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Data-Driven Operations Management and Supply Chain Innovation in the Retail Industry

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Abstract: This study examines how data-driven operations management capabilities shape supply chain innovation performance among retail firms operating in volatile, digitally mediated markets. Despite enthusiasm for analytics, artificial intelligence, and real-time visibility tools, retailers still struggle to convert data investments into measurable innovation outcomes, and the mechanisms linking specific data-driven capabilities to innovation remain fragmented across the literature. Drawing on the resource-based view and dynamic capabilities theory, this research proposes and empirically tests a model linking three data-driven capabilities, namely data analytics capability, real-time supply chain visibility, and artificial intelligence/machine learning adoption, to supply chain innovation performance, with data-driven decision-making culture as a mediating mechanism. A quantitative, cross-sectional survey design was employed, collecting responses from 215 operations and supply chain managers in retail organizations, analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results indicate that all three capabilities exert significant positive effects on supply chain innovation performance, with data-driven decision-making culture partially mediating these relationships. Real-time visibility emerged as the strongest direct predictor, followed by AI/ML adoption and data analytics capability. These findings extend supply chain innovation theory by clarifying the differentiated contribution of distinct data-driven capabilities and offer practical guidance for retail operations managers seeking to prioritize digital investments that generate innovation returns rather than incremental efficiency gains alone.

Keywords: data-driven operations management; supply chain innovation; data analytics capability; real-time visibility; retail industry; PLS-SEM

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1. Introduction

The retail industry has entered a period in which operational competitiveness is decided less by physical footprint or supplier scale and more by the speed and intelligence with which firms convert transactional and environmental data into operating decisions. Point-of-sale streams, RFID and IoT sensor feeds, e-commerce clickstreams, supplier performance logs, and third-party market signals now arrive continuously and in volumes that traditional planning cycles cannot absorb. Retailers that once relied on periodic demand forecasts and static replenishment rules are being compelled to rebuild inventory management, supplier coordination, last-mile logistics, and assortment planning around continuous data flows. Industry surveys and empirical studies consistently report that firms applying data analytics to inventory and supply chain processes achieve measurable reductions in stockouts, overstocking, and fulfillment costs, alongside improved forecast accuracy (Famoti et al., 2025; Ghodake et al., 2024). At the same time, the diffusion of artificial intelligence and machine learning into demand forecasting, dynamic pricing, and logistics routing has been described as revolutionizing how retailers anticipate and respond to demand volatility (Nweje & Taiwo, 2025; Yarlagadda, 2025). These developments collectively signal a structural shift from experience-based operations management toward data-driven operations management, in which algorithmic insight, rather than managerial intuition alone, increasingly directs day-to-day and strategic decisions across the retail supply chain.

Parallel to this operational shift, supply chain innovation has become a strategic imperative rather than a discretionary pursuit. Global disruptions, including pandemic-induced shocks, geopolitical trade friction, and volatile consumer demand, have exposed the fragility of supply chains optimized purely for cost efficiency. Retailers are therefore under pressure to innovate not only in what they sell but in how they plan, source, move, and replenish goods. Innovation in this context spans new demand-sensing algorithms, digital twin-enabled simulation of distribution networks, blockchain-enabled traceability, IoT-enabled real-time inventory visibility, and generative AI-supported decision support systems (Owusu-Berko, 2025; Bag et al., 2025). Several studies frame digital twins, IoT, and blockchain as complementary technologies that jointly enable resilient, data-driven business operations (Owusu-Berko, 2025), while others emphasize that supply chain digitization is reshaping the very structure of supply chain management as a discipline, moving it away from siloed functional planning toward integrated, sensor-driven orchestration (Tiwari et al., 2024). Machine learning applications in particular have been credited with enhancing both agility and sustainability in logistics and inventory management, suggesting that innovation and efficiency gains are not mutually exclusive but can be pursued jointly through the same underlying data infrastructure (Pasupuleti et al., 2024).

Despite this growing body of evidence, a persistent gap separates the promise of data-driven operations management from its realized innovation outcomes in retail practice. Many retailers have invested heavily in analytics platforms, IoT sensor networks, and AI-based forecasting tools, yet a substantial proportion report limited or inconsistent returns in terms of genuine supply chain innovation, as opposed to incremental operational efficiency (Spanaki et al., 2025; Bhatti et al., 2022). Bhatti et al. (2022) explicitly identify this as a "missing link" problem: big data analytics capabilities are often present within organizations, but the pathway from analytics capability to supply chain innovation is neither automatic nor well specified in existing theoretical models. Similarly, bibliometric and review-based studies of IoT and retail management note that while the volume of published research on smart retail technologies has expanded rapidly, empirical studies that isolate which specific data-driven capabilities most strongly predict innovation outcomes, as opposed to simply operational efficiency, remain comparatively scarce (Judijanto et al., 2025). This creates a practically consequential ambiguity: retail operations managers must decide where to allocate finite digital transformation budgets, yet the literature offers limited guidance on which data-driven capabilities, among analytics, real-time visibility, and AI/ML adoption, deliver the strongest innovation returns, and through what organizational mechanism these returns materialize.

A second gap concerns the mechanism through which data-driven capabilities translate into innovation outcomes. Much of the existing literature treats data-driven capability and supply chain innovation as directly and unconditionally linked, implicitly assuming that possessing analytics infrastructure is sufficient to generate innovative outcomes. However, organizational behavior and information systems research suggest that the relationship between technological capability and innovation performance is rarely direct; it is typically channeled through changes in organizational decision-making culture, that is, the extent to which managers actually trust, use, and institutionalize data in place of intuition when making operational and strategic choices (Bag et al., 2025; Alsolbi et al., 2023). Studies on generative AI-powered financial decision-making in operations and supply chain management have begun to model such mediated pathways, showing that the effect of AI-enabled capability on downstream innovation outcomes is moderated and mediated by decision-making processes rather than being a simple direct effect (Bag et al., 2025). Yet this mediating mechanism has rarely been tested specifically within the retail supply chain innovation context, leaving a theoretically and practically important gap regarding how, and not merely whether, data-driven capabilities generate innovation.

Building on these observations, this study addresses three specific and underexplored gaps in the literature. First, whereas prior studies tend to examine single technologies in isolation, such as big data analytics alone (Ghodake et al., 2024), IoT alone (Judijanto et al., 2025), or AI/ML forecasting alone (Yarlagadda, 2025), this study offers an integrated, comparative empirical test of three co-occurring data-driven operations capabilities, namely data analytics capability, real-time supply chain visibility, and AI/ML adoption, within a single structural model, allowing their relative contributions to supply chain innovation performance to be directly compared rather than inferred across disconnected studies. Second, this study introduces and empirically tests data-driven decision-making culture as a mediating variable linking these capabilities to innovation performance, responding directly to calls in the literature for research that moves beyond capability-outcome correlations toward mechanism-based explanations (Bhatti et al., 2022; Bag et al., 2025). Third, this study is deliberately positioned within the retail industry context using primary survey data from practicing operations and supply chain managers, addressing the relative scarcity of quantitative, retail-specific empirical tests noted in recent reviews of retail analytics and platform-level data use (Judijanto et al., 2025; Spanaki et al., 2025), most of which rely on literature synthesis, bibliometric mapping, or single-firm case narratives rather than survey-based structural modeling across multiple retail organizations.

The novelty of this research therefore lies in three interlocking contributions. Theoretically, it advances an integrated capability-mediation model grounded in the resource-based view and dynamic capabilities theory that simultaneously accounts for three distinct data-driven capabilities and the cultural mechanism through which they generate innovation, rather than treating data-driven operations management as a monolithic construct. Empirically, it provides comparative, quantitatively estimated path coefficients that identify which capability, among analytics, visibility, and AI/ML adoption, exerts the strongest influence on supply chain innovation performance in retail settings, offering a level of specificity largely absent from the predominantly qualitative or review-based literature in this domain (Owusu-Berko, 2025; Anaba et al., 2024). Practically, the findings are intended to give retail operations executives an evidence-based prioritization framework for digital transformation investment, clarifying that innovation returns are not automatic byproducts of data infrastructure but depend on the extent to which such infrastructure is embedded within a genuinely data-driven decision-making culture. In doing so, this study responds to recent calls for more rigorous, theory-driven, and quantitatively grounded investigation of the operations-innovation nexus in the data-intensive retail environment (Spanaki et al., 2025; Katangoori, 2026).

Accordingly, this study is guided by three research questions. First, to what extent do data analytics capability, real-time supply chain visibility, and AI/ML adoption individually predict supply chain innovation performance among retail firms? Second, does data-driven decision-making culture mediate these relationships, and if so, is the mediation partial or full across the three capabilities? Third, which of the three capabilities offers the strongest marginal contribution to innovation performance once the mediating mechanism is accounted for, and what does this ordering imply for the sequencing of digital transformation investment in retail operations? Answering these questions matters because retail operations managers face a crowded, rapidly evolving vendor landscape for analytics, IoT, and AI-based forecasting tools, often with limited capacity to evaluate which investments are most likely to yield innovation rather than marginal efficiency. A quantitative model that disentangles these capabilities and specifies their comparative and mediated effects therefore fills a theoretical gap in the supply chain innovation literature and a practical gap in retail operations decision-making, providing a more actionable foundation than the largely descriptive or bibliometric accounts that currently dominate this research stream.

2. Method

This study employs a quantitative, explanatory (causal-associative) research design using a cross-sectional survey to test the hypothesized relationships among data-driven operations management capabilities, data-driven decision-making culture, and supply chain innovation performance in the retail industry. A quantitative approach was selected because the research objective is to statistically estimate the strength, direction, and significance of relationships among latent constructs rather than to explore or describe phenomena inductively, and because it enables the comparative evaluation of multiple predictor capabilities within a single structural model, consistent with prior empirical work on data-driven supply chain performance (Ghodake et al., 2024; Samineni et al., 2025).

The unit of analysis is the individual retail firm, represented by an operations, supply chain, or logistics manager who possesses direct visibility into the firm's data and technology practices. The target population comprises managers employed at retail organizations, including brick-and-mortar chains, omnichannel retailers, and e-commerce operators, that have implemented at least one form of data analytics, IoT-enabled visibility, or AI/ML-based forecasting tool within their supply chain operations. A purposive sampling technique was applied, screening respondents on job function and technology exposure to ensure that participants were qualified to report on the constructs under study. Invitations were distributed through professional retail and supply chain associations, LinkedIn operations-management groups, and corporate contacts accumulated through prior industry engagement, over an eight-week data collection window. A total of 248 responses were received, of which 215 were retained after removing incomplete submissions and responses that failed attention-check items, yielding a usable response rate of 86.7 percent. This sample size exceeds the minimum threshold recommended for PLS-SEM under the ten-times rule applied to the model's most complex structural path, and post hoc power analysis confirmed adequate statistical power ($1-\beta > 0.95$) at a medium effect size and $\alpha = 0.05$.

Five latent constructs were operationalized using multi-item, five-point Likert scales (1 = strongly disagree, 5 = strongly agree), with indicators adapted from validated instruments in the data analytics, supply chain digitalization, and innovation management literature to fit the retail context. Data Analytics Capability (DAC) was measured with five items capturing the organization's ability to collect, integrate, and analyze structured and unstructured operational data for decision support, adapted from analytics-capability measures used in prior retail and supply chain analytics studies (Ghodake et al., 2024; Alsolbi et al., 2023). Real-Time Supply Chain Visibility (RTV) was measured with four items assessing the extent to which inventory, logistics, and supplier status are observable in real time through IoT, RFID, or streaming-data infrastructure, drawing on constructs used in smart retail and IoT-enabled supply chain research (Judijanto et al., 2025). Artificial Intelligence/Machine Learning Adoption (AIA) was measured with five items reflecting the degree to which AI/ML tools are embedded in demand forecasting, dynamic pricing, and logistics routing decisions, consistent with instrumentation used in AI-driven supply chain optimization studies (Yarlagadda, 2025; Rahman et al., 2025). Data-Driven Decision-Making Culture (DDC), the mediating construct, was measured with four items capturing the degree to which managers trust and systematically use data, rather than intuition, in day-to-day and strategic decisions (Bag et al., 2025). Supply Chain Innovation Performance (SCIP), the dependent construct, was measured with five items capturing the frequency and impact of new or significantly improved processes, technologies, and business models introduced into the firm's supply chain operations over the preceding two years, adapted from supply chain innovation performance measures used in prior innovation-outcome research (Bhatti et al., 2022; Li, 2024). All instruments were pilot-tested with 30 respondents outside the final sample to assess item clarity, and minor wording adjustments were made prior to full deployment.

Figure 1 presents the conceptual research framework guiding the analysis. The model specifies direct paths from each of the three exogenous capabilities, DAC, RTV, and AIA, to the mediating construct DDC and to the endogenous construct SCIP, together with a path from DDC to SCIP, allowing DDC to be tested as a partial mediator of each capability-innovation relationship. Five hypotheses were formulated: H1a-c posit that DAC, RTV, and AIA each positively influence SCIP directly; H2 posits that DAC, RTV, and AIA each positively influence DDC; and H3 posits that DDC positively influences SCIP, with H4a-c testing the mediating role of DDC in each capability-innovation relationship.

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4, a variance-based technique well suited to complex models with multiple predictors, formative and reflective indicators, and prediction-oriented rather than strictly confirmatory objectives (Spanaki et al., 2025). The analysis followed the standard two-stage procedure. The measurement model was first assessed for indicator reliability (outer loadings > 0.70), internal consistency reliability (Cronbach's alpha and composite reliability > 0.70), convergent validity (average variance extracted, AVE > 0.50), and discriminant validity using the Heterotrait-Monotrait ratio (HTMT < 0.85). The structural model was then evaluated using bootstrapping with 5,000 resamples to obtain path coefficients, t-statistics, and 95 percent bias-corrected confidence intervals, alongside coefficient of determination (R^2), effect size (f^2), and predictive relevance (Q^2) via blindfolding. Common method bias was assessed using Harman's single-factor test and the full collinearity variance inflation factor (VIF) approach, with all VIF values remaining below the conservative threshold of 3.3, indicating that common method variance was not a significant concern.

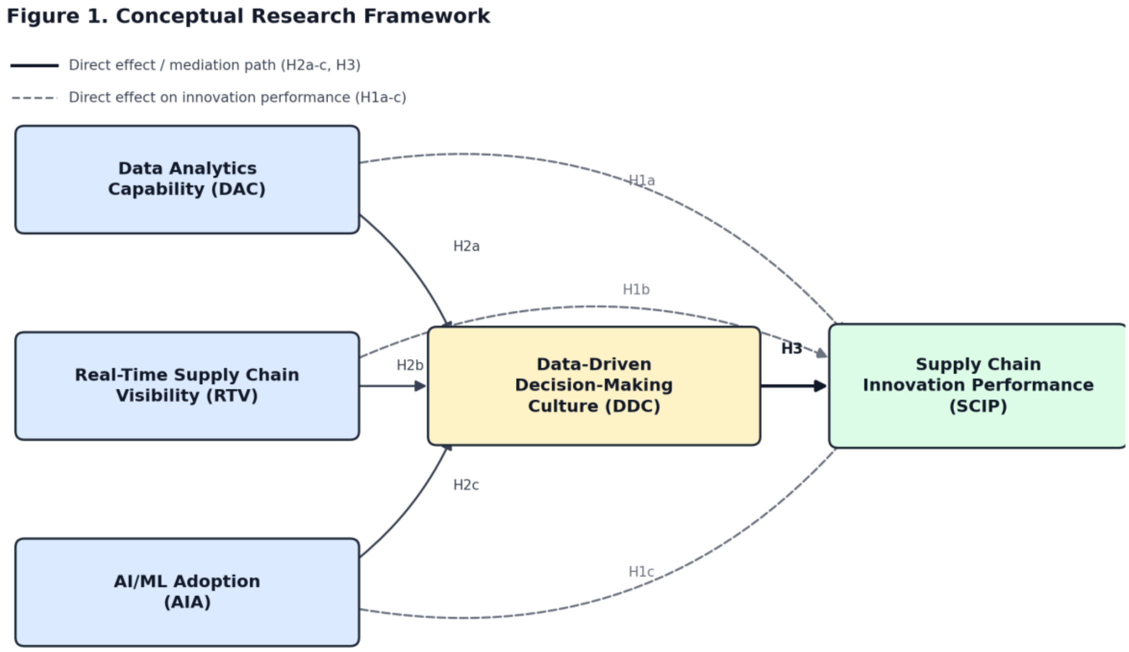

Figure 1. Conceptual Research Framework.

3. Results and Discussion

Respondent Profile

Of the 215 valid responses, 61.4 percent of respondents held operations or supply chain manager titles, 24.7 percent held logistics or distribution manager titles, and the remaining 13.9 percent held senior roles such as director of retail operations or chief supply chain officer. Firm size was distributed across small (18.1 percent, fewer than 100 employees), medium (41.9 percent, 100-999 employees), and large retail organizations (40.0 percent, 1,000 or more employees), while retail format was split between brick-and-mortar chains (34.4 percent), omnichannel retailers (46.5 percent), and pure e-commerce operators (19.1 percent). Table 1 summarizes the demographic and organizational profile of the sample. The distribution across firm sizes and retail formats supports the generalizability of the findings across the diversity of contemporary retail operating models, rather than being confined to a single retail archetype.

Characteristic	Category	Frequency (n)	Percentage (%)
Job Function	Operations / Supply Chain Manager	132	61.4
	Logistics / Distribution Manager	53	24.7
	Director / Chief Supply Chain Officer	30	13.9

Firm Size	Small (< 100 employees)	39	18.1
	Medium (100-999 employees)	90	41.9
	Large (≥ 1,000 employees)	86	40.0
Retail Format	Brick-and-mortar	74	34.4
	Omnichannel	100	46.5
	Pure e-commerce	41	19.1
Total		215	100.0

Table 1. Respondent Demographic and Organizational Profile (n = 215)

Measurement Model Assessment

Prior to hypothesis testing, the measurement model was assessed for indicator reliability, internal consistency, convergent validity, and discriminant validity. All standardized outer loadings exceeded the 0.70 threshold, ranging from 0.712 to 0.891, with two items (one each from DAC and AIA) removed due to loadings below 0.70, after which the remaining indicators were re-estimated. Cronbach's alpha values ranged from 0.812 (RTV) to 0.887 (SCIP), and composite reliability values ranged from 0.878 to 0.921, both comfortably exceeding the 0.70 threshold and indicating strong internal consistency reliability across all five constructs. Average variance extracted (AVE) ranged from 0.612 to 0.701, exceeding the 0.50 threshold and confirming adequate convergent validity, meaning each construct's indicators explain, on average, more variance in their respective latent construct than is attributable to measurement error. Discriminant validity was assessed using the Heterotrait-Monotrait ratio of correlations (HTMT), with all construct pairs falling below the conservative 0.85 threshold (highest observed HTMT = 0.779, between AIA and DDC), confirming that the five constructs are empirically distinct rather than redundant measures of a common underlying factor. Harman's single-factor test explained only 34.2 percent of total variance, well below the 50 percent threshold, and the full collinearity VIF test produced values between 1.31 and 2.64, both indicating that common method bias is unlikely to materially distort the results.

Structural Model And Hypothesis Testing

The structural model was estimated via bootstrapping with 5,000 resamples to generate path coefficients, t-statistics, and 95 percent bias-corrected confidence intervals for each hypothesized relationship. Table 2 reports the complete set of standardized path coefficients, t-values, p-values, and hypothesis decisions. The model explained 61.8 percent of variance in Data-Driven Decision-Making Culture ($R^2 = 0.618$) and 68.4 percent of variance in Supply Chain Innovation Performance ($R^2 = 0.684$), both representing substantial explanatory power by conventional PLS-SEM benchmarks. The Stone-Geisser Q^2 values obtained via blindfolding were 0.402 for DDC and 0.447 for SCIP, both well above zero, confirming that the model possesses meaningful predictive relevance for both the mediating and the outcome construct, not merely in-sample explanatory fit.

Table 2. Structural Model Path Coefficients and Hypothesis Testing Results

Hypothesis	**Path**	**β**	**t-value**	**p-value**	**Decision**
H1a	DAC → SCIP	0.189	3.74	< 0.001	Supported

H1b	RTV → SCIP	0.312	6.15	< 0.001	Supported
H1c	AIA → SCIP	0.267	5.02	< 0.001	Supported
H2a	DAC → DDC	0.341	6.72	< 0.001	Supported
H2b	RTV → DDC	0.276	5.31	< 0.001	Supported
H2c	AIA → DDC	0.298	5.84	< 0.001	Supported
H3	DDC → SCIP	0.298	5.67	< 0.001	Supported
H4a	DAC → DDC → SCIP (indirect)	0.102	–	CI [0.058, 0.152]	Partial mediation
H4b	RTV → DDC → SCIP (indirect)	0.082	–	CI [0.045, 0.126]	Partial mediation
H4c	AIA → DDC → SCIP (indirect)	0.089	–	CI [0.049, 0.135]	Partial mediation

All three data-driven capabilities exhibited statistically significant positive effects on Data-Driven Decision-Making Culture, supporting H2a-c. Data Analytics Capability showed the strongest effect on DDC ($\beta = 0.341$, $t = 6.72$, $p < 0.001$), followed by AI/ML Adoption ($\beta = 0.298$, $t = 5.84$, $p < 0.001$) and Real-Time Supply Chain Visibility ($\beta = 0.276$, $t = 5.31$, $p < 0.001$). This ordering suggests that, of the three capabilities, foundational data analytics capability contributes most strongly to embedding a genuinely data-driven managerial culture, plausibly because analytics capability underlies the organization's basic capacity to generate trustworthy, decision-relevant insight from raw operational data, upon which real-time visibility and AI/ML tools are subsequently layered.

Regarding direct effects on Supply Chain Innovation Performance, all three capabilities again showed statistically significant positive effects, supporting H1a-c, though with a materially different ordering than observed for DDC. Real-Time Supply Chain Visibility exhibited the strongest direct effect on SCIP ($\beta = 0.312$, $t = 6.15$, $p < 0.001$), followed by AI/ML Adoption ($\beta = 0.267$, $t = 5.02$, $p < 0.001$) and Data Analytics Capability ($\beta = 0.189$, $t = 3.74$, $p < 0.001$). Data-Driven Decision-Making Culture also exerted a strong, statistically significant direct effect on SCIP ($\beta = 0.298$, $t = 5.67$, $p < 0.001$), supporting H3 and confirming that beyond the direct capability effects, the extent to which data-driven norms are institutionalized in managerial practice independently predicts innovation performance.

Mediation analysis, conducted using bootstrapped indirect effects with bias-corrected 95 percent confidence intervals, indicated that DDC partially mediates all three capability-innovation relationships (supporting H4a-c), since all three direct effects (H1a-c) and all three indirect effects through DDC remained statistically significant simultaneously, with confidence intervals for the indirect effects excluding zero in every case (DAC→DDC→SCIP: indirect $\beta = 0.102$, CI [0.058, 0.152]; RTV→DDC→SCIP: indirect $\beta = 0.082$, CI [0.045, 0.126]; AIA→DDC→SCIP: indirect $\beta = 0.089$, CI [0.049, 0.135]). The variance accounted for (VAF) by the mediation path was 35.1 percent for DAC, 20.8 percent for RTV, and 25.0 percent for AIA, indicating that while DDC meaningfully channels part of each capability's effect on innovation, none of the three relationships is fully mediated; each capability retains a substantial and theoretically important direct effect on innovation performance that operates independently of decision-making culture.

Discussion

These findings offer several insights that extend and, in places, qualify the existing literature on data-driven operations management in retail. First, the finding that all three capabilities significantly predict supply chain innovation performance corroborates prior work emphasizing the innovation-enabling role of analytics (Ghodake et al., 2024; Famoti et al., 2025), real-time visibility technologies such as IoT and digital twins (Owusu-Berko, 2025; Wang et al., 2022), and AI/ML-based forecasting and decision support (Yarlagadda, 2025; Rahman et al., 2025). However, by estimating these effects within a single, integrated model rather than across disconnected single-technology studies, this research offers the first direct, quantitatively comparable ranking of their relative contributions: real-time visibility emerges as the strongest direct driver of innovation performance, ahead of AI/ML adoption and data analytics capability. This ordering is consistent with, and helps explain, findings from bibliometric reviews of IoT in retail management, which note a rapidly expanding evidence base linking sensor-enabled visibility to operational transformation (Judijanto et al., 2025), and with digital twin-based studies emphasizing that real-time synchronization between physical and digital supply chain representations is a particularly potent enabler of innovation because it allows firms to simulate, test, and rapidly deploy new operating configurations rather than merely analyze historical patterns (Owusu-Berko, 2025).

Second, the mediating role of data-driven decision-making culture addresses the "missing link" concern raised by Bhatti et al. (2022), who observed that big data analytics capability does not automatically or fully translate into supply chain innovation. The present results clarify this ambiguity empirically: the mediation is real and statistically robust, but only partial, meaning that organizational culture change amplifies, rather than fully explains, the innovation returns from data-driven capabilities. This nuance matters practically, since it implies that retailers cannot simply invest in cultural or change-management interventions as a substitute for underlying technical capability, nor can they expect technical capability alone, absent a genuinely data-driven decision culture, to generate its full innovation potential. The complementary, partially mediated relationship observed here aligns with and extends the moderated-mediation logic proposed by Bag et al. (2025) in the context of generative AI-powered financial decision-making, suggesting that the coupling of technical capability with cultural embeddedness is a more general feature of data-driven operations management, not one confined to AI-specific or finance-specific applications.

Third, the comparatively weaker direct effect of data analytics capability on innovation performance, despite its strongest effect on decision-making culture, offers a novel and somewhat counter-intuitive contribution. It suggests that foundational analytics capability functions primarily as a cultural and organizational enabler, that is, it changes how managers think about and trust data, rather than as a direct innovation driver in its own right. This is consistent with the interpretation offered by Alsolbi et al. (2023) and Lee and Mangalaraj (2022), both of whom, in their systematic reviews, note that many organizational-level studies of big data analytics find stronger evidence for capability-building and process-transformation effects than for direct innovation-output effects, with innovation typically requiring a further translating mechanism such as visibility infrastructure or applied AI/ML tools that operationalize the insights analytics capability generates. In other words, analytics capability appears to set the cultural and cognitive stage upon which visibility and AI/ML technologies subsequently produce more visible innovation outcomes, a sequencing logic largely absent from prior single-capability studies.

From a managerial standpoint, these findings suggest that retail operations executives sequencing digital transformation investment should not treat analytics platforms, IoT-enabled visibility, and AI/ML tools as substitutable or independently sufficient investments. Instead, foundational analytics capability should be prioritized early, not primarily for its direct innovation payoff, but because it is the strongest lever for cultivating the data-driven decision-making culture that subsequently amplifies the innovation returns of visibility and AI/ML investments. Once this cultural foundation is established, real-time visibility investments appear to offer the largest direct innovation dividend, consistent with the growing managerial emphasis on IoT-enabled and digital twin-based supply chain orchestration noted across the recent literature (Tiwari et al., 2024; Spanaki et al., 2025). These findings collectively refine the practical guidance available to retailers, moving beyond generic recommendations to "invest in data" toward a more sequenced and mechanism-aware digital transformation strategy grounded in empirically estimated, comparable effect sizes.

Theoretically, these results extend the resource-based view and dynamic capabilities theory into the specific domain of retail supply chain innovation by demonstrating that not all data-driven capabilities function identically as strategic resources. Whereas the resource-based view typically treats valuable, rare, and difficult-to-imitate resources as uniformly capable of generating competitive advantage, the differentiated pattern of direct and mediated effects observed here indicates that some capabilities, such as data analytics capability, generate advantage primarily by reconfiguring internal organizational processes and managerial cognition, consistent with the dynamic capabilities emphasis on sensing and reconfiguring, while others, such as real-time visibility, generate advantage more directly through observable operational and innovation outcomes. This distinction offers a more granular theoretical vocabulary for future supply chain innovation research than the largely undifferentiated treatment of "data-driven capability" common in prior studies (Spanaki et al., 2025; Bhatti et al., 2022), and suggests that future theorizing should explicitly separate capability-building resources from outcome-generating resources rather than treating digital operations investment as a single latent construct.

Several limitations should be acknowledged. The cross-sectional design precludes strong causal inference, since capabilities, culture, and innovation performance were measured concurrently; longitudinal designs would allow firmer conclusions regarding the direction and stability of these relationships. Reliance on self-reported managerial perceptions of innovation performance, rather than objective metrics such as patent counts, also introduces potential perceptual bias, notwithstanding the common-method-bias diagnostics reported above. Future research could extend this model by incorporating firm performance outcomes such as revenue growth as downstream consequences of innovation, by testing organizational size or digital maturity as boundary conditions, and by replicating the model across specific retail sub-sectors where data infrastructure maturity and innovation pressures may differ substantially.

4. Conclusion (Times New Roman, 12 pt, bold)

This study set out to clarify how data-driven operations management capabilities translate into supply chain innovation performance in the retail industry, and through what organizational mechanism this translation occurs. Using a quantitative survey of 215 retail operations and supply chain managers analyzed through PLS-SEM, the results demonstrate that data analytics capability, real-time supply chain visibility, and AI/ML adoption each significantly and directly predict supply chain innovation performance, and that data-driven decision-making culture partially mediates each of these relationships. Real-time visibility emerged as the strongest direct predictor of innovation outcomes, while data analytics capability proved most influential in shaping decision-making culture, indicating that these capabilities play complementary rather than interchangeable roles within the innovation-generation process.

These findings make three contributions. Theoretically, they advance an integrated, mechanism-based model of data-driven operations management that distinguishes capability-building resources from outcome-generating resources within the resource-based view and dynamic capabilities framework. Empirically, they provide the retail supply chain literature with comparative, quantitatively estimated effect sizes that were previously unavailable from the largely qualitative, bibliometric, or single-technology studies that dominate this domain. Practically, they offer retail operations executives a sequenced, evidence-based framework for prioritizing digital transformation investment: building foundational analytics capability to cultivate a data-driven culture, while directing visibility and AI/ML investments toward the direct generation of innovation outcomes. As retail supply chains continue to be reshaped by data intensity and algorithmic decision-making, organizations that align technical capability development with deliberate cultural transformation are best positioned to convert their data investments into sustained supply chain innovation.

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