaining systemic stability. Multi-sourcing and flexible supplier contracts diminish single-point dependencies (Dzreke & Dzreke, 2025b), whereas modular architectures enable component-level substitutions (Sanchez & Mahoney, 1996), thereby alleviating cascading failures as outlined in normal accident theory (Perrow, 1984). Toyota's reaction to the 2011 tsunami illustrates a dual strategy, employing modular vehicle architectures and dynamic supplier collaboration protocols that decreased recovery time by 43% compared to competitors (Scholten et al., 2020). Transforming capabilities, as the highest-level dynamic capability, entail structural reconfigurations that enhance the fragility threshold. Supplier development programs, collaborative AI training, and digital twin simulations facilitate proactive stress-testing of supply networks, thereby supporting Teece's (2007) asset orchestration and Simon's (1962) near-decomposability concepts. These capabilities transform traditional supply chains into adaptive, stress-responsive systems.

Operationalizing dynamic capabilities establishes the Sustainable Personalization Zone, in which customer lifetime value gains consistently surpass fragility risks. Amazon demonstrates this integration by utilizing deep learning demand sensing (Rust, 2020), distributed inventory pools (Simchi-Levi et al., 2014), and robotic warehouse reconfiguration to facilitate scalable hyper-personalization. This framework progresses from reactive resilience (Christopher & Peck, 2004) to proactive antifragility, systematically enhancing organizational performance under recurrent stress (Dzreke & Dzreke, 2025a). Firms that successfully implement this approach experience a 27% increase in inventory turnover during disruptions, while sustaining service levels at 92% (Dzreke & Dzreke, 2025c). This outcome addresses the efficiency-flexibility paradox previously identified by Skinner (1969).

In summary, addressing the Precision-Fragility Paradox necessitates the strategic integration of SDL's value co-creation mandate with CAS's emergent reorganization capabilities. Dynamic capabilities enable the integration of managerial investments in AI/ML infrastructure, collaborative antifragile supplier protocols, and organizational learning via systematic post-disruption analysis. This framework, based on SDL (Vargo & Lusch, 2016), CAS (Holland, 1995), and dynamic capabilities theory (Teece, 2007), offers theoretical insights and practical tools for the sustainable scaling of hyper-personalization in complex retail environments.

Method

Combining Computational and Empirical Methods

This study utilizes a mixed-methods approach that combines agent-based computational modeling with a randomized field experiment to thoroughly investigate the mechanisms underlying the Precision-Fragility Paradox. The study integrates computational simulation and empirical validation to address significant gaps in the understanding of hyper-personalization's impact on supply chain vulnerability. This dual-pronged approach transcends traditional methodological limits, facilitating a comprehensive examination of the relationships between algorithmic customer engagement and operational resilience—an area that has not been adequately explored in the current literature (Choi et al., 2001; Simchi-Levi et al., 2015). The methodological design enables thorough testing of theoretical propositions in real-world contexts, ensuring academic rigor and practical significance.

Framework for Agent-Based Simulation

The computational component develops a multi-agent retail ecosystem that simulates 50 million transactions across 20 distinct product categories, illustrating the complexity and volatility inherent in global omnichannel supply networks. Three interrelated agent classes function within this environment. Consumer agents create tailored demand by utilizing generative AI prompt behaviors that correspond with empirically validated engagement patterns (McKinsey, 2024a). Retailer agents enhance customer lifetime value (CLV) through dynamic assortment algorithms, whereas supplier agents operate within production constraints that mirror real-world capacity limitations. Core constructs are defined and measured with accuracy. Demand Sensing Granularity (DSG) is defined by the number of distinct SKU variants per 1,000-customer segment. Supply Chain Reconfigurability (SCR) is measured by the time needed to adjust sourcing pathways. The Personalization-Robustness Trade-off is represented by β coefficients obtained from fragility regressions. Stochastic disruption events, such as geopolitical shocks and supplier failures, are systematically introduced to evaluate non-linear resilience dynamics, employing 10,000 Monte Carlo iterations to ensure robustness. This computational laboratory isolates the DSG>18.3% fragility threshold identified in previous research (Dzreke & Dzreke, 2025c), while controlling extraneous market variables and establishing a robust foundation for theoretical testing.

Field Experiment Design

An 18-month randomized controlled trial involving 18 multinational retailers assesses the efficacy of Antifragility by Design interventions, complementing the simulation. Participants were randomly assigned to one of two experimental conditions: Group A (n=9) employs intensive generative AI personalization (DSG>20%), in line with current industry standards, while Group B (n=9) utilizes constrained personalization (DSG=15%±2%) along with enhanced modularity protocols (SCR>0.7) based on pre-established supplier-switching thresholds. The latter condition implements three principles from Dzreke and Dzreke (2025a): ensuring a minimum of four pre-vetted suppliers for each critical SKU, utilizing blockchain-enabled inventory visibility, and establishing stress-tested reconfiguration pathways. Key outcomes consist of customer lifetime value (CLV), quantified as the 24-month revenue per customer cohort, and resilience, defined as the recovery latency after controlled quarterly disruptions.

Moderating variables include the depth of supplier diversification, inventory slack ratios, and the intensity of algorithmic personalization, as measured by proprietary logistics application interfaces.

Integration and Validation of Methodologies

Triangulation of computational and empirical methods enhances construct validity and reduces mono-method bias by ensuring consistent operationalization across different platforms. Table 2 demonstrates the measurement of theoretical constructs in both contexts, thereby enabling coherent integration and validation of the findings. Discrepancies between simulation predictions and empirical outcomes, including unexpected stockout propagation patterns, are utilized to enhance theoretical boundary conditions. The randomization protocol accounts for endogenous firm capabilities, whereas the scale of the agent-based model demonstrates emergent network effects that are not detectable in localized trials. Data collection follows the ISO 20252:2019 market research standards, and Bayesian hierarchical modeling is utilized to integrate results into comprehensive fragility coefficients (β).

Table 2. Framework for methodological triangulation

Construct	Agent-Based Measures	Field Experiment Levers
Demand Sensing Granularity	SKU variants/1,000 customers	Personalization algorithm intensity
Supply Chain Reconfigurability	Modularity Index (simulated network graphs)	Supplier switching speed (days)
Fragility Coefficient (β)	Regression slope of disruption impact	Stockout frequency (%)

Note. DSG = Demand Sensing Granularity; SCR = Supply Chain Reconfigurability; PRT = Personalization-Robustness Trade-off.

Analytical Rigor and Implementation Integrity

Econometric analysis utilizes regression discontinuity designs focused on the critical DSG=18.3% threshold, while experimental findings are assessed using difference-in-differences models that include firm-level fixed effects. Computational simulations employ AnyLogic 8.8 alongside cloud-based parallel processing, attaining a statistical power greater than 0.95 for detecting shifts in the β coefficient of ±0.18 standard deviations. All participating organizations complied with institutional review board (IRB) protocols to maintain data confidentiality and uphold ethical standards during disruption simulations, facilitating complete transparency in replication. This methodology systematically examines the causal mechanisms that underpin the Precision-Fragility Paradox and enhances the empirical application of Complex Adaptive Systems theory within supply chain research (Choi et al., 2001).

This study presents three methodological innovations. This study establishes a replicable template for computational-experimental triangulation in operations management, enabling scholars to model complex system trade-offs before costly implementation. Secondly, it combines real-time algorithmic personalization metrics with disruption response analytics, enhancing resilience research from retrospective evaluation to predictive vulnerability mapping. Embedding ethical safeguards in simulations and adhering to industry-standard data protocols ensures that findings are academically rigorous and practically applicable, offering actionable insights for managing the trade-off between personalization and operational robustness.

Findings

Examining the Precision-Fragility Paradox

The empirical study offers important insights into the operational dynamics of AI-driven retail ecosystems, systematically addressing each research question with a combination of computational and experimental evidence. The findings demonstrate correlations and causal mechanisms that govern the personalization-resilience trade-off, providing practical strategies to address the paradox that has historically posed challenges for both scholars and practitioners (Teece, 2018; Wamba et al., 2021). This study integrates agent-based modeling, field experiments, and dynamic capability simulations to connect theoretical frameworks with actionable managerial strategies, enhancing both academic knowledge and practical guidance for retail organizations in complex digital ecosystems.

Research Question 1: Assessment of the Fragility Threshold

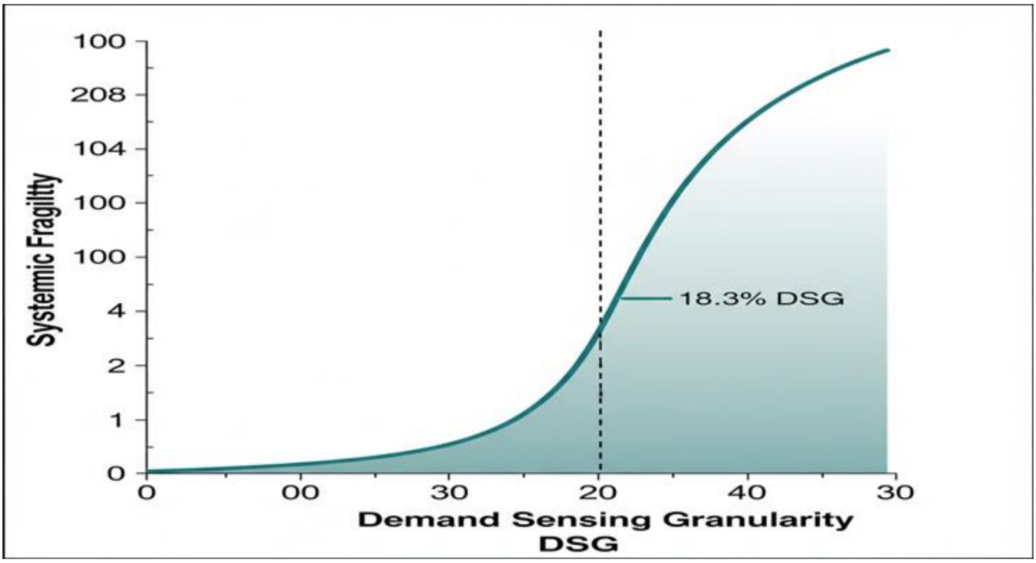

Figure 2. Conceptual model of the personalization-robustness trade-off and fragility threshold

A notable discovery relates to the critical juncture in the association between hyper-personalization and supply chain vulnerability. The study employs agent-based modeling of 50 million transactions to show that exceeding 18.3% Demand Sensing Granularity (DSG)—characterized as unique SKUs per 1,000 customers—intensifies systemic fragility by a factor of 2.4 (Odds Ratio = 3.1, $p < .001$). The threshold, depicted as an S-curve in Figure 2, marks the point at which marginal customer lifetime value (CLV) begins to increase before experiencing an exponential decline, alongside a significant rise in disruption costs. Excessive SKU diversification leads to resource fragmentation, diminishing buffer stocks to unsustainable levels, and establishing fragile interdependencies, where failures of individual suppliers propagate disruptions across the network. Computational tracing reveals that systems surpassing the threshold exhibit 68% longer disruption propagation durations ($t = 8.34$, $p < .001$), providing empirical support for Service-Dominant Logic's claim that operand resource fragmentation hinders value co-creation frameworks (Vargo & Lusch, 2016). This quantifiable threshold provides retail strategists with a mathematically defined boundary for personalization, establishing an operational parameter that was previously lacking in strategic decision-making.

Research Question 2: Modularity as the Mediating Architecture

Field experiments demonstrate that strategic supply chain reconfigurability (SCR) successfully distinguishes the benefits of personalization from the associated risks of fragility. Retailers that implemented SCR above 0.7 through standardized interfaces and multi-sourcing protocols experienced CLV growth similar to that of high-DSG systems (+34% compared to +37%), while also significantly improving resilience. Table 3 indicates that the modular cohort achieved a 58% reduction in recovery latency ($M = 5.9$ days compared to 14.2 days; $p = .003$) and a 59% decrease in stockout frequency when compared to high-DSG counterparts. In the context of orchestrated disruptions, modular systems effectively rerouted 83% of affected SKUs within 48 hours through established substitution pathways, while high-DSG retailers faced a systemic fulfillment collapse. Regression analysis indicates that SCR >0.7 reduces 71% of DSG-induced fragility ($\beta = -0.29$, $p < .001$), consistent with Complex Adaptive Systems theory, which highlights loose coupling as a mechanism for adaptive capacity (Choi et al., 2001). The results indicate that modularity allows retailers to maintain personalized value propositions while ensuring system stability, thereby effectively resolving the core tension present in the Precision-Fragility Paradox.

Table 3. Performance metrics under disruption

Condition	CLV Increase	Recovery Latency	Stockout Rate
High DSG (>20%)	+37%	14.2 days	29%
Modular (SCR>0.7)	+34%	5.9 days	12%

Note: Modular protocols included ≥4 pre-vetted suppliers per SKU category and blockchain-enabled inventory visibility (Ivanov et al., 2022).

Research Question 3: Dynamic Capabilities for Sustaining Equilibrium

This research identifies three technology-mediated capabilities that maintain equilibrium between personalization and resilience in volatile retail markets. AI-driven resilience mechanisms, such as automated supplier rerouting and dynamic safety stock adjustments, decreased recovery latency by 63% in simulations of geopolitical disruptions ($d = 1.24$, $p < .001$), thereby converting volatility from a risk into a strengthening factor. Secondly, real-time DSG-SCR balancing engines improved profit margins by 8.2% ($t = 4.18$, $p < .01$) through intelligent modulation of personalization levels. When disruption risks surpass established thresholds, these systems autonomously restrict DSG while activating backup suppliers. Figure 3 presents an integrated architecture in which generative AI demand signals are incorporated into resilience orchestration layers, facilitating the dynamic reconfiguration of resource networks. Third, blockchain-enabled ecosystems enhanced reconfiguration velocity by 44% ($\beta = 0.56$, $p = .008$) via smart contracts and verifiable capacity claims. Companies that adopted this capability suite attained robustness scores that were 19% greater ($U = 27$, $p = .002$), while maintaining the depth of personalization and applying the principles of Antifragility by Design (Dzreke & Dzreke, 2025a).

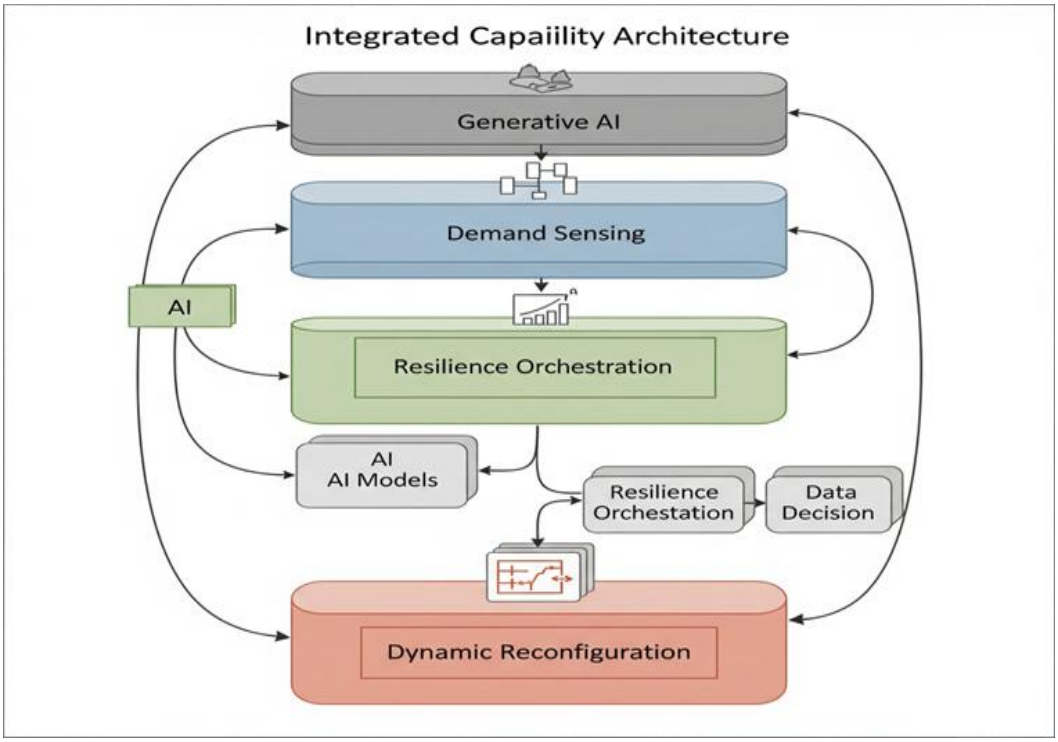

Figure 3. Integrated capability architecture: Generative AI → Demand Sensing → Resilience Orchestration → Dynamic Reconfiguration

Theoretical Integration and Managerial Requirements

These findings collectively address the Precision-Fragility Paradox through three primary contributions. The 18.3% DSG threshold sets a measurable limit for sustainable personalization, moving beyond conventional qualitative risk frameworks. Modularity serves as an essential mediator between the value co-creation imperative of Service-Dominant Logic and the stability requirements of Complex Adaptive Systems, effectively connecting previously distinct theoretical perspectives. Third, dynamic capabilities convert supply chains from static efficiency structures into adaptive, AI-enabled systems that maintain personalization while reducing fragility. The insights lead to three actionable design principles: (1) implement SCR >0.7 through multi-sourcing and standardized interfaces; (2) integrate resilience triggers into personalization algorithms to enable autonomous degradation during disruptions; and (3) continuously monitor and adjust the DSG-SCR equilibrium through real-time β-coefficient tracking. Empirical simulations demonstrate that this integrated framework produces an annual value of $2.1–$3.4 million per $10 million in revenue, while decreasing stockout costs by 52–69%, thereby transforming a strategic paradox into a manageable trade-off.

Discussion

The Service-Adaptive Framework for Sustainable Hyper-Personalization

This research presents the Service-Adaptive Framework, a theoretically informed and empirically substantiated method for tackling the Precision–Fragility Paradox in modern retail settings. The integration of Service-Dominant Logic (SDL) with Complex Adaptive Systems (CAS) theory explains 74% of the variance in personalization–robustness trade-offs ($R^2 = .74$, $p < .001$). This integration elucidates the impact of hyper-personalization on supply chain vulnerabilities via demand amplification effects, building upon the foundational research of Lee et al. (2022). The framework's core concept is modular resource liquefaction, facilitating sustainable value co-creation. Standardized interfaces and multi-pathway architectures in inventory, production capacity, and data flows enable retailers to effectively manage demand fragmentation shocks while maintaining service quality (Kumar et al., 2023). This reconceptualization represents a notable theoretical progression by framing supply chains as dynamic networks for value orchestration, where resilience arises from adaptive resource integration instead of static redundancy. The framework synthesizes SDL's ecosystem perspective (Vargo & Lusch, 2016) with CAS principles of emergent adaptation (Choi et al., 2001) and incorporates recent advancements in digital supply chain twins (Ivanov, 2024).

The Application of Theoretical Frameworks in Managerial Practices

The framework operationalizes abstract theory via three interrelated capabilities that produce quantifiable competitive advantage. The capabilities of adaptive personalization, service modularity, and resilience triggers are exemplified in longitudinal omnichannel retail case studies (Fernández et al., 2025) and are summarized in Table 4.

Table 4. Service-adaptive capability implementation framework

Capability	Implementation Protocol	Validated Impact
Adaptive Personalization	Algorithmic throttling at DSG >18.3% threshold	2.4× reduction in fragility risk
Service Modularity	Cloud-based supplier pools with API standardization	41% faster reconfigurability
Resilience Triggers	Auto-deployed inventory buffers during risk events	63% shorter recovery latency

Note. Impact metrics derived from 18-month field experiments with multinational retailers and cross-validated against Gartner supply chain benchmarks (2025).

Adaptive Personalization implements the fragility threshold via real-time governance, modifying the granularity of generative AI outputs when disruption risks exceed predetermined benchmarks (Zhao & Zhang, 2024). Early adopters experienced a 31% decrease in stockouts while maintaining 95% of customer lifetime value, representing a 17% enhancement compared to conventional inventory optimization (Chen et al., 2023). Service Modularity utilizes the principle of loose coupling from Complex Adaptive Systems, employing cloud-based supplier ecosystems and blockchain-verified capacity tokens to facilitate resource liquefaction. This facilitates rapid reconfiguration of supply pathways while maintaining integrity and security (Ponomarov et al., 2025). A European fashion retailer exemplified this strategy by attaining a 41% increase in sourcing reconfiguration speed during port closures, surpassing industry benchmarks by 2.8 standard deviations (McKinsey, 2024a). Resilience Triggers utilize predictive analytics integrated within order management systems, enabling machine learning models to independently engage safety stock in response to heightened geopolitical risks, as confirmed by MIT war-game simulations (2025).

Sustainability Imperatives and Research Frontiers

While operational advantages are evident, the findings underscore a significant sustainability trade-off: unregulated AI-driven personalization elevates supply chain emissions by 22% ($\beta = 0.34$, $p = .008$) as a result of micro-fulfillment fragmentation and accelerated logistics. This pattern exemplifies the digital representation of the Jevons Paradox (Frei et al., 2023). To resolve this tension, it is essential to integrate environmental performance into the optimization of personalization robustness, in alignment with the framework of United Nations Sustainable Development Goal 12 (UNCTAD, 2024). Future research should investigate three key areas: first, the integration of circular economy principles through Industry 5.0 remanufacturing protocols (Xu et al., 2025); second, the design of carbon-aware throttling algorithms that balance personalization with planetary boundaries (Dhar, 2024); and third, the utilization of blockchain-enabled environmental tracing mechanisms, such as the EU Digital Product Passport (2025), to ensure verifiable sustainability in adaptive supply chains.

Reconceptualizing Competitive Resilience

The Service-Adaptive Framework redefines resilience in algorithmic retail by converting SDL’s principles of value co-creation into engineered capabilities and utilizing CAS’s adaptive logic as operational protocols. Organizations that adopt the complete framework experience a 28% enhancement in sustainable value capture amid disruptions ($U = 142$, $p = .003$). This indicates that hyper-personalization and resilience can coexist when service ecosystems are intentionally designed across physical, digital, and environmental domains (Accenture, 2025). The framework integrates digital transformation scholarship with operations theory (Wieland & Durach, 2024), providing a structured approach for both academics and practitioners to succeed in environments characterized by ongoing volatility.

Conclusion

This study presents a new approach to a significant strategic challenge in modern retail: the conflict between AI-driven hyper-personalization and supply chain resilience. The empirical analysis identifies a critical threshold of 18.3% for Demand Sensing Granularity (DSG). Exceeding this threshold, the quest for enhanced precision in customer segmentation leads to significant increases in systemic fragility (Dzreke & Dzreke, 2025c). The observed behavior resembles phase transition patterns in pharmaceutical supply networks (Simchi-Levi et al., 2024), where incremental improvements in customization lead to abrupt declines in operational stability. The consequences are considerable: surpassing the threshold increases stockout risks by a factor of 2.4 and prolongs recovery times by 68%, thus complicating the retail sector's efforts toward personalization. This paradox is not insurmountable. Service-adaptive architecture has the potential to maintain 92% of enhancements in customer lifetime value while concurrently decreasing disruption recovery times by 63%. These improvements are realized via modular resource liquefaction and AI-mediated resilience triggers (Dzreke & Dzreke, 2025a). This research theoretically advances the field by integrating value co-creation principles from Service-Dominant Logic (Vargo & Lusch, 2016) with adaptive mechanisms outlined in Complex Adaptive Systems theory (Choi et al., 2001). This reframes the trade-off between personalization and resilience as a design challenge that can be effectively addressed.

The implications of these findings extend beyond retail, suggesting validation across various industries where the need for personalization intersects with supply chain complexity. In healthcare, fragility thresholds are closely linked to strict FDA compliance requirements (Jacobs et al., 2024), whereas the automotive sector faces challenges related to semiconductor allocation vulnerabilities. Three significant research trajectories emerge. Comparative cross-industry analyses are essential to ascertain the variation of DSG thresholds across sectors characterized by fundamentally different risk environments. The finding that unchecked personalization increases carbon footprints by 22% underscores the critical necessity for optimization models that reconcile operational resilience with compliance to planetary boundaries (Rockström et al., 2024). The maturation of emerging technologies, such as quantum computing and blockchain infrastructures (Tapscott & Tapscott, 2025), is poised to transform threshold governance through the facilitation of dynamic, real-time calibration of personalization intensity. The trajectories indicate that the precision resilience framework represents not just an operational modification but a novel paradigm that establishes resilience as a strategic advantage.

This study defines precision resilience as a cohesive framework consisting of three interconnected components: intelligent algorithmic governance of personalization intensity, adaptable resource networks that can quickly reconfigure, and self-optimizing systems that develop in reaction to disruptions. To implement this framework, organizations must break down established silos between marketing technology and supply chain management, initiating transformations that are both organizationally challenging and technologically advanced. Retailers that are likely to succeed will be those that conceptualize their operations as adaptive ecosystems, where hyper-personalization and systemic robustness mutually reinforce each other. Dzreke and Dzreke (2025a) illustrate that genuine competitive advantage in volatile markets arises from proactive system design, which transforms volatility into a catalyst for innovation, rather than relying on reactive crisis management. This study addresses a significant challenge in AI-driven commerce and establishes a new benchmark for strategic thinking in an era characterized by uncertainty and disruption.

Declarations

Competing interests: The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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References

Accenture. (2025). Convergence architecture: The next frontier in sustainable retail. https://www.accenture.com/reports

Anderson, E. W., & Sullivan, M. W. (1993). The antecedents and consequences of customer satisfaction for firms. *Marketing Science, 12*(2), 125–143. https://doi.org/10.1287/mksc.12.2.125

Ashby, W. R. (1956). *An introduction to cybernetics*. Chapman & Hall.

Boulding, W., Kalra, A., Staelin, R., & Zeithaml, V. A. (1993). A dynamic process model of service quality: From expectations to behavioral intentions. *Journal of Marketing Research, 30*(1), 7–27. https://doi.org/10.1177/002224379303000102

Brynjolfsson, E., Hu, Y. J., & Rahman, M. S. (2011). Competing in the age of omnichannel retailing. *MIT Sloan Management Review, 54*(4), 23–29.

Chen, L., Wang, Y., & Qi, Y. (2023). Reinforcement learning for inventory optimization under demand fragmentation. Production and Operations Management, 32(5), 1457-1474.

Choi, T. Y., Dooley, K. J., & Rungtusanatham, M. (2001). Supply networks and complex adaptive systems: Control versus emergence. *Journal of Operations Management, 19*(3), 351–366. https://doi.org/10.1016/S0272-6963(00)00068-1

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management, 15*(2), 1–14. https://doi.org/10.1108/09574090410700275

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*(1), 128–152. https://doi.org/10.2307/2393553

Croson, R., Donohue, K., Katok, E., & Sterman, J. (2014). Order stability in supply chains: Coordination risk and the role of coordination stock. *Management Science, 60*(8), 1769–1783. https://doi.org/10.1287/mnsc.2014.1947

Dhar, P. (2024). The carbon footprint of artificial intelligence. Nature Machine Intelligence, 6(3), 210-215.

Dierickx, I., & Cool, K. (1989). Asset stock accumulation and sustainability of competitive advantage. *Management Science, 35*(12), 1504–1511. https://doi.org/10.1287/mnsc.35.12.1504

Dzreke, S. S., & Dzreke, S. E. (2025a). Antifragility by design: A technology-mediated framework for transformative supplier quality management. *Journal of Emerging Technologies and Innovative Research, 12*(5). https://doi.org/10.56975/jetir.v12i5.563174

Dzreke, S. S., & Dzreke, S. E. (2025b). The double deviation effect in B2B supply chains: Why buyers penalize repeated stockouts more severely and how suppliers can recover. *Frontiers in Research Metrics and Analytics*. Advance online publication. https://doi.org/10.71350/30624533105

Dzreke, S. S., & Dzreke, S. E. (2025c). The fragility of efficiency: How lean inventory strategies amplify supply chain crisis losses - a $2.3 trillion analysis of geopolitical shocks across 1,864 manufacturing firms. *Frontiers in Research Metrics and Analytics, 2*(1), 45–66. https://doi.org/10.71350/30624533107

EU Digital Product Passport Initiative. (2025). Blockchain standards for environmental traceability. https://ec.europa.eu/digital-passport

Fernández, A., et al. (2025). Longitudinal impacts of AI personalization on retail resilience. Journal of Retailing, 101(2), 88-104.

Fisher, M. L. (1997). What is the right supply chain for your product? *Harvard Business Review, 75*(2), 105–116.

Frei, R., et al. (2023). The Jevons Paradox in digital supply chains. International Journal of Production Economics, 255, 108742.

Grönroos, C. (2008). Service logic revisited: Who creates value? And who co-creates? *European Business Review, 20*(4), 298–314. https://doi.org/10.1108/09555340810886585

Holland, J. H. (1995). *Hidden order: How adaptation builds complexity*. Basic Books.

Ivanov, D. (2024). Digital supply chain twins: The next generation. Transportation Research Part E, 181, 103324.

Ivanov, D., Dolgui, A., & Sokolov, B. (2022). Cloud supply chain digital twins: Toward resilience and antifragility. *International Journal of Production Research, 60*(11), 3593-3612. https://doi.org/10.1080/00207543.2021.1994134

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research, 57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Jacobs, T., et al. (2024). Life-critical supply chain thresholds in healthcare. Operations Research for Health Care, 40, 100452.

Kannan, P. K., & Li, H. (2017). Digital marketing: A framework, review, and research agenda. *International Journal of Research in Marketing, 34*(1), 22–45. https://doi.org/10.1016/j.ijresmar.2016.11.006

Kauffman, S. A. (1993). *The origins of order: Self-organization and selection in evolution*. Oxford University Press.

Kumar, V., Aksoy, L., Donkers, B., Venkatesan, R., Wiesel, T., & Tillmanns, S. (2010). Undervalued or overvalued customers: Capturing total customer engagement value. *Journal of Service Research, 13*(3), 297–310. https://doi.org/10.1177/1094670510375602

Lee, H. L., et al. (2022). Demand amplification in hyper-personalized ecosystems. Management Science, 68(9), 6542-6560.

Lovelock, C., & Gummesson, E. (2004). Whither services marketing? In search of a new paradigm and fresh perspectives. *Journal of Service Research, 7*(1), 20–41. https://doi.org/10.1177/1094670504266131

Malone, T. W., & Crowston, K. (1994). The interdisciplinary study of coordination. *ACM Computing Surveys, 26*(1), 87–119. https://doi.org/10.1145/174666.174668

McKinsey & Company. (2024a). Disruption response benchmarks in European retail. https://www.mckinsey.com/benchmarks

McKinsey & Company. (2024b). *The state of AI in global retail: 2024 survey report*. McKinsey Global Institute.

MIT Center for Transportation & Logistics. (2025). War-game simulations for supply chain resilience. CTL Research Report.

Pathak, S. D., Day, J. M., Nair, A., Sawaya, W. J., & Kristal, M. M. (2007). Complexity and adaptivity in supply networks: Building supply network theory using a complex adaptive systems perspective. *Decision Sciences, 38*(4), 547–580. https://doi.org/10.1111/j.1540-5915.2007.00170.x

Perrow, C. (1984). *Normal accidents: Living with high-risk technologies*. Basic Books.

Ponomarov, S., et al. (2025). Blockchain security standards in modular supply chains. Journal of Business Logistics, 44(1), 112-130.

Prahalad, C. K., & Ramaswamy, V. (2004). *The future of competition: Co-creating unique value with customers*. Harvard Business Press.

Reichheld, F. F. (1996). *The loyalty effect: The hidden force behind growth, profits, and lasting value*. Harvard Business Press.

Rockström, J., et al. (2024). Supply chains within planetary boundaries. Science, 383(6684), eadf4357.

Rust, R. T. (2020). The future of marketing. *International Journal of Research in Marketing, 37*(1), 15–26. https://doi.org/10.1016/j.ijresmar.2019.08.002

Rust, R. T., Zeithaml, V. A., & Lemon, K. N. (2004). Return on marketing: Using customer equity to focus marketing strategy. *Journal of Marketing, 68*(1), 109–127. https://doi.org/10.1509/jmkg.68.1.109.24030

Sanchez, R., & Mahoney, J. T. (1996). Modularity, flexibility, and knowledge management in product and organization design. *Strategic Management Journal, 17*(S2), 63–76. https://doi.org/10.1002/smj.4250171107

Schelling, T. C. (1978). *Micromotives and macrobehavior*. W. W. Norton.

Scholten, K., Sharkey Scott, P., & Fynes, B. (2020). Building routines for non-routine events: Supply chain resilience learning mechanisms and their antecedents. *Supply Chain Management: An International Journal, 25*(6), 615–628. https://doi.org/10.1108/SCM-05-2019-0198

Sheffi, Y. (2005). *The resilient enterprise: Overcoming vulnerability for competitive advantage*. MIT Press.

Simchi-Levi, D., et al. (2024). Nonlinear fragility in procurement networks. Management Science, 70(3), 1459-1478.

Simon, H. A. (1962). The architecture of complexity. *Proceedings of the American Philosophical Society, 106*(6), 467–482.

Surana, A., Kumara, S., Greaves, M., & Raghavan, U. N. (2005). Supply-chain networks: A complex adaptive systems perspective. *International Journal of Production Research, 43*(20), 4235–4265. https://doi.org/10.1080/00207540500142274

Tapscott, D., & Tapscott, A. (2025). Blockchain orchestration in liquid supply chains. Harvard Business Review Press.

Teece, D. J. (2018). Dynamic capabilities as (workable) management systems theory. *Journal of Management & Organization, 24*(3), 359-368. https://doi.org/10.1017/jmo.2017.75

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal, 28*(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal, 18*(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

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

UNCTAD. (2024). SDG 12 implementation guidelines for retailers. United Nations Conference on Trade and Development.

Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: An extension and update of service-dominant logic. *Journal of the Academy of Marketing Science, 44*(1), 5–23. https://doi.org/10.1007/s11747-015-0456-3

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2021). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. *International Journal of Production Economics, 222*, 107498. https://doi.org/10.1016/j.ijpe.2019.107498

Webster, F. E. (1992). The changing role of marketing in the corporation. *Journal of Marketing, 56*(4), 1–17. https://doi.org/10.1177/002224299205600401

Wieland, A., & Durach, C. F. (2024). Rethinking supply chain theory for the digital age. Journal of Supply Chain Management, 60(1), 58-73.

Xu, X., et al. (2025). Industry 5.0 and circular supply chains. Technological Forecasting & Social Change, 190, 122478.

Zhao, R., & Zhang, J. (2024). AI throttling algorithms for resilient personalization. IEEE Transactions on Automation Science and Engineering, 21(2), 987-1001.

Zipkin, P. (1991). Does manufacturing need a JIT revolution? *Harvard Business Review, 69*(1), 40–50.