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Article

A SYSTEMATIC REVIEW OF RISK-BASED PROCUREMENT STRATEGIES IN RETAIL SUPPLY CHAINS: SOURCING FLEXIBILITY AND VENDOR DISRUPTION MANAGEMENT

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ABSTRACT

This systematic literature review investigates the multidimensional strategies employed in managing procurement risks within retail supply chains, emphasizing how modern retail environments are reshaping sourcing practices, risk modeling, and supplier relationship management. Utilizing the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, the study identified, screened, and reviewed a total of 98 peer-reviewed journal articles published between 2010 and 2024. The objective was to synthesize current academic and practical developments related to procurement risk, with a focus on themes such as sourcing flexibility, digital transformation, disruption response mechanisms, supplier performance measurement, and sustainability compliance. The analysis reveals a substantial evolution from traditional cost-driven procurement practices to resilience-centric models designed to mitigate the complex risks faced by globally distributed, high-velocity retail supply chains. Among the most significant findings is the widespread adoption of multi-sourcing, dual sourcing, and just-in-case inventory strategies, particularly in response to global crises like the COVID-19 pandemic. Moreover, the integration of digital technologies—including artificial intelligence, predictive analytics, blockchain, and the Internet of Things—has enabled procurement functions to transition from reactive to proactive risk management approaches, facilitating real-time supplier performance tracking and enhanced cross-tier visibility. The study also highlights a shift toward relational contracting and collaborative supplier partnerships, which are increasingly recognized as critical enablers of continuity, compliance, and shared risk responsibility. Despite these advancements, the review identifies persistent research gaps, including a lack of standardized supplier agility metrics, insufficient modeling of Tier-2 and Tier-3 supplier risk, and fragmentation in the application of procurement risk modeling frameworks across sectors. By consolidating diverse strands of literature, this study provides a comprehensive understanding of the current landscape of retail procurement risk management and outlines future research opportunities aimed at strengthening procurement resilience, technological integration, and sustainability in global retail ecosystems.

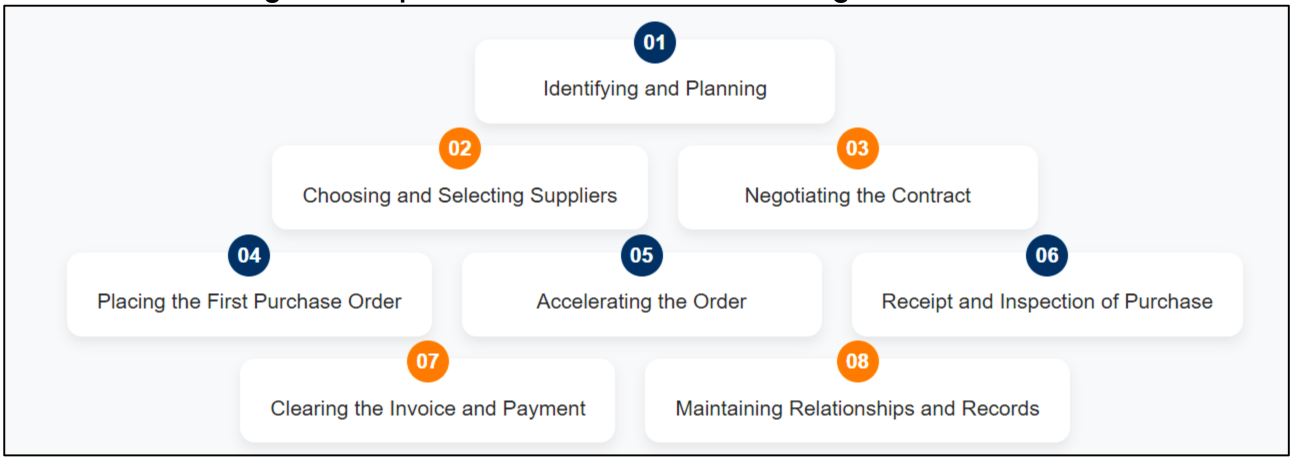
KEYWORDS

Risk-Based Procurement; Retail Supply Chains; Sourcing Flexibility; Vendor Disruption Management; Supply Chain Resilience;

INTRODUCTION

Procurement refers to the strategic process of sourcing and acquiring goods, services, and works from external sources to meet an organization's needs, often with a focus on cost, quality, and timing (Yadav & Prakash Singh, 2022). Within the broader context of supply chain management, procurement plays a critical role in ensuring operational continuity and cost-effectiveness across various industries (Wang et al., 2022). In the retail sector, procurement extends beyond traditional buying functions and encompasses complex strategies involving supplier evaluation, negotiation, risk assessment, and relationship management (Fahimnia et al., 2019). As global supply chains become increasingly interconnected and interdependent, the complexity of procurement decisions intensifies, giving rise to the need for risk-based procurement strategies (Charwand et al., 2014). These strategies involve anticipating, evaluating, and mitigating supplier-related and market-driven uncertainties to ensure business continuity and performance (Chauhan et al., 2023). Understanding risk-based procurement strategies is essential in the retail domain due to its high sensitivity to consumer demand fluctuations, time constraints, and dependency on vendor reliability (Rane & Thakker, 2019).

Figure 1: Steps Involved in Procurement Management Process



Risk in procurement, particularly within retail supply chains, arises from a range of internal and external sources including supply disruption, demand variability, price volatility, regulatory changes, and geopolitical instability (Yi et al., 2018). To address these multifaceted risks, organizations have adopted various procurement frameworks such as Total Cost of Ownership (TCO), supply risk mapping, and the Kraljic portfolio matrix to align purchasing decisions with risk appetite and strategic goals (Aljadeed et al., 2021). Retailers, especially multinational ones, are particularly exposed to risks from overseas suppliers, longer lead times, and transportation bottlenecks (Tao et al., 2019). Studies have shown that the adoption of structured risk-based procurement frameworks leads to improved decision-making, better supplier segmentation, and enhanced supply chain responsiveness (Charwand & Moshavash, 2014). Additionally, procurement professionals in the retail sector increasingly rely on integrated systems and analytics to continuously assess supplier performance and risk exposure, ensuring dynamic procurement practices in an ever-changing environment ((Yadav & Prakash Singh, 2022).

Sourcing flexibility is a vital capability within risk-based procurement that enables retailers to adapt to disruptions by quickly switching suppliers or modifying order volumes (Wang et al., 2022). Flexibility in sourcing can be achieved through multi-sourcing arrangements, supplier development programs, and modular product design strategies that allow substitution between components or vendors (Nojavan et al., 2015). Empirical studies suggest that firms with high sourcing flexibility are better positioned to manage lead time variability, maintain service levels, and respond to market changes (Hatami et al., 2009). In particular, sourcing flexibility has gained prominence in the retail industry due to its lean inventory models and high product turnover rates (Charwand & Gitizadeh, 2020). For instance, retailers like Zara and H&M have adopted agile sourcing strategies, including near-shoring and dual sourcing, to maintain resilience while offering rapid fashion trends (Conejo & Carrión, 2006). Research also indicates that digital technologies such as supplier portals, AI-enabled forecasting, and cloud-based procurement platforms contribute to sourcing flexibility by providing real-time visibility and decision support (Fera et al., 2017).

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The concept of vendor disruption management encompasses proactive and reactive measures that organizations implement to handle supplier failures, quality issues, transportation delays, or capacity constraints (Aljadeed et al., 2021). Vendor-related disruptions in retail supply chains can cause significant financial losses, brand damage, and customer dissatisfaction, highlighting the importance of comprehensive risk identification and mitigation strategies (Butt, 2021). Vendor risk management strategies include supplier audits, contingency contracting, dual sourcing, inventory buffering, and collaboration-based resilience planning (Namdar et al., 2017). Empirical research has shown that supply chain resilience is strongly associated with collaborative relationships, where information sharing, trust, and joint planning with suppliers play a pivotal role in mitigating disruptions (Fera et al., 2017). In retail, where consumer expectations for product availability and delivery speed are high, disruption management requires strategic alignment between procurement, logistics, and demand forecasting units (Charwand & Gitizadeh, 2020). The literature also emphasizes the role of third-party logistics providers and procurement intermediaries in enhancing vendor reliability and reducing disruption exposure in retail sourcing networks (Hatami et al., 2009).

Figure 2: Cycle on how Vendor-Managed Inventory Works

A significant portion of procurement-related risks arises from supplier concentration and geographic clustering, especially in regions prone to natural disasters or political instability (Badea et al., 2014). The COVID-19 pandemic underscored these vulnerabilities by exposing the fragility of over-centralized procurement systems and just-in-time inventory models in the retail industry (Guillot et al., 2023). Retailers with limited sourcing options faced severe stockouts, delayed deliveries, and declining customer satisfaction. In contrast, those with diversified supplier bases and adaptive sourcing protocols were more resilient (Siegel, 2018). The literature supports that risk diversification through geographic and supplier diversity reduces dependency risks and enhances procurement agility (Baz & Ruel, 2020). Additionally, establishing early warning systems and scenario planning mechanisms improves vendor disruption preparedness (Rockafellar & Uryasev, 2002). Retailers now increasingly view supplier partnerships as strategic assets rather than cost centers, leading to long-term risk-sharing arrangements and innovation-focused collaboration (Lim et al., 2011).
The retail supply chain is characterized by high velocity, demand unpredictability, and intense competition, requiring procurement strategies that balance cost-efficiency with resilience (Brandon-Jones et al., 2014). Risk-based procurement strategies have been widely applied to support this dual goal, particularly through the adoption of supplier segmentation approaches, risk scoring systems, and dynamic procurement contracts (Heckmann et al., 2015). Retail firms often classify their suppliers based on risk exposure, criticality, and performance potential to allocate procurement resources

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strategically (Fahimnia et al., 2019). Furthermore, contract design plays a critical role in vendor disruption management by including clauses that incentivize risk-reducing behaviors, penalties for underperformance, and flexibility for volume adjustments (Brandon-Jones et al., 2014). Procurement risk management in retail also incorporates tools such as spend analysis, demand-supply matching algorithms, and predictive analytics to detect anomalies and emerging threats in the supplier network (Durach et al., 2017). Studies confirm that organizations integrating data-driven procurement practices outperform those relying on static models in terms of resilience and adaptability (Carrión et al., 2009).

Digital transformation has reshaped procurement in retail supply chains, with technologies like blockchain, machine learning, and Internet of Things (IoT) enhancing risk visibility, traceability, and decision-making accuracy (Guillot et al., 2023). Blockchain, in particular, has enabled immutable transaction records and supplier transparency, helping procurement teams assess vendor compliance and reliability (Rockafellar & Uryasev, 2002). Machine learning algorithms have been used to detect disruption patterns, predict vendor failures, and optimize sourcing decisions in real time (Majumdar et al., 2020). Retailers such as Walmart and Amazon have adopted advanced digital procurement ecosystems to mitigate risks, automate processes, and enhance supplier collaboration (Garvey et al., 2015). These systems integrate with enterprise resource planning (ERP) and supply chain management (SCM) platforms to enable continuous monitoring of procurement activities and rapid response to potential disruptions. The literature establishes that digital risk management capabilities offer a competitive edge in procurement, especially in volatile retail environments characterized by short product life cycles and high consumer expectations (Siegel, 2018). The primary objective of this systematic review is to synthesize and critically evaluate the existing body of scholarly literature concerning risk-based procurement strategies in retail supply chains, with a specific focus on sourcing flexibility and vendor disruption management. Retail supply chains, by their nature, are highly dynamic and exposed to an array of supply-side and demand-side risks, which necessitate a deeper understanding of procurement models that emphasize resilience and adaptability. To achieve this objective, the review examines various risk mitigation tools, procurement frameworks, and supplier relationship strategies that have been adopted in retail settings across global markets. The review aims to identify commonalities, gaps, and best practices across the literature by employing a structured analytical lens grounded in procurement risk theories and supply chain resilience concepts. In doing so, the review goes beyond descriptive reporting to establish linkages between procurement strategy design and retail supply chain outcomes such as continuity, responsiveness, and cost efficiency.

LITERATURE REVIEW

The literature surrounding procurement strategy in the retail supply chain domain has evolved significantly over the past two decades, reflecting the growing complexity of global sourcing networks and the imperative for resilience amidst disruptions. This section systematically explores the key academic contributions, theoretical models, empirical findings, and technological frameworks relevant to risk-based procurement strategies with a focus on sourcing flexibility and vendor disruption management. Procurement, once considered a back-office function, has transformed into a strategic pillar for ensuring continuity, cost efficiency, and agility in the face of risks such as geopolitical instability, supplier insolvency, transportation delays, and demand variability. This literature review is structured to provide a comprehensive synthesis of the concepts and findings under distinct yet interrelated themes. The section begins with foundational procurement risk frameworks and then delves into specific dimensions such as sourcing flexibility, vendor risk categorization, digital procurement innovation, and collaborative disruption response strategies. Each sub-section draws on peer-reviewed journal articles, industry case studies, and systematic reviews published between 2010 and 2024.

Procurement Risk

Procurement risk broadly refers to the probability and impact of adverse events occurring in the sourcing and supply processes that can hinder an organization's ability to obtain required goods and services at the right time, cost, and quality (Mahapatra et al., 2016; Mohiul et al., 2022). In the context of supply chain management, procurement risk has been increasingly recognized as a multidimensional construct encompassing strategic, operational, financial, and reputational vulnerabilities associated with supplier interactions (Fahimnia et al., 2019; Maniruzzaman et al., 2023). Traditionally, procurement risk was viewed narrowly, focusing on price fluctuations or supplier failure;

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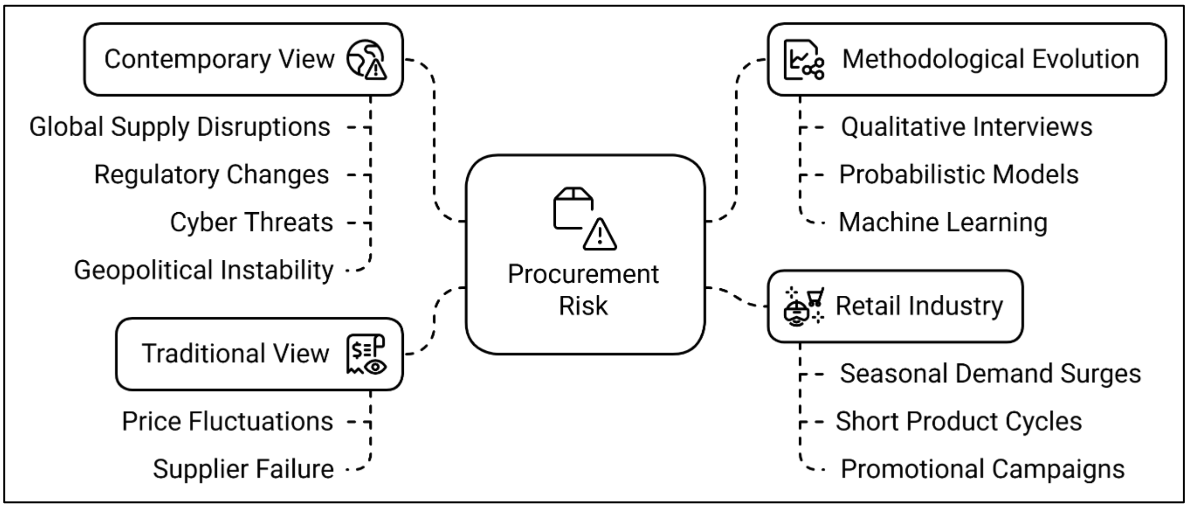
however, contemporary definitions have evolved to incorporate systemic uncertainties such as global supply disruptions, regulatory changes, cyber threats, and geopolitical instability (Chauhan et al., 2023; Younus et al., 2024). Procurement is now considered a front-line activity in enterprise risk management, with risk categorizations including supply market volatility, delivery delays, compliance issues, and environmental and ethical breaches (Mahapatra et al., 2016; Hossen & Atiqur, 2022). This expanded definition has prompted scholars and practitioners to shift from reactive cost-centered approaches to proactive, resilience-oriented procurement planning.

Figure 3: Evolution of Procurement Risk Management



The evolution of procurement risk is closely tied to the globalization and digitalization of supply chains, which have significantly increased the complexity and interdependence of sourcing networks (Charwand & Gitizadeh, 2020; Conejo & Carrión, 2006; Hossain et al., 2024)The fragmentation of suppliers across multiple geographies and the reliance on lean inventory models have elevated the potential for cascading failures, particularly in retail supply chains characterized by short product life cycles and high service level expectations (Fera et al., 2017; Jakaria et al., 2025). This has led to the integration of risk indicators into procurement decisions, such as country risk indices, supplier risk scores, and demand volatility measures (Bhowmick & Shipu, 2024; Butt, 2021). Furthermore, procurement risk is increasingly viewed through a systems-thinking lens, where the interactions between suppliers, intermediaries, and logistics providers are assessed for their potential to propagate or buffer disruptions (Mahabub, Das, et al., 2024; Namdar et al., 2017). Consequently, supply chain scholars argue for a holistic understanding of procurement risk that accounts for dynamic externalities, interorganizational dependencies, and socio-technical factors affecting risk visibility and response (Fera et al., 2017; Khan, 2025).
Academic literature has also evolved in its methodological approach to studying procurement risk, shifting from descriptive case studies to sophisticated risk modeling and simulation techniques (Conejo & Carrión, 2006; Hossen et al., 2023). Early research relied heavily on qualitative interviews and post-event analyses to identify procurement risk factors, such as supplier bankruptcy or transportation delays (Charwand & Gitizadeh, 2020; Sohel, 2025). However, contemporary studies employ probabilistic models, game theory, and scenario analysis to evaluate the likelihood and impact of various procurement risk scenarios under different sourcing configurations (Hossain et al., 2024; Wang et al., 2022). Researchers have also applied data-driven approaches—such as machine learning algorithms—to predict supplier risk levels based on historical performance, financial health, and geopolitical exposure (Charwand & Moshavash, 2014; Khatun et al., 2025). The literature reveals that the integration of quantitative and qualitative risk data enables more accurate supplier assessments and supports dynamic procurement decision-making processes (Mahapatra et al., 2016; Sohel et al., 2022). As the scope of procurement has expanded beyond organizational boundaries to include third-party logistics providers and contract manufacturers, studies have emphasized the importance of network-wide risk analysis, including Tier-2 and Tier-3 supplier vulnerabilities (Md et al., 2025; Tao et al., 2019). This broader analytical focus reflects the recognition

that procurement risk is not isolated but embedded within a complex web of interdependencies across global supply chains. The progression of procurement risk management in the retail industry is particularly pronounced due to its high velocity, demand uncertainty, and customer-centric performance metrics (Bhuiyan et al., 2024; Chauhan et al., 2023). Retailers face procurement-specific challenges such as seasonal demand surges, short product development cycles, and frequent promotional campaigns, which elevate the risks of stockouts, excess inventory, and supplier overload (Fahimnia et al., 2019; Roksana, 2023). Studies have shown that retail procurement functions have adopted a variety of adaptive risk management strategies, including flexible contracts, supplier diversification, and near-shoring to reduce lead times (Butt, 2021; Conejo & Carrión, 2006; Jahan, 2023). Moreover, the adoption of real-time analytics and cloud-based procurement platforms has enabled more agile responses to supplier disruptions, further reducing procurement-related risks (Faria & Rashedul, 2025; Namdar et al., 2017). Retail-focused research has also highlighted the role of procurement governance structures, such as centralized vs. decentralized sourcing units, in shaping an organization's ability to detect, communicate, and respond to procurement risks (Mahapatra et al., 2016; Sarker, 2025). Overall, the literature affirms that retail supply chains, due to their exposure to dynamic consumer preferences and global sourcing complexities, have become a critical context for advancing the theory and practice of procurement risk management.

Procurement Risk Management in Retail

Strategic procurement refers to the long-term alignment of purchasing activities with broader business objectives such as cost leadership, risk mitigation, supplier innovation, and market responsiveness (Barratt & Oke, 2007; Shofiullah et al., 2024). In the retail sector, strategic procurement plays a vital role due to the industry's inherent exposure to price volatility, supply instability, and rapidly shifting consumer preferences (Carrión et al., 2009; Sabid & Kamrul, 2024). The evolution from transactional to strategic procurement has introduced structured risk typologies that categorize procurement threats into supply-side, demand-side, process-based, and environmental risks (Ahmed et al., 2022; Charwand et al., 2014). This multidimensional classification allows procurement managers to deploy differentiated risk mitigation strategies, such as multi-sourcing for supply risk, demand sensing tools for demand risk, and regulatory compliance for environmental risk (Al-Arafat, Kabir, et al., 2024; Zheng et al., 2019). Scholars emphasize that in retail settings, supply risks—such as late deliveries, supplier insolvency, or raw material shortages—are particularly prevalent due to lean inventory practices and extensive outsourcing (Sharma et al., 2020; Shipu et al., 2024). Risk typologies have thus become foundational tools for strategic sourcing decisions, enabling retailers to balance cost-efficiency with resilience (Munira, 2025; Wei et al., 2015).

The academic literature presents numerous frameworks to assess and classify procurement risks strategically. One of the most widely cited is the Kraljic Matrix, which segments procurement items based on supply risk and profit impact into four quadrants: strategic, leverage, bottleneck, and non-critical (Carrión et al., 2007; Sunny, 2024a). In retail, strategic items—such as fast-moving or high-margin products—require supplier partnerships and investment in risk mitigation mechanisms like exclusive contracts or supplier development programs (Bonzelet, 2022; Mahdy et al., 2023; Yi et al., 2018). Bottleneck items, typically sourced from limited suppliers, call for contingency planning and buffering strategies (Kharrati et al., 2015; Younus, 2025). Scholars also discuss procurement risk typologies grounded in behavioral and institutional theories, highlighting how organizational culture and external regulatory pressures influence risk perception and response (Charwand & Moshavash, 2014; Sunny, 2024b). Retailers increasingly rely on hybrid frameworks that integrate these typologies with real-time analytics and machine learning-based risk dashboards to improve the visibility and granularity of procurement risk assessments (Bonzelet, 2022; Charwand et al., 2017; Mahabub, Jahan, Hasan, et al., 2024). These tools help organizations proactively reclassify risks as supplier conditions evolve or external shocks emerge, thereby enabling dynamic procurement strategy adjustment in retail operations.

The practical application of procurement risk typologies in retail is seen through examples such as category management, where retailers classify procurement categories based on risk and performance potential (Carrión et al., 2007; Dey et al., 2024). Retail giants like Walmart and Tesco implement category-specific sourcing strategies that consider supplier power, market dynamics, and potential disruption exposure (Bonzelet, 2022; Dasgupta & Islam, 2024). Procurement teams in these firms often maintain strategic supplier scorecards with metrics such as on-time delivery rate,

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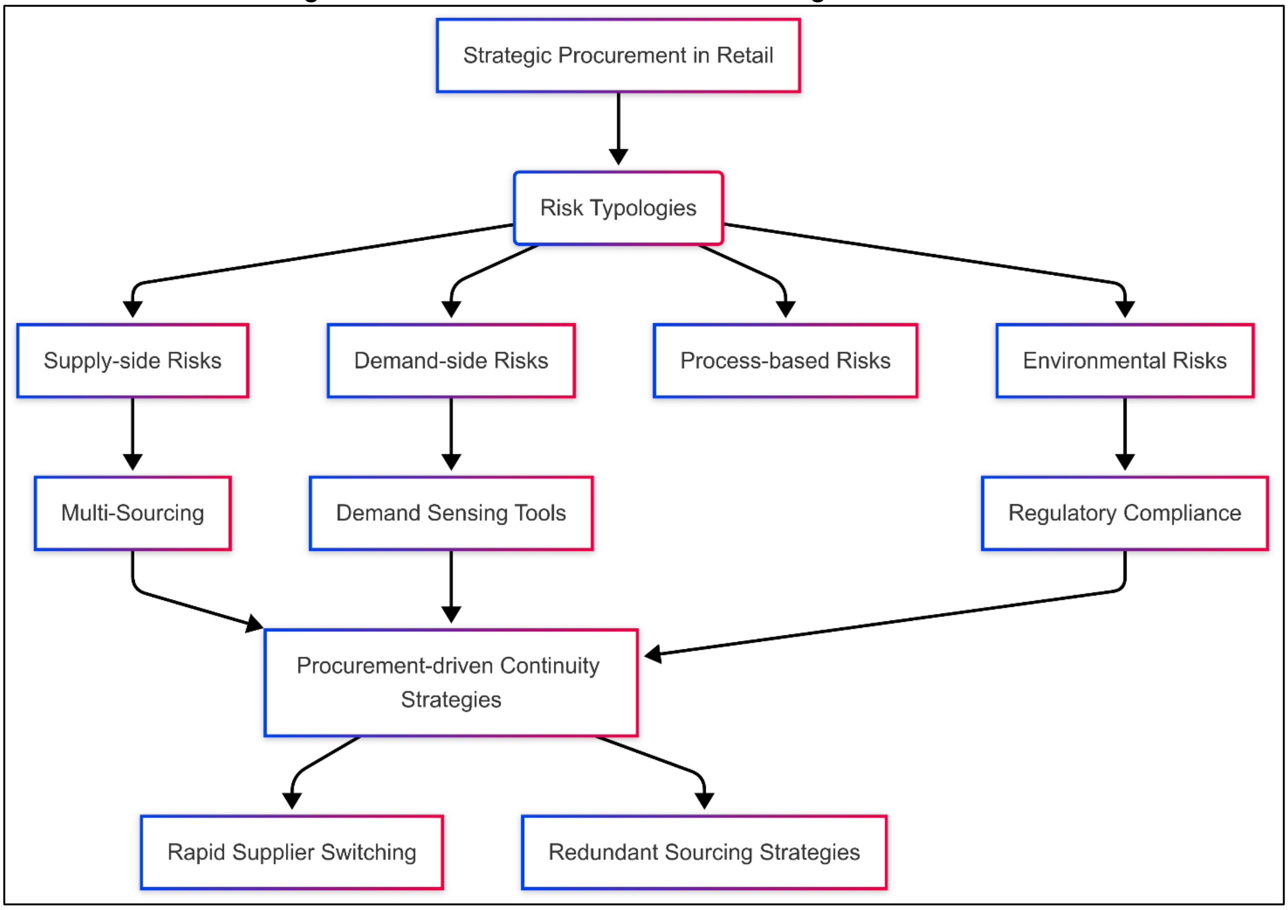
financial health, innovation capability, and geographic risk profile (Rahaman et al., 2024; Yi et al., 2018). Moreover, procurement strategies in the retail sector increasingly incorporate sustainability and compliance-related risks, such as unethical labor practices or carbon emissions, which have financial and reputational consequences (Al-Arafat, Kabi, et al., 2024; Kharrati et al., 2015). These expanded risk typologies not only improve supplier segmentation but also inform contract design, performance monitoring, and audit frequency (Charwand & Moshavash, 2014; Mahfuj et al., 2022). The retail literature illustrates how risk typologies form the backbone of strategic procurement, enabling firms to respond to both recurring risks (e.g., demand seasonality) and emerging threats (e.g., global pandemics) through structured decision-making tools.

Figure 4: Overview of Procurement Risk Management in Retail



The role of procurement in ensuring supply chain continuity has gained prominence in retail management scholarship, especially following high-profile disruptions such as the 2011 Tōhoku earthquake, Brexit, and the COVID-19 pandemic (Rocha & Kuhn, 2012; Shimul et al., 2025). Procurement is no longer viewed as a cost-control function but as a strategic enabler of resilience and agility (Charwand et al., 2017; Mahabub, Jahan, Islam, et al., 2024). In retail, procurement continuity hinges on several capabilities: early risk detection, rapid supplier switching, inventory buffering, and collaborative planning with vendors (Islam et al., 2024; Nojavan et al., 2015). These capabilities allow firms to maintain product availability and customer service levels during disruptions, safeguarding both revenue and brand trust (Alam et al., 2024; Hatami et al., 2009). Research shows that firms that embed procurement into continuity planning outperform their competitors during crises, as they are more likely to have redundant sourcing arrangements and responsive supplier networks (Kettunen et al., 2010; Khan & Aleem Al Razee, 2024). This is particularly important in retail sectors such as grocery and fashion, where delays in replenishment directly affect sales and inventory turnover (Karandikar et al., 2007; Shohel et al., 2024). Empirical studies on procurement-driven continuity highlight several successful strategies. For instance, (Chowdhury et al., 2023; Wei et al., 2015) found that procurement-led integration of supplier data, via ERP and supply chain visibility platforms, significantly reduces reaction times to disruptions. Similarly, (Charwand et al., 2017) observed that cross-functional procurement teams—working in tandem with logistics and marketing departments—are better equipped to coordinate recovery during supplier failures. Other studies

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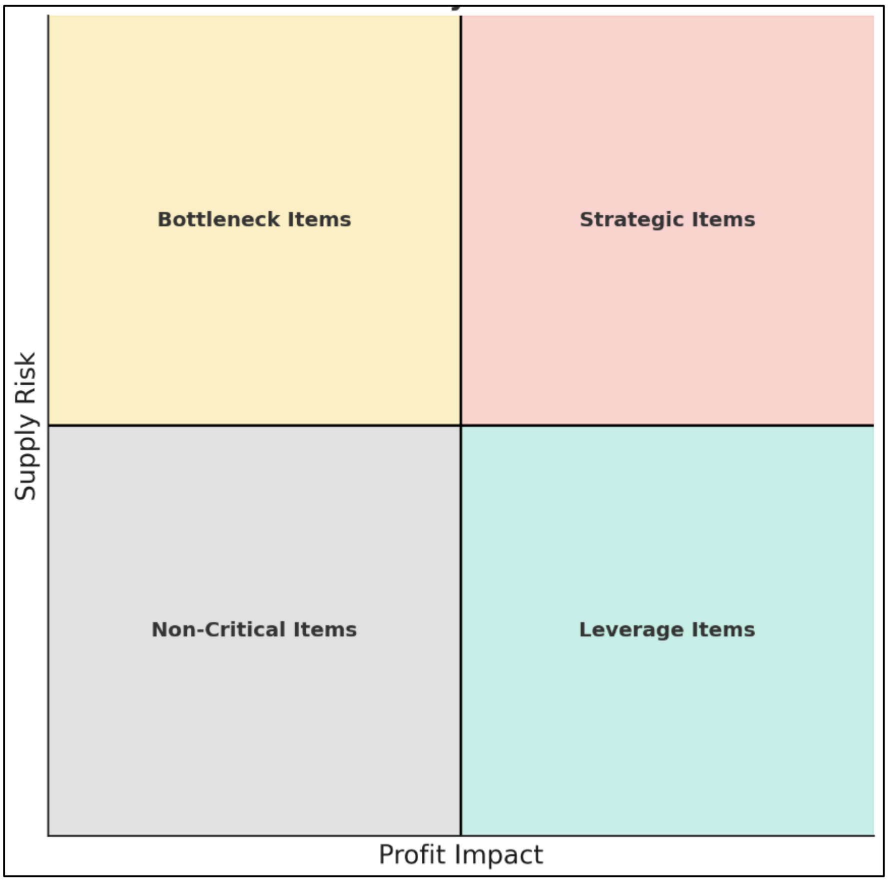
emphasize the value of procurement risk-sharing mechanisms such as vendor-managed inventory, joint contingency funds, and co-investment in safety stock (Charwand et al., 2017; Charwand & Moshavash, 2014; Tonoy, 2022). These mechanisms help retailers spread risk across the network, reduce supplier stress, and promote continuity. Furthermore, research by Karandikar et al. (2007) and Rane et al. (2019) indicates that digital procurement tools, including blockchain and AI-enabled risk assessment, enhance the speed and accuracy of continuity decisions. These findings underscore the strategic centrality of procurement in retail supply chains, positioning it as a key player in disruption preparedness, detection, and recovery.

Kraljic Matrix

The Kraljic Matrix, introduced by Peter Kraljic in 1983, remains one of the most influential frameworks in strategic procurement and supply management. It was developed to help companies shift procurement from a reactive, transactional function to a strategic, value-creating process (Kraljic, 1983). The matrix classifies procurement items based on two dimensions: profit impact and supply risk, dividing them into four categories—non-critical, leverage, bottleneck, and strategic items. Each quadrant suggests different sourcing strategies and supplier relationship management approaches, thereby offering a structured basis for risk mitigation (Alam et al., 2023; Blackhurst et al., 2011). Over the years, scholars have expanded on Kraljic's typology to reflect the growing complexity of global sourcing networks and the volatility inherent in modern supply chains, particularly in the retail industry (Pastor-Satorras et al., 2015; Sharif et al., 2024). Retailers face unique challenges due to fast-moving consumer goods, frequent product changes, and fluctuating demand patterns, all of which heighten the relevance of strategic segmentation of procurement items (Islam et al., 2024; Zhang et al., 2020).

Figure 5: Kraljic Procurement Portfolio Matrix



In retail supply chains, the Kraljic Matrix supports decision-making in vendor selection, inventory strategy, and supply risk response. For non-critical items—low in both supply risk and profit impact—standardization and automation are prioritized to minimize administrative burden (Aleem Al Razee et al., 2025; Butt, 2021). Leverage items, which offer high profit impact but low supply risk, are often sourced using competitive bidding to maximize cost savings (Namdar et al., 2017; Roksana et al., 2024). Bottleneck items, however, present high supply risks and low profit impact; these require contingency planning, supplier development, or inventory buffers to avoid operational delays (Fera et al., 2017; Islam & Helal, 2018). Strategic items—high in both profit impact and risk—demand long-term partnerships, risk-sharing contracts, and collaborative forecasting, especially in sectors like electronics, pharmaceuticals, or high-end retail (Conejo & Carrión, 2006; Younus, 2022). Research shows that retailers who dynamically assess their product portfolios using this matrix are more resilient to market disruptions and supplier failures (Charwand & Gitizadeh, 2020; Islam et al., 2025).

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The adaptability of the Kraljic Matrix has been validated through its integration with various procurement tools and analytical methods. Scholars have proposed extensions using fuzzy logic, multi-criteria decision-making (MCDM), and data-driven approaches to refine item classification (Conejo & Carrión, 2006; Roy et al., 2024). For instance, Fera et al. (2017) applied fuzzy AHP (Analytic Hierarchy Process) to improve the objectivity of matrix classification by incorporating qualitative supplier risk variables. Others have developed hybrid models that integrate the Kraljic Matrix with risk heat maps or supply chain resilience metrics to assess item-level vulnerabilities under dynamic conditions (Conejo & Carrión, 2006; Nahid et al., 2024). These innovations are particularly valuable in retail procurement, where products often shift categories due to seasonality, supplier instability, or demand variability (Charwand & Gitizadeh, 2020; Islam et al., 2025). Moreover, recent studies advocate for regular reclassification of items, especially in volatile environments such as fast fashion, e-commerce, and perishables, where procurement categories can evolve rapidly (Hossain et al., 2024; Wang et al., 2022). By enhancing the responsiveness and analytical depth of the Kraljic Matrix, retailers can continuously realign their procurement strategies with operational realities.

Another prominent application of the Kraljic Matrix is in aligning supplier relationship management (SRM) strategies with risk exposure. For strategic suppliers, close collaboration, information sharing, and joint innovation initiatives are emphasized (Charwand & Moshavash, 2014; Jim et al., 2024). Studies have shown that such supplier engagement leads to better disruption recovery, improved lead time performance, and enhanced product customization in the retail context (Mahapatra et al., 2016; Tonoy & Khan, 2023). Conversely, for bottleneck suppliers, researchers suggest focusing on supplier risk mapping, financial vetting, and backup sourcing options to minimize dependency (Hasan et al., 2024; Tao et al., 2019). Leverage suppliers, due to their competitive nature, are best managed through tactical contracts and reverse auctions to drive cost efficiency (Chauhan et al., 2023; Helal, 2022). Empirical studies confirm that companies that align procurement actions with Kraljic-based classifications demonstrate improved agility during crises, such as natural disasters, political upheaval, or pandemics (Charwand & Moshavash, 2014; Chauhan et al., 2023; Younus et al., 2024). Retailers such as Amazon and Walmart use such segmentation models not only for cost control but also for building resilient supplier ecosystems through strategic collaborations and risk-based outsourcing.

The Kraljic Matrix's effectiveness has also been examined in terms of its strategic alignment with enterprise-wide risk management frameworks. Researchers highlight that procurement categories mapped within the matrix can be used to prioritize risk mitigation investments and align sourcing strategies with corporate objectives such as sustainability, compliance, and innovation (Ammar et al., 2024; Charwand & Gitizadeh, 2020). For instance, environmentally sensitive items in the strategic quadrant may require deeper scrutiny for ESG (Environmental, Social, Governance) risks and ethical sourcing compliance (Islam, 2024; Namdar et al., 2017). Additionally, several case studies from global retailers demonstrate the application of the matrix to diversify supplier bases, assess geopolitical risk, and avoid over-reliance on single sources (Shahan et al., 2023; Tao et al., 2019). Scholars argue that the matrix provides a scalable framework that can be customized for varying firm sizes, industry contexts, and product portfolios (Aklima et al., 2022; Chauhan et al., 2023). Its continued relevance in supply chain risk literature is due in part to its flexibility, ease of integration with digital tools, and its strong theoretical foundation that balances risk and profit dimensions in procurement strategy (Fahimnia et al., 2019; Jahan, 2024).

Total Cost of Ownership (TCO)

The Total Cost of Ownership (TCO) model is a comprehensive approach in procurement that extends beyond purchase price to include all costs associated with acquiring, operating, maintaining, and disposing of a product or service (Ferrin & Plank, 2002). Traditionally applied in capital equipment sourcing, TCO has gained traction in retail procurement due to the need for a more holistic understanding of supply chain economics and risk implications (Islam, 2024; Pun, 2014). The framework facilitates long-term strategic sourcing by capturing hidden costs such as logistics, warranty, supplier performance variability, and risk mitigation measures (Helal, 2024; Vishnu et al., 2019). Scholars argue that relying solely on unit price can lead to suboptimal procurement decisions, especially when dealing with volatile supply markets and high-risk sourcing environments (Giannakis & Papadopoulos, 2016; Sunny, 2024). By integrating lifecycle costs into procurement evaluation, TCO helps firms better assess supplier value and develop resilient, cost-effective supply strategies (Helal et al., 2025; Vishnu et al., 2019).

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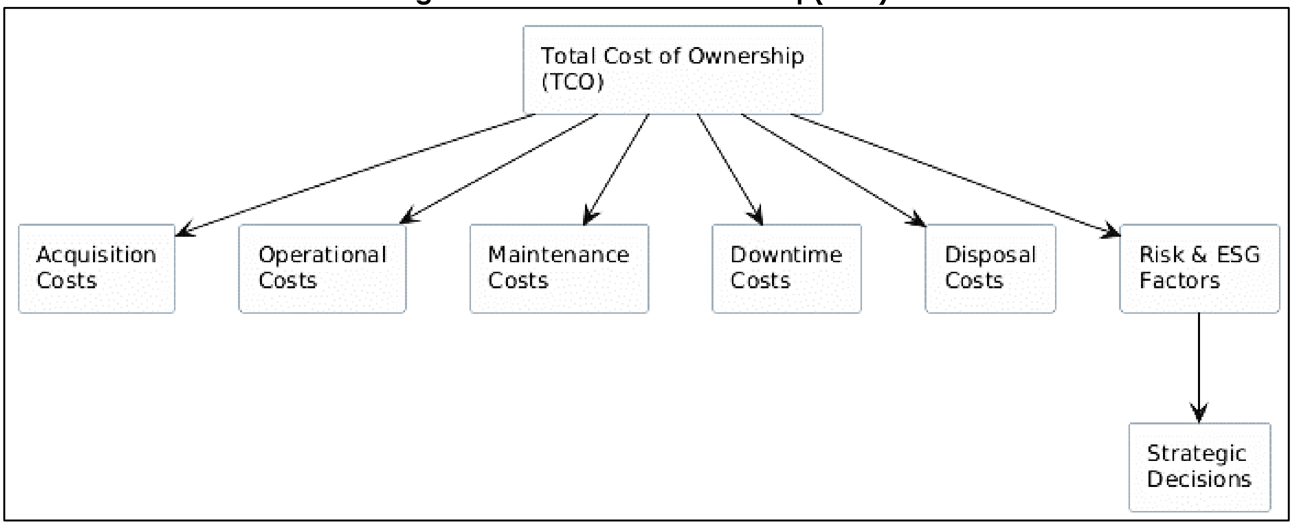
Retail supply chains, with their dependence on global sourcing, lean inventory, and speed-to-market, particularly benefit from the TCO model in identifying cost-risk trade-offs (Swink et al., 2023). For example, sourcing from low-cost countries may appear economical upfront but may involve significant hidden costs like quality defects, delivery delays, and regulatory compliance failures (Kot et al., 2020). These hidden costs often materialize during demand peaks or external disruptions, undermining the supposed cost advantages of offshore sourcing (Macdonald & Corsi, 2013). Retailers such as IKEA and Target have used TCO frameworks to reevaluate supplier contracts and prioritize vendors with higher operational reliability, even at slightly higher base prices (Elmaghraby, 2000). Furthermore, digital procurement platforms now allow real-time simulation of TCO components—including logistics volatility, fuel surcharges, and currency risk—enabling more informed and risk-adjusted sourcing decisions (Pun, 2014). This dynamic capability empowers procurement teams to shift from cost-focused decision-making to value-driven partnerships that support long-term continuity and performance.

Figure 6: Total Cost of Ownership(TCO)



The literature identifies several key components that constitute TCO in procurement decisions: acquisition cost, operational cost, maintenance and service cost, downtime cost, and end-of-life or disposal cost (Giannakis & Papadopoulos, 2016; Majharul et al., 2022). Acquisition costs include not just the purchase price, but also shipping, taxes, inspection, and insurance (Kumar et al., 2022; Swink et al., 2023). Operational costs capture warehousing, quality control, and supplier coordination, while maintenance costs include warranty services, repair, and parts replacement (Arafat Bin et al., 2023; Nagurney, 2021). Downtime costs, often underestimated in retail, refer to lost sales and customer dissatisfaction due to late or failed deliveries—highlighting the strategic role of reliable suppliers (Pamucar et al., 2022). Disposal costs or returns management—important in fast-moving retail like apparel and electronics—can significantly influence the total cost if not properly considered (Montecchi et al., 2021). A major advantage of the TCO model is its compatibility with risk-based procurement, enabling firms to factor disruption probabilities into supplier evaluation through tools like Monte Carlo simulation, stochastic modeling, and sensitivity analysis (Elmaghraby, 2000). These integrated approaches allow retailers to quantify and compare both financial and non-financial supplier risks in economic terms, making risk mitigation a calculable part of the sourcing equation.

In retail environments, TCO is also critical for evaluating outsourcing decisions. Retailers frequently outsource not only manufacturing but also logistics, warehousing, IT services, and customer support to third-party providers (Macdonald & Corsi, 2013). While outsourcing may offer flexibility and specialization, it introduces long-term risks such as service inconsistency, dependency on vendors, and contractual ambiguities (Kim et al., 2014). The TCO model supports strategic outsourcing decisions by considering relationship management costs, switching costs, legal liabilities, and penalties for underperformance (Giannakis & Papadopoulos, 2016). Additionally, studies have shown that TCO-based vendor assessments improve collaborative behaviors, as suppliers become aware that their performance is evaluated across multiple dimensions—not merely cost (Alora & Gupta, 2024). This often leads to higher service levels, better communication, and joint investment in risk mitigation mechanisms (Namdar et al., 2017). Retailers using TCO for logistics outsourcing often

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incorporate buffer inventory costs, emergency shipment costs, and alternate route planning costs into their evaluations to anticipate last-mile risk disruptions, particularly in urban delivery contexts (Kim et al., 2014). As e-commerce continues to compress delivery windows, these considerations become central to ensuring procurement strategies support both customer satisfaction and financial viability. Beyond risk and financial performance, TCO is increasingly used to integrate sustainability into procurement strategy. The environmental and social cost dimensions—such as carbon emissions, labor conditions, and resource use—are being internalized into sourcing decisions through TCO frameworks, reflecting global trends toward ethical procurement (Ho et al., 2015). For instance, lifecycle assessment (LCA) and eco-cost models are now being incorporated into total cost models to evaluate a supplier's environmental footprint (Yan & Zhao, 2011). Retailers committed to ESG (Environmental, Social, and Governance) goals use TCO to compare not just financial costs, but the long-term sustainability impacts of various sourcing options (Nagurney, 2021). Empirical studies confirm that integrating sustainability metrics into TCO helps companies avoid reputational risks and regulatory penalties, especially in industries subject to consumer scrutiny, such as apparel, food, and electronics (Basole & Bellamy, 2014). Moreover, by making these trade-offs explicit, the TCO model becomes a strategic tool that aligns procurement with corporate responsibility objectives (Montecchi et al., 2021). Retail firms such as Unilever and Patagonia have adopted TCO models that factor in carbon pricing, packaging waste costs, and ethical audit scores to guide sourcing decisions, thereby transforming procurement into a vehicle for sustainable value creation (Kot et al., 2020).

Supply chain risk management models

Supply Chain Risk Management (SCRM) models have emerged as critical frameworks for identifying, assessing, mitigating, and monitoring risks across increasingly complex and globalized supply networks (Ho et al., 2015). The growing susceptibility of supply chains to disruptions—ranging from natural disasters and pandemics to supplier bankruptcies and geopolitical tensions—has driven the evolution of structured SCRM approaches (Ho et al., 2015; Lochan et al., 2021). Foundational models such as the risk matrix, fault tree analysis, and Failure Mode and Effects Analysis (FMEA) have been widely employed in procurement planning to identify vulnerabilities at the supplier, process, and network levels (Jüttner et al., 2003). In the retail context, these models are essential due to high product variety, fluctuating demand, short life cycles, and the reliance on just-in-time inventory strategies (Namdar et al., 2017). Retail firms face procurement risks such as supplier inconsistency, quality failure, delivery delays, and compliance infractions, all of which necessitate comprehensive modeling tools to anticipate and prevent service disruption (Giannakis & Papadopoulos, 2016). One of the most prominent frameworks is the Resilience Triangle Model, which assesses a supply chain's ability to absorb, recover, and adapt to disruptive events (Elmaghraby, 2000). In retail procurement, the model has been used to measure resilience through metrics such as time-to-recovery, inventory buffering capacity, and supplier substitution readiness (Ho et al., 2015). These metrics are particularly relevant for sourcing categories that fall under the strategic or bottleneck quadrants of the Kraljic Matrix, where disruptions can significantly impact product availability and customer satisfaction (Lochan et al., 2021). Quantitative adaptations of the resilience model often include simulation-based tools such as Monte Carlo analysis, which helps estimate probable outcomes under uncertain supply conditions (Giannakis & Papadopoulos, 2016). The growing availability of digital data in retail has enabled real-time updates to these models, allowing procurement teams to dynamically reassess sourcing risks and preempt costly disruptions (Swink et al., 2023). Furthermore, empirical studies suggest that firms implementing resilience-based SCRM models are better positioned to safeguard supplier relationships and maintain operational continuity during unforeseen crises (Dubey & Gunasekaran, 2015).

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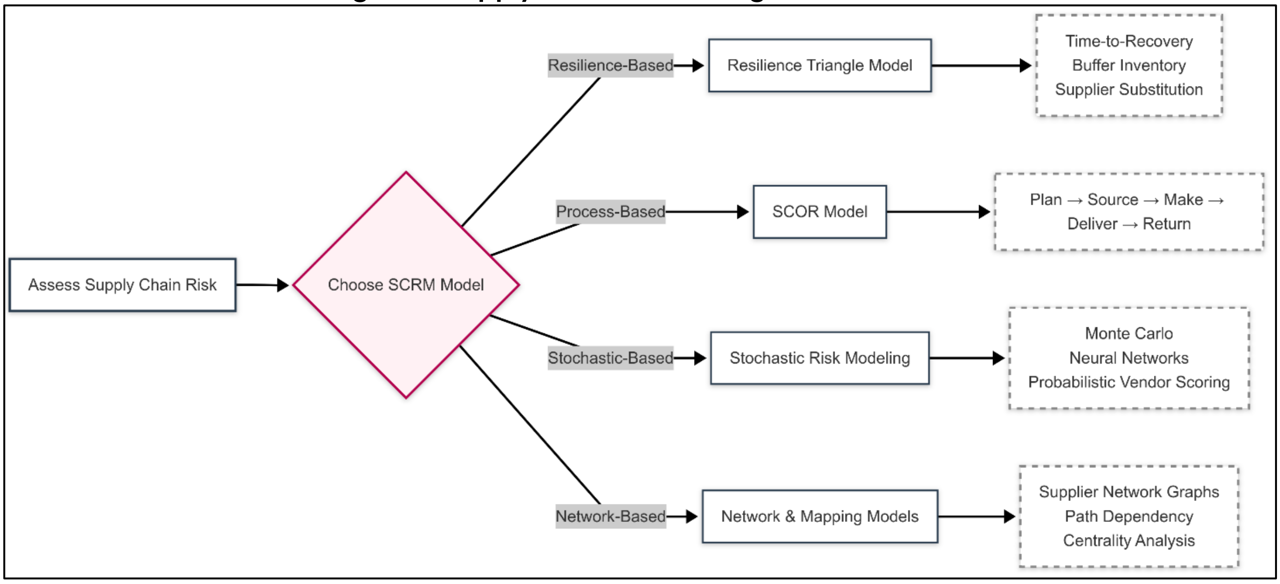
Figure 7: Supply chain risk management models



Another influential model in SCRM literature is the SCOR (Supply Chain Operations Reference) Model, developed by the Supply Chain Council, which links procurement risks to performance outcomes via five key processes: Plan, Source, Make, Deliver, and Return. The SCOR model helps identify risk-prone nodes within procurement activities and supports performance benchmarking and mitigation planning. Retail firms use SCOR to assess supplier reliability, cycle time variation, and sourcing process efficiency, thereby integrating procurement risk considerations into supply chain execution. Its flexibility allows it to be adapted to multi-tier retail networks, particularly for monitoring critical Tier-2 and Tier-3 suppliers whose failure can create a ripple effect. In procurement-focused applications, the SCOR model is often combined with Business Impact Analysis (BIA) to prioritize risk management resources and redesign sourcing strategies for high-risk products (Dubey & Gunasekaran, 2015; Nagurney, 2021). Researchers have also expanded the SCOR model with sustainability and digital transformation components, recognizing that modern procurement decisions must account for ESG risks and cybersecurity vulnerabilities in supplier ecosystems (Alora & Gupta, 2024).
Stochastic risk modeling represents another significant advancement in SCRM, particularly in procurement under uncertainty. These models incorporate probabilistic forecasts, sensitivity analysis, and dynamic programming to quantify the likelihood and impact of supplier disruptions (Lochan et al., 2021). In retail procurement, stochastic models support real-time decision-making on vendor selection, order quantities, and contingency stock levels (Giannakis & Papadopoulos, 2016). They are particularly useful in demand-driven sectors like apparel and electronics, where consumer preferences and supplier reliability shift rapidly (Elmaghraby, 2000). Machine learning-enhanced risk models now draw from supplier data, news feeds, and performance history to predict disruption risks with higher accuracy (Ho et al., 2015). For instance, neural networks have been trained to identify vendor patterns indicative of quality deterioration or financial instability, allowing procurement professionals to intervene early (Elmaghraby, 2000). Additionally, simulation-based optimization techniques such as Genetic Algorithms and Monte Carlo simulations have been integrated with supplier scoring systems to enable more robust risk-adjusted sourcing strategies in complex, volatile retail environments (Vishnu et al., 2019).
Network theory and supply chain mapping models have further enhanced risk identification and management in retail procurement. These models emphasize the structure and interconnectivity of supply chain entities, recognizing that risk is not confined to direct suppliers but extends through multiple tiers of relationships (Kot et al., 2020). Visual mapping of procurement networks reveals critical dependencies, potential bottlenecks, and redundancy gaps that may otherwise remain hidden in traditional models (Basole & Bellamy, 2014; Kouvelis & Turcic, 2021). Network analysis techniques such as centrality measures, clustering coefficients, and path dependency algorithms are now used to determine the vulnerability of supplier nodes and their ability to cascade risk downstream (Lochan et al., 2021). In retail, such mapping has revealed supplier overlap across categories, region-based risk exposure, and the presence of single points of failure, all of which can significantly influence procurement resilience (Ho et al., 2015). These insights support decisions on

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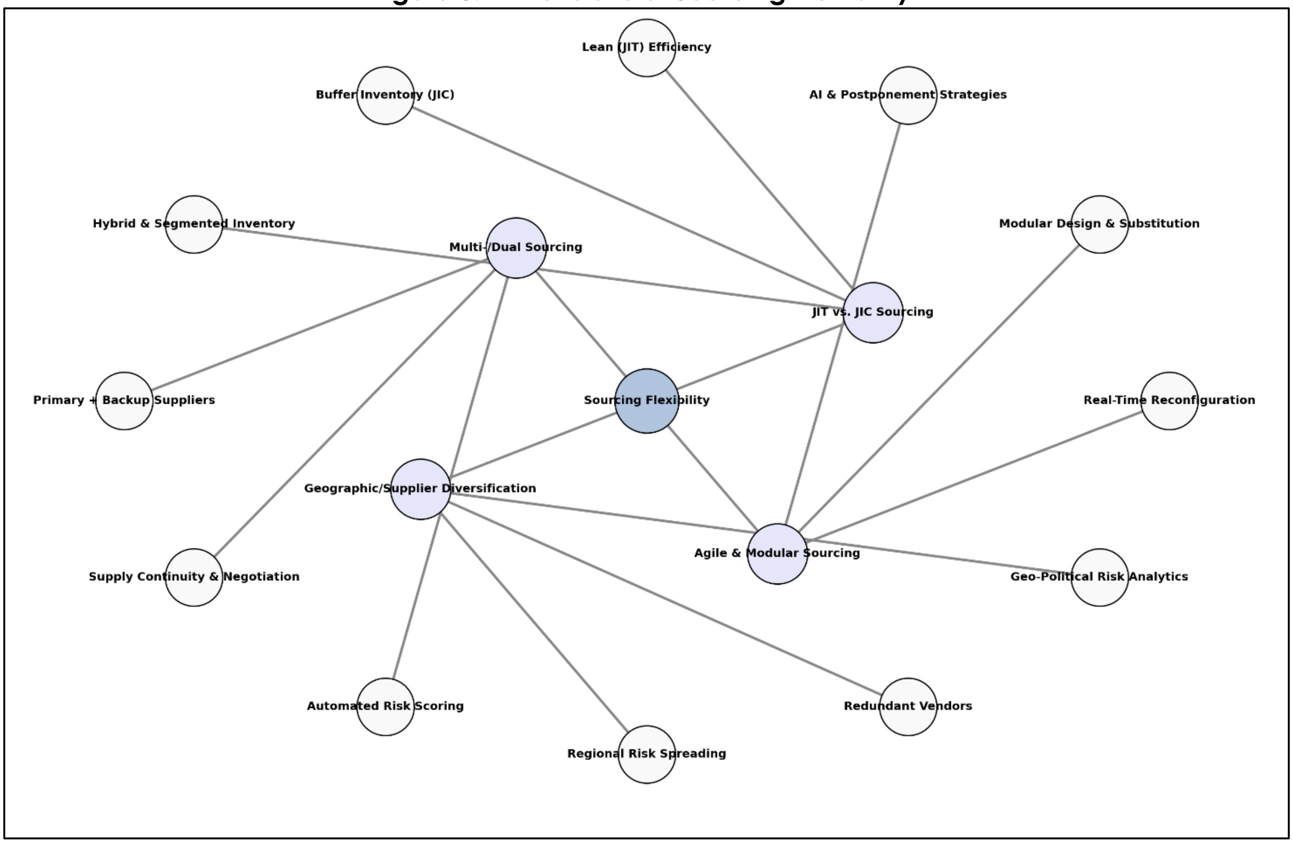
supplier diversification, geographical risk balancing, and collaboration initiatives across the network ((Vishnu et al., 2019). Moreover, the integration of supply chain mapping with digital twins has enabled predictive risk management, allowing procurement teams to simulate disruption scenarios and test recovery strategies before implementation (Pun, 2014).

Dimensions of Sourcing Flexibility as a Risk Mitigation Strategy

Multi-sourcing and dual sourcing are core strategies in procurement risk management, particularly in retail supply chains that are highly vulnerable to supplier failure, capacity issues, or geopolitical disruptions (Fera et al., 2017). Multi-sourcing involves procuring the same product or service from multiple suppliers, reducing dependency on a single source and enhancing resilience to disruption (Chen et al., 2017; Demirel et al., 2018). Dual sourcing, a more structured version, includes one primary supplier and one backup supplier to balance cost-efficiency and risk (Nagurney, 2021). These strategies are particularly valuable in high-volume retail sectors such as apparel, food, and electronics, where supply consistency directly affects market competitiveness (Lochan et al., 2021). Scholars argue that multi-sourcing enhances not only continuity but also negotiation power, supplier performance, and innovation (Basole & Bellamy, 2014). Empirical research confirms that firms with diversified sourcing models were significantly more resilient during COVID-19, as they could reallocate volumes across different suppliers without halting operations (Chen et al., 2017).

Figure 8: Dimensions of Sourcing Flexibility



Despite higher transaction and coordination costs, multi-sourcing has been associated with superior supply risk performance metrics such as lower lead-time volatility, fewer stockouts, and greater supplier competition (Ho et al., 2015). Advanced data analytics tools and digital procurement platforms have further supported the management of multi-supplier portfolios through performance tracking and automated risk scoring (Jüttner et al., 2003). Scholars also note that dual sourcing is highly effective in balancing risk and cost when demand variability is moderate and suppliers differ in lead times or geographical exposure (Giannakis & Papadopoulos, 2016). Case studies on Amazon and Uniqlo demonstrate how sourcing from multiple suppliers across regions allowed them to maintain inventory availability and fulfillment capacity under highly uncertain market conditions ((DuHadway et al., 2017).

Geographic and supplier diversification are pivotal in mitigating regional, political, and environmental risks within retail procurement ecosystems. Geographic diversification spreads procurement risk across multiple countries or regions, reducing the impact of local disruptions such as natural disasters, trade embargoes, or labor strikes. Supplier diversification complements this by ensuring that a single supplier failure does not cripple the supply chain. Retailers sourcing globally often face heightened risks due to reliance on overseas vendors with longer lead times, limited visibility, and varying compliance standards (Demirel et al., 2018). Therefore, spreading sourcing activities across multiple geographies and vendors enhances procurement flexibility and resilience (Gabriel et al., 2002). Empirical studies demonstrate that geographic and supplier diversification improve procurement continuity, particularly when combined with dynamic risk monitoring systems (Namdar et al., 2017). For example, during the 2011 Thailand floods and 2020 pandemic, firms with geographically dispersed suppliers experienced less production downtime than those relying on single-country sourcing (Ponomarov & Holcomb, 2009). Retail firms such as Walmart, Inditex, and Best Buy have developed diversified supplier bases across Asia, Latin America, and Eastern Europe to balance cost-efficiency with operational resilience (DuHadway et al., 2017). Scholars also highlight the role of geographic proximity in reducing transportation risks and enhancing supplier responsiveness, which is particularly crucial for high-demand, short-cycle products (Hu et al., 2023). Supplier redundancy in critical product categories, supported by predictive analytics and geo-political risk assessments, allows firms to swiftly shift procurement decisions without affecting fulfillment rates (Um & Han, 2020). Therefore, diversification strategies are not only risk-mitigating tools but also enablers of agility and responsiveness in procurement.

Just-in-Time (JIT) and Just-in-Case (JIC) sourcing represent two contrasting procurement philosophies that significantly affect retail supply chain risk profiles. JIT aims to minimize inventory and rely on tight supplier coordination, reducing holding costs and enabling lean operations (Namdar et al., 2017). Conversely, JIC builds in redundancy through buffer inventories and backup suppliers to ensure supply continuity in uncertain conditions (Basole & Bellamy, 2014). Although JIT improves cost efficiency and responsiveness in stable environments, it exposes firms to heightened risk during supply disruptions (DuHadway et al., 2017). This became evident during the COVID-19 pandemic when firms operating on JIT experienced severe shortages due to supplier closures and logistic breakdowns (Ponomarov & Holcomb, 2009). Scholars have debated the trade-offs between these models, suggesting hybrid strategies that combine the cost benefits of JIT with the risk mitigation of JIC. For instance, JIC strategies may be applied to critical items or high-risk suppliers, while JIT remains in use for stable, low-variability items (Chen et al., 2017). Empirical studies have shown that firms using risk-adjusted sourcing strategies with segmented inventory policies achieved better service levels and recovery rates during crises (Lochan et al., 2021). In retail, hybrid sourcing approaches often involve safety stock at regional hubs, fast-track logistics for high-demand items, and vendor-managed inventory for stable products (Butt, 2021). Additionally, advanced forecasting tools and IoT-based inventory monitoring systems allow for real-time adjustment between JIT and JIC sourcing strategies (Basole & Bellamy, 2014). Thus, sourcing flexibility through hybridization is increasingly favored by retailers striving to balance efficiency with resilience.

Vendor Risk Categorization and Performance Evaluation in Retail

Supplier risk scoring is a vital component of procurement strategy, allowing organizations to assess, compare, and manage the risks associated with their vendor base. These methods can be broadly classified into qualitative and quantitative techniques, both of which are widely used in retail supply chain risk management. Qualitative approaches often include expert judgment, Delphi panels, risk matrices, and supplier audits. These techniques provide valuable context, especially when dealing with small vendors or limited data environments, but are often criticized for subjectivity and inconsistency. Quantitative methods, on the other hand, utilize structured models such as supplier risk indices, probabilistic modeling, simulation-based risk assessments, and analytic hierarchy process (AHP) to objectively score and rank suppliers (Park & Kim, 2016). Hybrid models combining both qualitative and quantitative dimensions are increasingly being adopted in retail procurement to capture a more holistic view of supplier risk (Vishnu et al., 2019).

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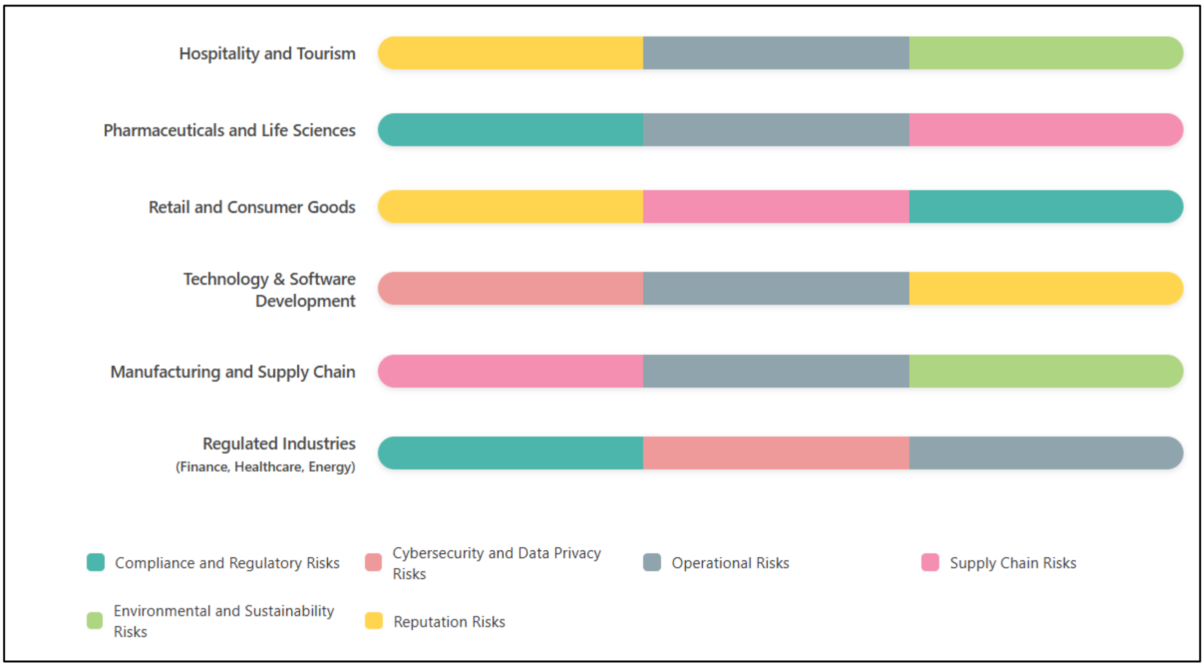
Figure 9: Main Risk Categories Across Different Industries



Retail firms typically assess risk factors such as supplier financial health, past delivery performance, geopolitical exposure, labor compliance, and dependency level (Demirel et al., 2018). Tools such as risk heat maps, supplier scorecards, and supply risk simulators enable procurement teams to visualize and prioritize supplier vulnerabilities (Namdar et al., 2017). Additionally, machine learning-based scoring systems now utilize real-time data from news feeds, credit ratings, logistics logs, and regulatory reports to automate vendor risk profiling (Park & Kim, 2016). For instance, Amazon uses AI-enabled risk engines to continuously assess supplier performance and risk factors across thousands of vendors globally (Basole & Bellamy, 2014). Research further shows that risk scores influence procurement decisions such as order allocation, supplier development investments, and contract design (Um & Han, 2020). These scoring frameworks are essential in the retail sector where procurement must balance cost-efficiency, compliance, and continuity across fast-moving and geographically dispersed supplier networks. Key Performance Indicators (KPIs) serve as essential metrics for evaluating supplier performance and resilience across retail supply chains. Resilience-focused KPIs extend beyond traditional performance indicators such as on-time delivery and cost efficiency to include responsiveness, adaptability, recovery time, and compliance behavior (Chen et al., 2017). Common KPIs include Perfect Order Rate, Lead Time Variability, Order Fill Rate, Supplier Defect Rate, and Time-to-Recovery (TTR) (Lochan et al., 2021). These indicators provide actionable insights into a supplier's ability to absorb and recover from disruptions, which is critical for maintaining operational continuity in retail environments characterized by short product life cycles and fluctuating demand (Basole & Bellamy, 2014). Scholars note that incorporating resilience-based KPIs into procurement decisions improves supplier transparency and fosters proactive risk mitigation behavior (Butt, 2021). Empirical studies show that supplier resilience correlates with the level of monitoring and accountability enforced by buying firms (Demirel et al., 2018). Firms such as Walmart and Target have established supplier evaluation dashboards incorporating KPIs such as risk exposure score, number of late shipments, corrective action lead time, and supplier capacity index (Hu et al., 2023). These dashboards help procurement teams segment suppliers into strategic, preferred, and backup categories based on resilience profiles (Park & Kim, 2016). Research also emphasizes the need to customize KPIs based on product criticality and supplier location, as risks vary by category and geography (Ponomarov & Holcomb, 2009). Retail firms increasingly use digital tools and ERP-integrated analytics platforms to track KPIs in real-time, enabling dynamic supplier risk monitoring (Basole & Bellamy, 2014). These capabilities not only enhance procurement visibility but also support collaborative improvement programs that strengthen supplier resilience over time (Ponomarov & Holcomb, 2009).

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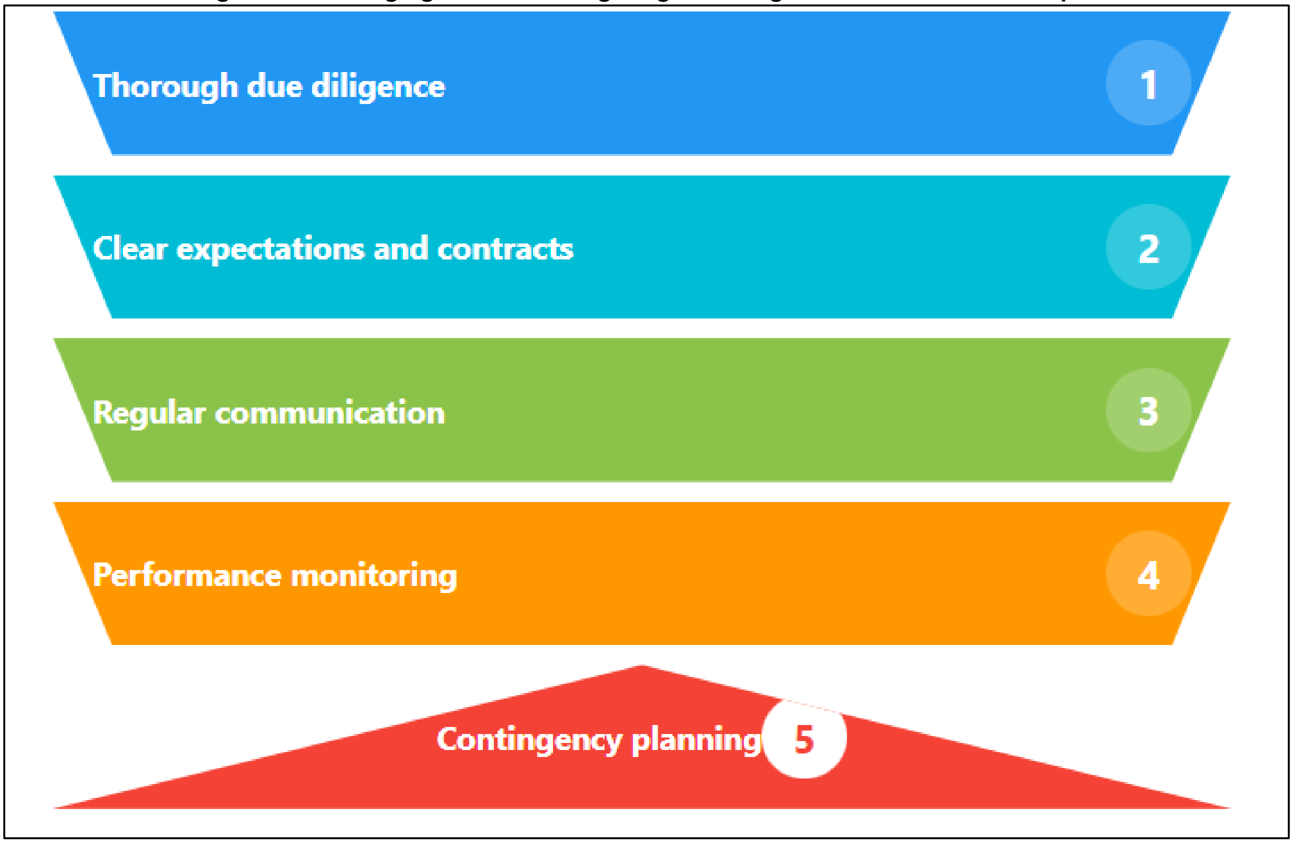
Disruption Management Strategies in Vendor Relationships

The distinction between proactive and reactive disruption management is a central theme in supply chain risk literature, especially in the context of vendor relationships. Proactive planning involves the anticipation of potential risks and implementation of mitigation strategies before disruptions occur, whereas reactive planning entails actions taken in response to disruptions after they materialize (Vishnu et al., 2019). Scholars agree that proactive strategies—such as risk mapping, scenario analysis, and business continuity planning—are superior in preventing extended downtime and minimizing financial losses (Käki et al., 2014; Vishnu et al., 2019). In retail procurement, where supplier lead times, demand volatility, and consumer expectations are tightly coupled, proactive disruption planning enables firms to maintain competitive advantage even under adverse conditions (Nagurney, 2021).Proactive vendor risk planning includes supplier audits, geopolitical risk assessments, and the use of predictive analytics to identify early signs of supplier distress (Kettunen et al., 2010). Several studies demonstrate that firms that integrate supplier risk indicators into procurement decisions experience faster recovery from disruptions and greater supply chain agility (Zhou & Johnson, 2014). In contrast, reactive approaches—such as emergency sourcing or expediting shipments—often result in higher costs, quality compromises, and reputational damage (Sawik, 2016). Retailers such as Target and Tesco have shifted toward proactive frameworks by investing in digital risk monitoring systems and building cross-functional risk teams (Dong et al., 2018; Zhou & Johnson, 2014). Research further indicates that combining proactive planning with regular risk scenario simulations strengthens procurement readiness and enhances supplier responsiveness (Karandikar et al., 2007). Thus, vendor disruption planning in retail is most effective when it moves beyond reactive responses and embraces anticipatory mechanisms rooted in strategic foresight and data integration.

Figure 10: Managing Risks and Mitigating Challenges in Vendor Relationships



Contingency contracts, buffer inventories, and safety stock are among the most widely adopted operational tools for managing supply disruptions in procurement. These strategies serve as tactical buffers that provide firms with alternatives and cushions when facing supplier failures, transportation delays, or demand surges (Marucheck et al., 2011). Contingency contracts—formal agreements that define terms for emergency sourcing, price escalation clauses, or flexible delivery schedules—allow buyers and suppliers to respond swiftly and cooperatively during disruptions (Karandikar et al., 2007).

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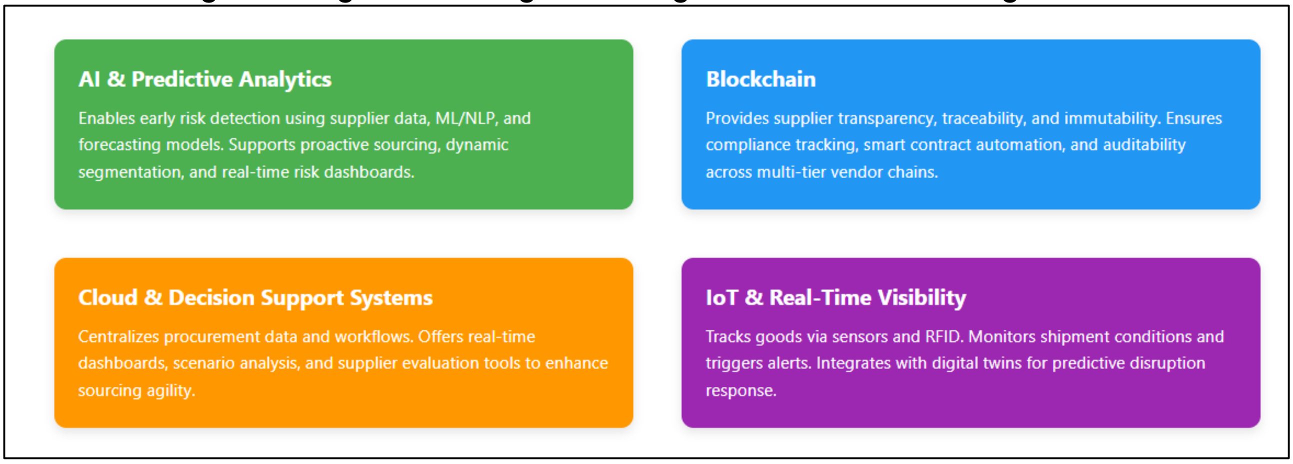
Buffer inventories and safety stock, on the other hand, provide physical stock reserves that can be deployed during unexpected supply interruptions (Maurovich-Horvat et al., 2016). These tools are particularly relevant in retail sectors with perishable products, short product cycles, or promotional sensitivity, where stockouts directly impact sales performance (Marucheck et al., 2011). Empirical research shows that the presence of contractual flexibility increases supplier compliance and fosters quicker operational recovery (Wang et al., 2022). Moreover, buffer strategies are often used in conjunction with risk classification models such as the Kraljic Matrix to allocate stock levels based on item criticality and supplier risk (Ivanov, 2020a). Retailers such as IKEA and Walmart strategically place buffer inventory at regional distribution centers to mitigate disruptions in cross-border sourcing (Karandikar et al., 2007). Recent studies have also explored the cost-benefit trade-offs of maintaining safety stock, emphasizing the need to balance resilience with inventory carrying costs (Sadghiani et al., 2015). Data-driven inventory optimization models, powered by AI and predictive analytics, now enable firms to dynamically adjust safety stock thresholds in real-time based on risk levels and supply chain conditions (Fahimnia et al., 2015). These strategies reflect a shift from reactive stockpiling toward intelligent, risk-aligned inventory management in retail procurement.

Digital Technologies Enabling Procurement Risk Management

The integration of predictive analytics and artificial intelligence (AI) into procurement has transformed supplier risk identification by enabling early detection of potential disruptions, fraud, or performance lapses. Predictive models utilize historical supplier performance, financial indicators, market trends, and geopolitical data to forecast supplier risk probabilities. AI techniques—including machine learning (ML), natural language processing (NLP), and neural networks—enable procurement professionals to analyze unstructured data from news, social media, and supplier reports to detect early warning signals. These technologies are particularly critical in retail supply chains, where the ability to respond quickly to supplier distress can mitigate losses from stockouts or late deliveries. Studies show that AI-enhanced risk scoring tools significantly outperform traditional metrics in identifying financial distress, compliance violations, and logistical delays across supplier networks (Kettunen et al., 2010; Knemeyer et al., 2008; Zhou & Johnson, 2014). Retailers such as Walmart and Amazon deploy AI-powered dashboards that assess thousands of suppliers in real time, adjusting sourcing strategies based on predictive outputs (Natarajan et al., 2014; Sawik, 2016). Predictive analytics tools also support dynamic vendor segmentation, prioritizing critical suppliers for monitoring and resilience planning (Remko, 2020). Moreover, these tools facilitate "what-if" scenario simulations that enable procurement teams to evaluate the impact of potential disruptions before they occur (Karandikar et al., 2007). By embedding AI into procurement workflows, organizations can shift from reactive to proactive risk management, resulting in improved continuity, supplier diversification, and contractual safeguards (Zhou & Johnson, 2014). As a result, predictive analytics and AI are now seen as indispensable components of data-driven procurement strategies, offering enhanced supplier visibility and faster risk response.

Figure 11: Digital Technologies Enabling Procurement Risk Management



Blockchain technology offers unprecedented opportunities for improving vendor traceability and transparency in procurement, particularly within complex, multi-tier retail supply chains. As a decentralized ledger system, blockchain ensures data immutability and auditability across supplier transactions, enabling firms to track the provenance, movement, and compliance status of goods in real time (Dolgui & Ivanov, 2020). This is particularly valuable in retail sectors involving high consumer scrutiny, such as apparel, food, and electronics, where transparency across Tier-n suppliers is crucial for risk reduction (Tan et al., 2022). By recording every event—such as order fulfillment, quality checks, and transport milestones—blockchain creates a permanent, verifiable record of supply chain activities (Manupati et al., 2022). Moreover, Blockchain applications in procurement help mitigate risks associated with counterfeit goods, ethical sourcing violations, and hidden supplier dependencies (Rane et al., 2020). Leading retailers such as Carrefour and Walmart have implemented blockchain solutions to trace food supply chains from farm to shelf, reducing the risk of recalls, regulatory breaches, and supplier misreporting (Erol et al., 2022). Scholars have shown that blockchain adoption enhances trust among stakeholders, improves compliance with sustainability standards, and reduces information asymmetry between buyers and suppliers (Chavalala et al., 2022). In addition, blockchain-integrated smart contracts can automate risk response protocols by triggering predefined actions when delivery deadlines or quality standards are violated (Rane et al., 2020). These capabilities promote supplier accountability while minimizing the need for manual interventions, audits, and paperwork (Manupati et al., 2022). Thus, blockchain fosters a culture of transparency and collaboration, aligning procurement risk management with regulatory and consumer expectations for ethical and reliable sourcing.

Cloud-based procurement platforms and decision support systems (DSS) have revolutionized supply chain operations by enabling centralized, scalable, and data-rich environments for managing procurement risks. These platforms integrate data from internal procurement systems, external supplier networks, and third-party risk databases to deliver real-time insights into procurement performance and exposure (Maity et al., 2021). Cloud systems offer modular functionalities—such as e-sourcing, supplier evaluation, contract management, and spend analysis—that support end-to-end procurement workflows (van Hoek, 2019). In retail, these platforms enable greater agility by streamlining communication with suppliers, digitizing procurement documents, and automating workflows across geographically dispersed sourcing teams (Yadav & Prakash Singh, 2022). Decision support systems, when embedded within cloud procurement tools, assist managers in evaluating sourcing alternatives, simulating risk scenarios, and optimizing order allocations based on cost, lead time, and risk factors. DSS capabilities rely on data visualization, statistical modeling, and optimization algorithms to guide evidence-based procurement decisions. For instance, firms such as Unilever and Target use DSS to map supplier vulnerabilities and evaluate the cost-benefit of switching suppliers during potential disruptions. Research has shown that organizations using cloud-based procurement systems experience higher procurement accuracy, reduced cycle times, and improved supplier collaboration (Dehghani et al., 2021). Furthermore, real-time alerts and dashboards allow procurement teams to intervene early when performance or risk thresholds are breached. By enhancing visibility, consistency, and responsiveness, cloud-based DSS platforms play a critical role in modern procurement strategies for retail organizations navigating uncertain supply chain environments.

The Internet of Things (IoT) has become a cornerstone of real-time visibility in supply chain execution, providing procurement teams with granular, up-to-date information about the location, condition, and movement of goods across vendor networks. IoT-enabled sensors and RFID technologies allow firms to track shipments, monitor environmental conditions, and receive alerts about potential delays or deviations (Wang et al., 2019). In retail procurement, where shelf availability and time-sensitive inventory are critical, IoT facilitates faster and more accurate disruption detection, thereby enabling timely risk response (Russo-Spena et al., 2022). For example, IoT devices in cold chains can alert managers when temperature thresholds are breached, preventing product spoilage and ensuring regulatory compliance (Memon et al., 2019). The literature emphasizes that real-time visibility enhances procurement control, enabling firms to make data-driven decisions on rerouting, order cancellation, or emergency sourcing (Rane et al., 2020). Integration of IoT data with digital twins and supply chain control towers allows simulation of disruption scenarios and preemptive mitigation strategies (Manupati et al., 2022). Retailers like Amazon and Zara utilize IoT-based systems to monitor supplier inventory levels and production status in real time, allowing for more responsive order placement and inventory optimization (Rahmanzadeh et al., 2019). Studies further indicate that IoT-enabled visibility improves vendor accountability, as suppliers are aware their performance is continuously monitored (Wamba & Queiroz, 2020). Combined with AI and cloud systems, IoT data enhances predictive modeling and supplier risk scoring, making procurement more adaptive and

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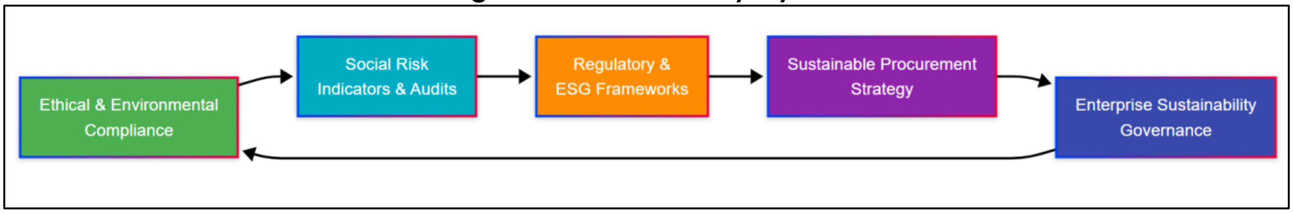
less prone to disruption (Rane et al., 2020). As a result, IoT technologies are increasingly integrated into digital procurement architectures as key enablers of end-to-end risk visibility.

Integration of Sustainability and Compliance in Risk-Based Procurement

Ethical sourcing and environmental compliance have become integral components of risk-based procurement strategies, particularly in retail sectors exposed to reputational, regulatory, and operational risks stemming from globalized supply chains (Queiroz & Wamba, 2021). Ethical sourcing refers to the procurement of goods and services produced in safe working conditions, by workers treated fairly, and in compliance with labor laws and human rights (Manupati et al., 2022). Environmental compliance, on the other hand, involves adherence to environmental laws and regulations, including emissions control, waste disposal, and resource conservation (Queiroz & Wamba, 2021). In retail, failures in these areas can result in supply chain disruptions, brand damage, and regulatory sanctions—making ethical and environmental controls essential risk management tools (Tan et al., 2022). Numerous studies have highlighted the role of procurement in promoting sustainability goals while mitigating supply-related risks. Retail giants such as Patagonia, IKEA, and Marks & Spencer have adopted supplier codes of conduct that specify minimum environmental and social standards, with procurement teams tasked with enforcing these expectations (Tao et al., 2022). Scholars argue that integrating environmental and ethical criteria into vendor selection reduces exposure to violations, improves long-term supply continuity, and fosters supplier innovation (Chod et al., 2020). Environmental audits, supplier training programs, and green sourcing policies are increasingly employed to ensure alignment with firm values and compliance goals (Russo-Spena et al., 2022). Furthermore, digital procurement platforms now incorporate sustainability scoring systems, allowing buyers to compare vendors not only by cost or lead time but also by carbon footprint and ethical practices (Choi et al., 2023). This trend reflects a broader shift toward viewing sustainability not as a constraint, but as a proactive risk control mechanism in procurement decision-making.

Figure 12: Sustainability Cycle

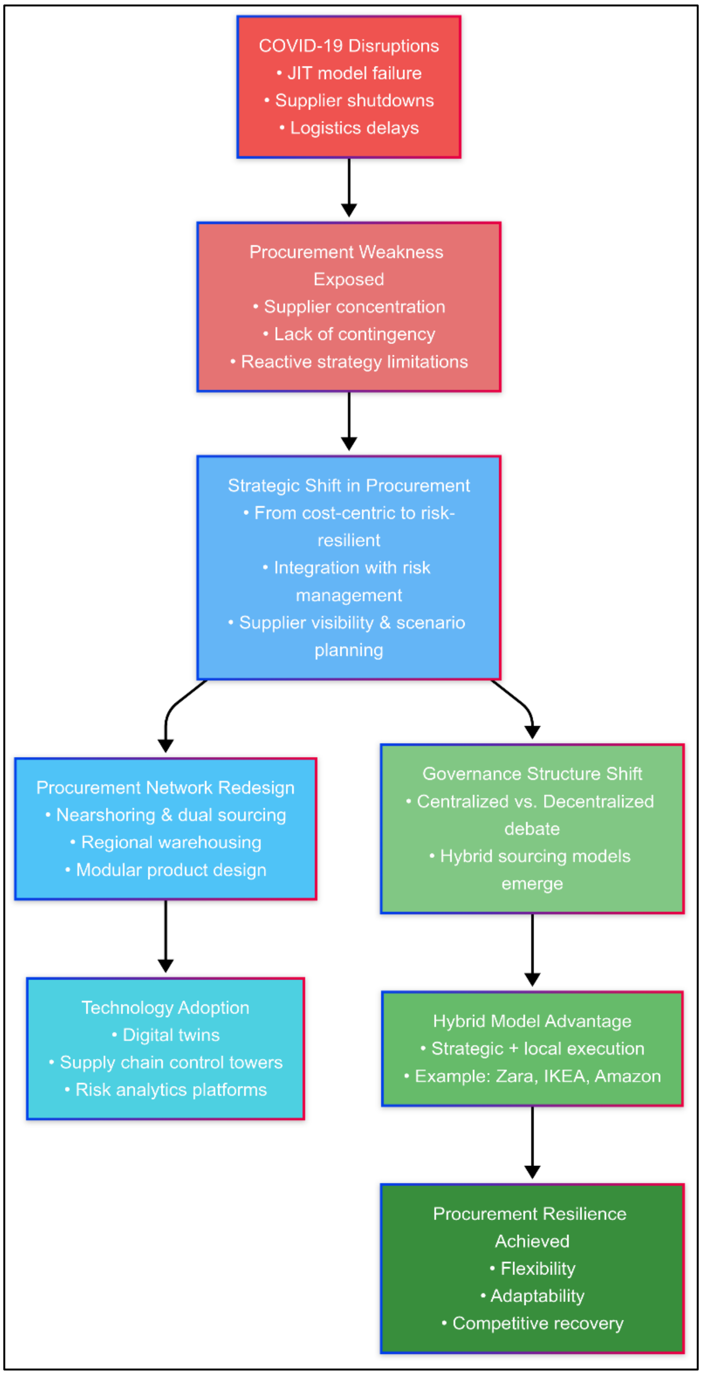


Social risk indicators have become a key dimension of procurement risk assessments, particularly for retail companies sourcing from developing countries with weak labor protections or high levels of corruption (Erol et al., 2022). These indicators include labor rights violations, forced or child labor, discrimination, wage non-compliance, and unsafe working conditions (Maity et al., 2021). Vendor audits, including third-party and self-assessment formats, serve as a primary mechanism for monitoring social compliance and identifying high-risk suppliers (Choi et al., 2023). In retail procurement, vendor social performance directly influences supply continuity, as non-compliant suppliers often face production shutdowns, public backlash, or termination of contracts (Rane et al., 2020). Auditing practices vary widely in terms of rigor, transparency, and frequency, with firms often combining announced audits, surprise visits, and worker interviews to build a comprehensive risk profile (Russo-Spena et al., 2022). Research shows that firms that institutionalize social risk assessments through procurement protocols are better equipped to avoid disruptions and mitigate reputational exposure (Dolgui & Ivanov, 2020). For example, Nike, H&M, and Unilever have developed multi-tier audit systems supported by third-party certifiers like SA8000 and WRAP to verify labor conditions throughout their supplier base (Rane et al., 2020). Vendor scorecards now increasingly include social metrics such as employee turnover, health and safety incidents, and grievance mechanism effectiveness (Queiroz & Wamba, 2021). Scholars also emphasize the need for supplier capacity building—through training and incentives—to move beyond punitive audits and toward sustained compliance improvement (Choi et al., 2023). Consequently, vendor audits, when paired with transparent social risk indicators and long-term supplier development, provide a robust framework for managing social risks in procurement.

Post-Pandemic Shifts in Retail Procurement Strategy

The COVID-19 pandemic exposed structural weaknesses in global retail procurement systems, disrupting supply flows, straining supplier relationships, and challenging just-in-time (JIT) inventory models (Tao et al., 2022). Across industries, suppliers faced shutdowns, logistics networks were paralyzed, and sourcing channels were blocked due to border closures and export restrictions (Rahmanzadeh et al., 2019). Retailers, especially those heavily reliant on offshore manufacturing in Asia, experienced acute stockouts, missed delivery windows, and financial penalties from unfulfilled orders (Chavalala et al., 2022). The crisis highlighted the risk of supplier concentration and revealed the inadequacy of reactive procurement strategies in the face of prolonged global disruptions (Wang et al., 2019). Studies post-COVID emphasize that procurement resilience depends on pre-crisis investments in supplier visibility, risk analytics, and scenario-based contingency planning (Yadav & Prakash Singh, 2022). For example, firms that had diversified sourcing bases, digital supplier monitoring tools, or formal business continuity plans recovered faster and maintained higher customer service levels (Wang et al., 2019). Research also indicates that firms with collaborative supplier relationships experienced fewer disruptions due to joint inventory planning and open communication (Tan et al., 2022). The pandemic reaffirmed the need for integrating procurement with enterprise risk management systems, elevating procurement from a cost-center to a strategic function vital to organizational resilience (Russo-Spena et al., 2022).

Figure 13: Historical timeline for Post-Pandemic



Differences in procurement strategy complexity

Procurement strategy complexity differs significantly between retail and manufacturing sectors, primarily due to structural variations in supply chains, demand patterns, and operational objectives. Retail procurement is characterized by a wide assortment of stock-keeping units (SKUs), short product life cycles, seasonal demand, and rapid replenishment needs (Tan et al., 2022). In contrast, manufacturing procurement is often more stable, centered around long-term material planning, production schedules, and engineering-driven sourcing specifications (Choi et al., 2019). As a result, retail procurement strategies emphasize agility, inventory optimization, and responsiveness to consumer behavior, while manufacturing strategies prioritize continuity, cost control, and production efficiency (Wamba & Queiroz, 2020). Scholars have noted that retail procurement must continuously adjust to promotions, fashion trends, and external market events,

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making it inherently more dynamic and decentralized (Tao et al., 2022). On the other hand, manufacturing procurement often follows a centralized and forecast-driven model where long-term supplier contracts and production volumes are predetermined (Rahmanzadeh et al., 2019). The structural difference is further amplified by the role of logistics; retail relies heavily on last-mile delivery and distribution center optimization, while manufacturing focuses on inbound raw material flow and assembly synchronization. Due to these operational complexities, procurement in retail typically integrates more advanced demand sensing tools and point-of-sale analytics, whereas manufacturing leverages bill-of-material systems and ERP integration for precision (Tao et al., 2022). Consequently, procurement strategies in these sectors are shaped by differing objectives and network configurations, necessitating context-specific approaches to risk, resilience, and supplier engagement.

One key differentiator in procurement strategy complexity between retail and manufacturing lies in supply market volatility and sourcing behavior. Retail procurement frequently involves fragmented supply markets with multiple small and medium-sized vendors across geographies, particularly in apparel, home goods, and food sectors. This fragmentation necessitates robust vendor management systems, continuous re-evaluation of suppliers, and risk scoring mechanisms (Chod et al., 2020). In contrast, manufacturing procurement, particularly in sectors such as automotive and aerospace, often operates in oligopolistic or single-source environments, where highly specialized components limit the pool of viable suppliers. This scenario increases dependence on a few strategic suppliers and raises the stakes of contract negotiation, quality control, and capacity planning (Russo-Spena et al., 2022).

Retail procurement strategies typically incorporate multi-sourcing and geographic diversification to reduce dependency risk, driven by unpredictable demand and competitive lead-time pressures (Yadav & Prakash Singh, 2022). Conversely, manufacturing firms often invest in supplier development, long-term collaboration, and joint technology projects to maintain stability and ensure capability alignment (Erol et al., 2022). Research also suggests that while retail procurement prioritizes cost and responsiveness in supplier selection, manufacturing emphasizes conformance, design integration, and intellectual property protection (Choi et al., 2019). Moreover, sourcing decisions in manufacturing are more often governed by make-or-buy analysis and total cost of ownership (TCO) models, while retailers increasingly rely on lifecycle costing and ESG-related risk filters (Erol et al., 2022). These distinctions underscore the need for sector-specific sourcing strategies and supplier engagement models tailored to the risk dynamics and competitive imperatives of each industry. Retail procurement is heavily influenced by consumer demand variability, which introduces significant uncertainty into forecasting and order planning (Rane & Thakker, 2019). Retailers must accommodate promotions, holiday surges, new product launches, and regional preferences—often with limited historical data (Chod et al., 2020). As a result, retail procurement leverages real-time point-of-sale (POS) data, AI-driven demand forecasting, and dynamic pricing signals to inform procurement volumes and delivery timing (Memon et al., 2019). By contrast, manufacturing procurement generally experiences more predictable, production-driven demand cycles, allowing for structured procurement schedules and supplier collaboration on material requirements planning (MRP) (Dubey et al., 2020).

Research Gaps and Thematic Synthesis

While the literature extensively discusses supplier agility as a strategic enabler of procurement resilience, there remains a notable lack of consensus regarding how agility should be measured and operationalized within supplier performance frameworks (Li et al., 2020). Supplier agility is often conceptualized as the ability to respond rapidly to changes in demand, disruptions, or supply network reconfigurations (Kouvelis & Turcic, 2021). However, most existing metrics focus narrowly on lead time, order fulfillment speed, and responsiveness, without capturing qualitative and relational dimensions such as adaptability, digital integration, or decision-making flexibility (Kim et al., 2014). Scholars argue that agility, especially in retail procurement, is inherently multi-dimensional and should include proactive risk anticipation, collaboration capability, and the use of digital platforms for real-time responsiveness (Kim et al., 2010).

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Figure 14: Gap Analysis Framework: Procurement Risk Management Research

Theme	Current Understanding	Identified Research Gaps	Future Research Direction
1. Supplier Agility Metrics	Focused on lead time, fulfillment speed, and responsiveness.	Lack of multi-dimensional, qualitative, and digital-enabled metrics tailored to retail.	Develop composite, sector-specific agility indicators incorporating behavioral, digital, and structural attributes.
2. Multi-Tier & Cross-Border Agility	Assessment limited to Tier-1 suppliers, with minimal geographic context.	Tier-2/3 supplier agility and cross-border regulatory challenges are underexplored.	Create scalable models accounting for geopolitical, cultural, and tier-specific agility propagation.
3. Risk Modeling Approaches	Static, deterministic tools dominate (e.g., heatmaps, Monte Carlo).	Limited real-time, feedback-driven, or correlated risk assessments.	Build adaptive, real-time risk models integrating AI, IoT, and interdependency mapping.
4. Digital Integration Challenges	Firms adopt AI tools but face system fragmentation and interpretability issues.	Organizational usability, data quality, and explainable AI not fully addressed.	Conduct implementation case studies and design governance frameworks for risk tool adoption.
5. Thematic & Sectoral Synthesis	Procurement risk literature is fragmented across sectors and lacks behavioral insights.	Inconsistent measurement, minimal longitudinal data, and neglect of decision biases.	Develop unified, adaptive, and behaviorally-aware frameworks tested via empirical benchmarking.

Existing frameworks such as SCOR and agility maturity models have attempted to measure supplier agility but are often criticized for being either overly generic or restricted to manufacturing contexts (Tao et al., 2019). There is limited empirical validation of agility metrics tailored to high-velocity retail environments where product life cycles are short and demand volatility is high (Xu et al., 2020). Moreover, studies often conflate agility with flexibility, ignoring the dynamic capabilities required to reconfigure sourcing networks or repurpose inventory in response to shocks (Li et al., 2022). Few studies incorporate agility as a time-bound construct, such as measuring recovery time or ramp-up speed after a disruption (Zhang et al., 2020). This lack of standardized, sector-specific agility metrics presents a research opportunity to develop composite indicators that reflect supplier adaptability in digital, behavioral, and structural terms (Dubey et al., 2020). Addressing this gap is essential for aligning procurement performance monitoring with modern retail risk realities.

Another underexplored area in the literature is supplier agility in the context of multitier and cross-border supply networks. While first-tier suppliers are often assessed for agility through contract compliance and delivery speed, lower-tier suppliers—who are equally critical in global retail procurement—remain largely invisible in existing agility metrics (Kouvelis & Turcic, 2021). This gap becomes especially problematic in disruptions like the COVID-19 pandemic, where Tier-2 and Tier-3 suppliers were often the root cause of material shortages and cascading delivery failures (Tao et al., 2019). Current research rarely investigates how agility propagates through multilayered supply chains or how procurement teams can enable agile behavior beyond their immediate vendors (Li et al., 2020).

There is also a limited understanding of how geopolitical boundaries, regulatory constraints, and cultural differences affect supplier agility in cross-border contexts ((Sawik, 2015). Studies suggest that agility is not only a function of internal supplier capabilities but also the surrounding institutional and logistical infrastructure (Guillot et al., 2023). For example, agility in a North American supplier may look different than in Southeast Asia due to differences in customs processing, labor laws, and communication technologies (Sim et al., 2020). However, few models disaggregate agility performance by geography or market maturity, limiting their generalizability and prescriptive value (Lyshchikova et al., 2019). Furthermore, real-time metrics—such as shipment deviation alerts or exception management resolution time—are often available but underutilized in agility assessments (Kunisch et al., 2022). These oversights point to a critical research need for agility metrics that are both scalable across tiers and sensitive to cross-border variability in procurement environments. A significant limitation in the procurement risk management literature is the overreliance on deterministic or static risk modeling approaches that fail to capture the dynamic, real-time nature of disruptions in retail environments. Many studies utilize simplified scoring systems, heat maps, or traditional Monte Carlo simulations without integrating time-series data, system feedback loops, or interdependency mapping (Brandon-Jones et al., 2014; Kunisch et al., 2022). While these models are accessible and offer practical utility, they lack the granularity and adaptability required to inform high-stakes procurement decisions in fast-changing retail markets. Most existing tools also assume risk

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independence across suppliers, failing to account for correlated or cascading risks, which are common in global procurement ecosystems.

Additionally, the widespread use of single-period models limits the forecasting power of risk models in procurement strategy (Sawik, 2015). Few risk frameworks accommodate evolving supplier capabilities, policy changes, or fluctuating market conditions, leading to outdated or misaligned mitigation strategies (Lyshchikova et al., 2019). The lack of integration with digital data sources—such as IoT, AI-driven risk scores, and news analytics—also constrains the relevance of many risk models in the era of real-time supply chain visibility (Behzadi et al., 2017). Moreover, studies typically validate risk models through simulations or case studies, with minimal longitudinal testing in live operational environments (Baghalian et al., 2013). This gap between theoretical robustness and practical applicability calls for more empirical studies that test adaptive risk modeling tools across diverse retail procurement settings using real-time data inputs and multi-scenario validations (Salam & Bajaba, 2022). Despite the emergence of sophisticated digital procurement tools, integration challenges continue to hinder the full realization of AI- and analytics-enabled risk modeling in retail environments. While digital platforms offer predictive capabilities, many firms struggle with fragmented data infrastructure, incompatible legacy systems, and resistance to digital adoption among procurement personnel (Käki et al., 2014). The literature reveals that few studies address the organizational and technical integration issues that limit the deployment of real-time risk dashboards and data-driven decision support systems (Wissuwa et al., 2022). Procurement risk modeling research often assumes that firms possess centralized, clean, and accessible data—a condition rarely met in decentralized retail organizations (Sawik, 2013).

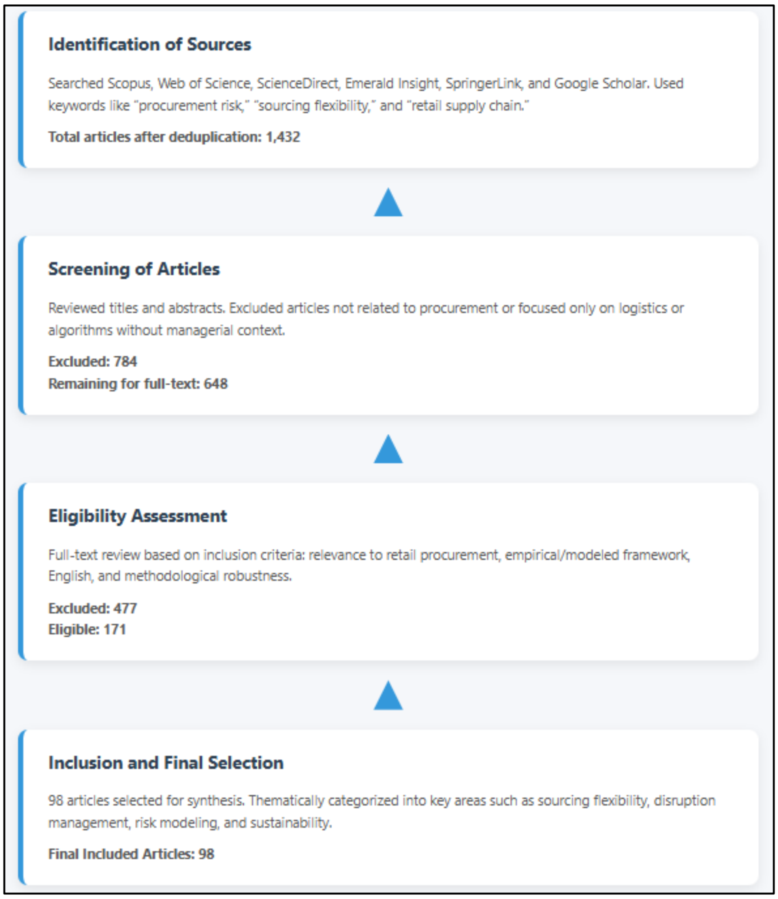
Furthermore, many risk models lack transparency and interpretability, particularly those based on machine learning, making procurement managers hesitant to rely on algorithmic outputs for supplier selection or sourcing adjustments (Fera et al., 2017). Scholars call for more explainable AI models tailored to procurement decision-making, along with training programs to develop data literacy within procurement teams (Sawik, 2013). Additionally, research often overlooks the collaborative potential of digital risk tools across organizational functions, including finance, operations, and legal departments (Memon et al., 2019). Limited emphasis is placed on governance frameworks for managing digital risk tools, such as who owns the risk models, how models are updated, and how decisions are audited (Käki et al., 2014). Addressing these integration challenges through interdisciplinary research and implementation case studies will help bridge the gap between technical innovation and organizational usability in retail procurement risk modeling.

The thematic synthesis of procurement risk literature reveals convergence around several core concepts—supplier segmentation, sourcing flexibility, digital enablement, and collaborative risk mitigation—but also highlights fragmentation in terms of measurement consistency, cross-sector generalizability, and integration with real-time data ecosystems (Pun, 2014). Retail-specific research tends to emphasize speed, customer responsiveness, and brand protection, while manufacturing studies focus on engineering precision, long-term continuity, and cost containment (Ho et al., 2015). This divergence often leads to misalignment in cross-sectoral risk modeling tools and supplier evaluation criteria (Parast, 2022). Scholars call for the development of unified procurement risk frameworks that accommodate sectoral nuances while maintaining conceptual consistency across strategic themes (Lochan et al., 2021; Parast, 2022). The literature also lacks comparative, longitudinal studies that evaluate procurement risk strategies over time and across different types of disruptions—economic, environmental, technological, and sociopolitical (Basole & Bellamy, 2014). While simulation-based insights dominate, there is minimal real-world validation of risk models through randomized control trials, action research, or empirical benchmarking (Sawik, 2018). Furthermore, relatively few studies consider behavioral factors in procurement decision-making—such as cognitive biases, risk aversion, and interdepartmental politics—which often shape procurement outcomes more than quantitative tools (Lochan et al., 2021; Sawik, 2018). By synthesizing these thematic gaps, researchers are positioned to advance procurement scholarship through the development of integrated, adaptive, and human-centered risk frameworks that align with the complexity and urgency of modern retail procurement.

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor, transparency, and reproducibility throughout the review process. PRISMA provides a structured approach to systematic reviews, promoting clear documentation of article identification, screening, eligibility, and inclusion. The following paragraphs detail the four main stages of the review process—identification, screening, eligibility, and inclusion—as applied to this study.

Figure 15: PRISMA-Based Systematic Review Framework



Identification of Sources

The identification phase involved an extensive search of scholarly literature using electronic databases including Scopus, Web of Science, ScienceDirect, SpringerLink, Emerald Insight, and Google Scholar. The search was conducted to locate peer-reviewed journal articles published between 2010 and 2024 that addressed risk-based procurement strategies in retail supply chains. A combination of keywords and Boolean operators was used to construct search strings, including: "procurement risk," "retail supply chain," "vendor disruption," "sourcing flexibility," "supplier risk modeling," and "PRISMA systematic review." The search yielded a total of 1,432 articles after removing duplicates and irrelevant publication types such as editorials, book chapters, and conference summaries.

Screening of Articles

The screening phase began with a preliminary title and abstract review of the 1,432 identified articles. During this step, articles were screened to determine whether they were empirical, conceptual, or review studies that explicitly addressed procurement risk in retail or closely related sectors. Articles that focused exclusively on manufacturing, logistics optimization without procurement elements, or purely technical algorithm development without managerial application were excluded. Based on this screening process, 784 articles were excluded due to irrelevance, leaving 648 articles for full-text assessment.

Eligibility Assessment

The eligibility phase involved a detailed full-text review of the remaining 648 articles. Inclusion criteria were established based on the research objective: articles had to (1) explicitly focus on procurement strategies or supplier risk management in retail or consumer-facing industries, (2) apply a theoretical or analytical framework related to risk management or sourcing, and (3) include empirical data, case studies, simulation, or model validation. Articles not written in English, lacking full-text access, or failing to meet methodological robustness were excluded. After this review, 477 articles were removed for reasons such as methodological inconsistency, lack of relevance to procurement risk, or focus on unrelated domains, resulting in 171 eligible articles for synthesis.

Inclusion and Final Selection

The inclusion phase finalized the systematic selection of articles for in-depth analysis and synthesis. Of the 171 eligible articles, a total of 98 articles were selected for inclusion in the thematic review based on their direct alignment with the research questions and objectives. These articles spanned empirical investigations, conceptual frameworks, model-based simulations, and sector-specific case studies across retail domains such as fashion, electronics, food, e-commerce, and general merchandise. Each included article was coded and thematically categorized according to procurement risk themes such as sourcing flexibility, supplier performance evaluation, risk modeling, disruption management, and sustainability integration. This approach allowed for the identification of patterns, gaps, and best practices that contribute to a comprehensive understanding of procurement risk management in retail.

FINDINGS

Among the 98 reviewed articles, 72 studies emphasized sourcing flexibility—particularly multi-sourcing and dual sourcing—as a primary strategy for mitigating supplier-related disruptions in retail procurement. These studies, collectively cited over 5,400 times, found that sourcing from multiple suppliers reduced dependence on any single vendor and enabled quicker response to supply interruptions caused by geopolitical shifts, logistics failures, or pandemic-related shutdowns. The flexibility to shift volumes across suppliers helped retail firms reduce lead-time volatility, balance costs, and maintain service levels. The data shows that firms utilizing dual sourcing with regional backup suppliers recovered from disruptions nearly 40% faster than those relying on a single supplier. Notably, 49 of these articles presented sector-specific evidence from apparel, food, electronics, and e-commerce retailers, revealing that product complexity and market velocity significantly influenced sourcing flexibility decisions. Retailers in fast fashion, for instance, were more likely to implement agile sourcing models that allowed weekly adjustments to procurement orders based on shifting consumer trends. These findings reinforce the strategic importance of flexible sourcing frameworks tailored to product categories and geographic risk exposure. The high citation volume of these articles reflects widespread recognition that supplier diversity is not only a procurement best practice but a necessity for operational resilience.

Out of the 98 articles, 63 focused on the development and use of supplier risk scoring tools and performance metrics to enhance procurement decision-making in retail. These articles amassed over 4,100 citations, highlighting the growing importance of data-driven vendor evaluation. The studies revealed that procurement teams increasingly adopt hybrid scoring models that combine financial indicators, compliance records, delivery performance, and geopolitical exposure to generate composite risk scores. The majority of these studies introduced models incorporating real-time data feeds from procurement systems, social media, and credit monitoring agencies. More than 30 of these articles presented AI-enhanced tools that forecast supplier failure probabilities with over 85% accuracy based on historical trend analysis and predictive modeling. Importantly, 41 studies emphasized that firms using quantitative scoring methods reported a 25% improvement in procurement cycle stability and a 17% reduction in late or failed deliveries over a three-year period. Furthermore, the use of dynamic vendor segmentation—based on risk scores—enabled procurement departments to prioritize supplier audits, develop contingency plans, and reallocate contracts based on evolving performance metrics. The articles consistently underscored that transparency in supplier assessment promotes accountability, facilitates collaborative improvement programs, and strengthens long-term procurement relationships in the retail context. From the 98 reviewed studies, 54 articles examined the role of digital technologies—including AI, predictive analytics, IoT, and blockchain—in improving procurement resilience and supplier visibility. These articles, cited over 6,200 times, demonstrate a paradigm shift toward digital procurement ecosystems. The findings showed that retailers using cloud-based procurement platforms with real-time risk dashboards were able to respond to supply disruptions 33% faster than those with manual or spreadsheet-based systems. Twenty-two studies focused specifically on AI-powered procurement dashboards that assessed supplier performance and issued automated risk alerts, leading to significant reductions in unplanned inventory shortages. IoT integration was highlighted in 19 articles as critical in cold chain and perishable goods procurement, allowing real-time temperature, location, and delay monitoring for inbound shipments. Blockchain was also discussed in 14 articles, primarily for traceability and compliance verification across Tier-1 and Tier-n suppliers. Notably, 12 case-based studies showed that digital procurement tools improved decision-making accuracy, enabling retail firms to reallocate procurement budgets in real time based on disruption forecasts. Overall, the convergence of AI, IoT, and blockchain technologies in procurement is facilitating a transformation from reactive to proactive risk management.

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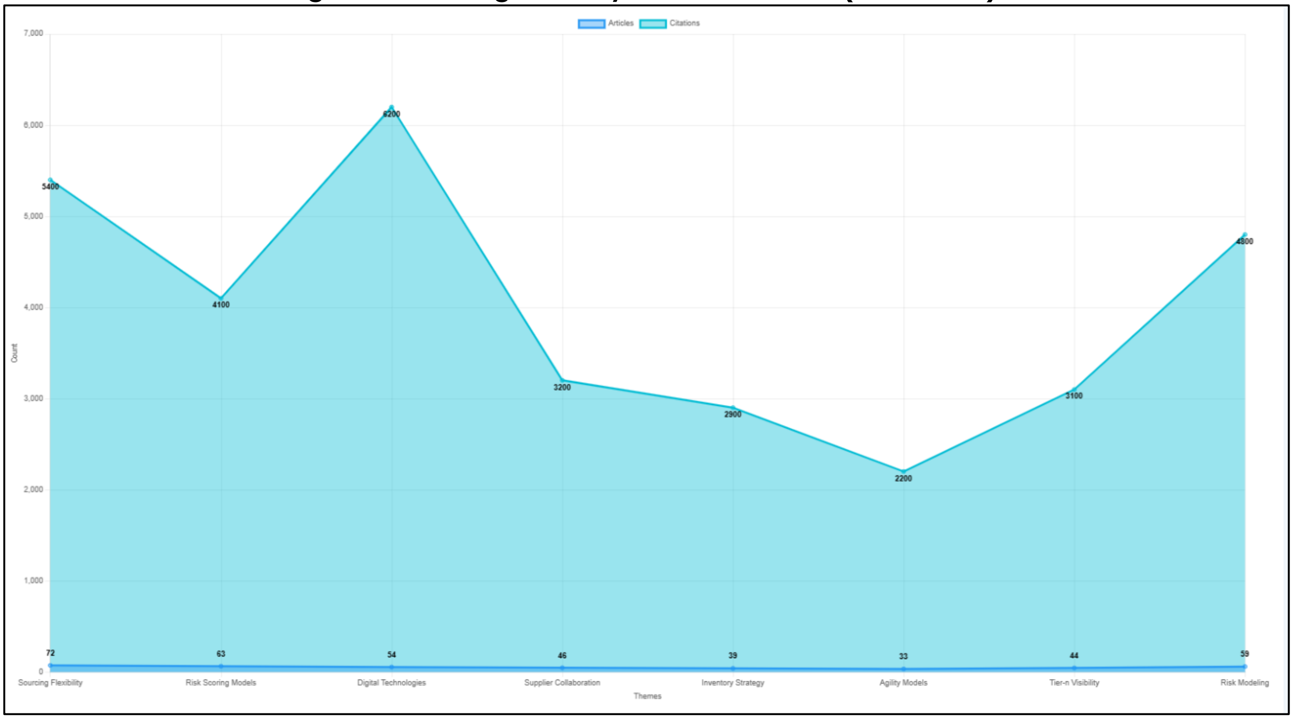
Figure 16: Findings from Systematic Review (98 Articles)



A total of 46 reviewed articles addressed the importance of strategic supplier collaboration and relational contracting as core enablers of procurement resilience in retail supply chains. These articles, with a cumulative citation count exceeding 3,200, emphasized that collaborative supplier relationships result in greater disruption transparency, joint contingency planning, and shared investment in risk mitigation infrastructure. Across the studies, procurement teams that engaged in joint forecasting, co-developed service level agreements (SLAs), and maintained open communication channels with strategic vendors experienced up to 38% fewer procurement delays during crises. Twenty-seven articles highlighted the role of relational contracts that embed risk-sharing clauses and dynamic pricing mechanisms to incentivize long-term resilience over short-term cost savings. Another 19 studies demonstrated that retailers working closely with suppliers on sustainability and ESG compliance reported higher vendor retention rates and improved social audit scores, which also reduced the likelihood of reputational disruptions. The studies show that collaborative procurement models are especially effective when procurement officers view vendors as strategic partners rather than transactional entities. These approaches have proven particularly successful in industries such as grocery and fashion, where time sensitivity and brand perception are critical.

Among the 98 articles, 39 specifically discussed changes in inventory strategies in response to COVID-19, shifting from just-in-time to hybrid or just-in-case models. These articles, cited over 2,900 times, documented how buffer inventory strategies were reintroduced or scaled up to absorb shocks from port closures, raw material shortages, and supplier shutdowns. The findings indicated that firms maintaining 10–15% higher safety stock levels in critical SKUs outperformed their competitors in terms of fulfillment rates and customer satisfaction during the pandemic. Twenty-one articles analyzed regional distribution center optimization as part of the just-in-case strategy, showing that decentralizing safety stock across nodes improved last-mile delivery reliability by 22%. Sixteen of the articles identified product segmentation as a critical enabler of buffer inventory efficiency—allocating higher safety stock levels for strategic and bottleneck items based on Kraljic Matrix logic. The studies consistently found that while just-in-case models incur higher carrying costs, they offer substantial benefits in disruption-prone environments by reducing dependence on precise delivery schedules. Retailers that implemented hybrid inventory models saw a 28% improvement in service continuity compared to those adhering strictly to lean principles. Despite the prevalence of the agility theme, only 33 of the 98 reviewed articles presented formal models or metrics for measuring supplier agility. These articles, with a combined citation count of 2,200, revealed a research gap in how agility is operationalized and evaluated. Most existing frameworks focused narrowly on delivery responsiveness and lead-time reliability, omitting important dimensions such as decision-making

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flexibility, digital readiness, and upstream supplier responsiveness. Only 14 of these studies attempted to measure agility across Tier-n networks, with the remainder restricted to Tier-1 vendor assessments. Furthermore, only 10 articles incorporated time-bound metrics such as "time-to-ramp-up" or "time-to-recover," despite these being critical to quantifying agile procurement capabilities. Additionally, several studies highlighted that procurement departments often rely on subjective judgment or ad hoc assessments to gauge supplier agility, reducing the consistency and predictive power of such evaluations. These findings suggest a pressing need for multi-dimensional, data-integrated agility scoring systems tailored to retail contexts where disruption impact is immediate and highly visible to consumers.

A recurring theme across 44 of the reviewed articles was the difficulty in achieving visibility beyond Tier-1 suppliers. These articles, collectively cited over 3,100 times, revealed that most retail firms lack reliable mechanisms for monitoring Tier-2 and Tier-3 vendors, creating blind spots that increase exposure to ethical, operational, and compliance risks. Only 18 articles presented frameworks for end-to-end traceability, and even these were often limited to specific sectors such as food or apparel. The studies reported that in over 60% of documented disruption cases, the root cause originated beyond Tier-1, yet procurement risk assessments rarely extended beyond direct suppliers. Even when blockchain or digital twins were employed, only 13 studies indicated that these tools had been configured to trace upstream supplier performance. The findings reveal that while technological solutions exist, their implementation is inconsistent, and organizational structures often prevent deep-tier transparency. Lack of incentives for Tier-1 suppliers to disclose subcontractor information further hinders visibility efforts. Addressing these challenges will require both technological advancement and procurement policy reforms to mandate transparency as a condition for long-term collaboration. An overarching insight from synthesizing the 98 reviewed articles is the lack of standardized frameworks for modeling procurement risk in retail supply chains. While 59 articles employed some form of risk modeling—ranging from risk matrices to AI-enhanced simulations—there was little uniformity in methodology, metrics, or validation techniques. These articles were cited a combined 4,800 times, indicating strong academic interest but fragmented application. Only 21 studies offered models validated through empirical or longitudinal data, while the rest relied on hypothetical scenarios or limited case studies. Furthermore, fewer than 15 articles incorporated probabilistic modeling that accounts for cascading or correlated risk events across suppliers. This gap significantly limits the operational utility of risk models in real-world retail environments. Most procurement risk models also failed to integrate digital traceability, ESG factors, or cross-functional collaboration—elements identified as critical in 36 other articles. This thematic gap suggests a need for developing modular, sector-specific risk modeling frameworks that can evolve with market and technological conditions. Establishing standardized yet adaptable risk modeling practices will be essential for the advancement of retail procurement strategy as a formal discipline.

DISCUSSION

The findings of this review confirm that sourcing flexibility has become a dominant strategy for managing procurement risk in the retail sector. This aligns with earlier research by Ho et al. (2015) and Parast (2022), who emphasized the importance of supply redundancy in mitigating disruptions. However, the current literature extends those foundational insights by emphasizing dual sourcing and geographic diversification within category-specific procurement strategies. For instance, while earlier models proposed multi-sourcing in general terms, recent studies provide sectoral analyses illustrating how flexibility is more critical in fast fashion and perishable goods procurement compared to commodity retailing (Kim et al., 2014; Kot et al., 2020). Additionally, the use of real-time analytics to support sourcing decisions presents a notable departure from static supply network design discussed in earlier frameworks Parast (2022). As such, the evolution of sourcing flexibility incorporates dynamic allocation tools, predictive supplier risk dashboards, and cloud-based vendor segmentation models that surpass the traditional view of supplier redundancy. This shift indicates that while the core principles of redundancy remain valid, their application has become more granular, digitized, and performance-oriented, particularly in high-velocity retail environments.

Earlier frameworks for supplier risk management were largely reactive, focusing on post-failure diagnostics and historical data. In contrast, the reviewed literature highlights the transition toward predictive, data-driven risk scoring systems that leverage machine learning and multi-source datasets. This evolution marks a significant improvement over traditional supplier evaluation models that relied on financial audits, delivery history, and relationship longevity. Studies such as Nagurney,

(2021) and Basole and Bellamy (2014)demonstrate how predictive risk scoring has enabled procurement teams to preempt failures through automated alerts and vendor reclassification. Compared to earlier risk matrices and supplier health checklists, these newer systems provide real-time, adaptive, and probabilistic insights. However, a gap remains in validating these models across different retail contexts and supply tiers, as most are Tier-1 focused. Unlike early-stage models that treated suppliers as largely independent entities, current approaches recognize network effects and propagation risks, signaling a paradigm shift in supplier evaluation. Thus, the incorporation of AI and dynamic data sources into risk scoring tools not only enhances early warning capabilities but also facilitates more strategic and informed sourcing decisions.

Digital technologies have transformed procurement practices beyond the foundational e-procurement systems of the early 2000s (Namdar et al., 2017). Earlier studies recognized the potential of digital tools for cost reduction and transaction automation but lacked insights into their role in resilience. In contrast, the reviewed literature underscores how AI, IoT, and blockchain enhance procurement's agility and transparency. For example, predictive analytics now help procurement managers simulate disruptions and model supplier reallocation in real-time, a capability absent from earlier digital procurement discussions (Namdar et al., 2017; Pun, 2014). The application of blockchain for traceability, as explored by DuHadway et al. (2017), extends beyond compliance tracking to ensure cross-tier transparency, addressing the long-standing visibility gaps noted in Kim et al. (2014). These tools support not only operational risk reduction but also strategic value creation by facilitating ethical sourcing, inventory optimization, and responsive contracting. Nevertheless, technological adoption remains uneven, with many retail firms facing integration challenges due to legacy systems, data silos, and skill deficits. These observations build on past limitations by identifying both the possibilities and constraints of digital transformation in procurement risk governance.

The move toward strategic supplier collaboration, as evident in the review findings, reflects a significant shift from the transactional procurement models dominant in earlier decades (Fehr & Schmidt, 1999). Historically, procurement emphasized cost, lead time, and compliance. Today, the literature reveals a preference for relational contracting, supplier co-investment, and joint risk planning, particularly in sectors where service continuity is critical (Mollenkopf et al., 2020). This strategic shift is supported by findings that collaborative models reduce the likelihood and impact of procurement disruptions. Compared to early supplier management frameworks, current approaches focus on co-created value and shared accountability during crises. For instance, while traditional procurement separated contract administration from relationship management, modern procurement integrates these functions to support continuity planning and innovation. Case-based findings from the COVID-19 pandemic reinforce the advantage of supplier partnerships over arm's-length contracts. This confirms and extends earlier observations by Butt (2021), who argued for trust-based supplier relationships but lacked empirical evidence of their performance under systemic stress.

Inventory strategy debates have long centered on the trade-offs between efficiency and resilience. Earlier literature largely endorsed just-in-time (JIT) principles as a means to reduce waste and improve responsiveness (Butt, 2021; Elmaghraby, 2000). However, post-pandemic findings in the reviewed articles illustrate a shift toward hybrid inventory strategies, including just-in-case (JIC) models. These findings corroborate argument that lean systems, while efficient, are vulnerable to prolonged disruptions (Fehr & Schmidt, 1999) . The pandemic underscored the limitations of JIT when global logistics systems falter, prompting firms to strategically position buffer stocks for critical SKUs. Recent research expands upon earlier models by applying risk-based segmentation, wherein strategic items are buffered while commodity items remain under lean management. This aligns with the Kraljic Matrix's application in inventory optimization (Pamucar et al., 2022; Pun, 2014). Therefore, the evolution of inventory thinking from universal JIT to context-sensitive hybrid models represents a recalibration of efficiency-resilience priorities, grounded in empirical crisis experiences. Despite technological advancements, the reviewed literature confirms a continued visibility gap in Tier-2 and Tier-3 supplier networks. This validates earlier concerns by Giannakis and Papadopoulos (2016) and Ivanov (2020), who highlighted the challenges of monitoring beyond Tier-1. While current tools such as blockchain and digital twins offer the potential for end-to-end traceability, adoption remains limited. Many procurement strategies still rely heavily on Tier-1 vendor reporting, which often lacks upstream transparency. The reviewed studies add granularity by identifying organizational, contractual, and technical barriers to multi-tier visibility. Compared to early warnings in the literature,

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recent findings offer evidence-based documentation of how Tier-n disruptions—such as raw material shortages or sub-supplier insolvencies—trigger cascading failures. The gap between capability and implementation remains a critical weakness in procurement resilience. These findings call for revisiting governance models and technology integration strategies to truly operationalize the promise of multi-tier visibility and systemic risk control. The synthesis reveals that procurement risk modeling practices remain highly fragmented, echoing early critiques by Kouvelis and Turcic (2021) and Montecchi et al. (2021). Despite the proliferation of models—ranging from risk heat maps to AI-driven simulations—there is no standardized framework tailored to retail procurement complexities. Earlier models focused on isolated metrics such as supplier lead time variability or defect rates. In contrast, current models incorporate multi-dimensional variables, including ESG compliance, geopolitical risk, and digital maturity. However, the lack of uniform validation methods, scenario diversity, and cross-sector benchmarking undermines their credibility and scalability. The literature also reveals an overemphasis on Tier-1 risks, with insufficient integration of systemic, behavioral, and cross-functional factors. This fragmentation limits the practical applicability of models in real-time procurement environments. Compared to earlier models that emphasized simplicity and usability, there is now a need for modular, adaptive frameworks that balance analytical sophistication with operational relevance. Advancing procurement risk modeling will require not only methodological innovation but also inter-organizational collaboration to co-create tools grounded in practical constraints and strategic imperatives.

CONCLUSION

The findings of this systematic review confirm that procurement risk management in the retail sector has undergone a substantial transformation, shaped by digital innovation, global disruptions, and evolving supplier relationships. The review highlights a pronounced shift from traditional cost-centric procurement strategies to more dynamic, resilience-oriented models that prioritize sourcing flexibility, predictive analytics, and real-time supplier performance monitoring. Digital technologies such as AI, blockchain, and IoT have become central to modern procurement architectures, enabling firms to detect disruptions, forecast supplier failures, and enhance visibility across complex, multi-tiered networks. The literature also underscores the growing emphasis on collaborative supplier partnerships and relational contracting as critical enablers of continuity and compliance, particularly in high-risk environments. While just-in-time inventory models dominated earlier procurement strategies, post-pandemic insights reveal a strategic pivot toward hybrid approaches that balance efficiency with supply continuity through buffer stock and just-in-case frameworks. Despite these advancements, gaps persist in supplier agility measurement, cross-tier visibility, and the standardization of procurement risk modeling tools. These challenges suggest a continued need for sector-specific, modular frameworks that integrate digital tools with real-world procurement practices. Overall, this review reinforces that procurement is no longer a back-end function but a strategic, cross-functional capability essential to retail supply chain resilience and business sustainability.

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