AI-Enabled Demand Forecasting Capability, Inventory Resilience, and Operational Performance among Vietnamese Retail SMEs: The Mediating Role of Decision Quality

Trần Văn Nam[1]*, Lê Thị Hồng Nhung[2]
[1]School of Business and Management, Hanoi University of Industry, Hanoi, Vietnam
Email: namtv@haui.edu.vn
[2]School of Economics and Management, Vinh University, Vinh City, Vietnam
Email: nhung.le@vinhuni.edu.vn
*Corresponding author: namtv@haui.edu.vn

Abstract

Retail SMEs across Southeast Asia increasingly experiment with AI-enabled analytics to improve demand forecasting, yet performance outcomes remain uneven because technology adoption does not automatically translate into better operational decisions. This study examines how AI-enabled demand forecasting capability influences operational performance among Vietnamese retail SMEs through inventory resilience and decision quality. Building on capability theory, information processing logic, and resilience perspectives, the model conceptualizes AI capability as a set of routines that combine data readiness, tool reliability, and managerial interpretive competence. Survey data were collected from 455 Vietnamese retail SMEs that had used digital analytics tools for forecasting or replenishment planning for at least six months. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test direct effects and parallel mediation. Results indicate that AI-enabled forecasting capability is positively associated with operational performance, with decision quality and inventory resilience operating as complementary mediators. Decision quality strengthens resilience by improving replenishment timing and reducing overreaction to short-term noise. The findings clarify why AI initiatives often fail when data and interpretation routines are weak, and they offer ASEAN-relevant insights for small retailers facing demand volatility and supply disruptions. Practical implications emphasize pairing analytics tools with data governance and managerial training, enabling SMEs to convert forecasts into robust inventory actions.

Keywords: *AI Analytics, Demand Forecasting, Retail Smes, Decision Quality, Inventory Resilience, Operational Performance, Vietnam, PLS-SEM.*

A. INTRODUCTION

Demand volatility has become a defining condition for retail operations across Southeast Asia. Shifts in consumer preferences, rapid promotion cycles, platform-driven demand spikes, and supply disruptions have increased the operational complexity faced by small and medium-sized retailers. For retail SMEs, which typically operate with limited buffer stock and constrained working capital, forecasting errors can be costly. Under-forecasting triggers stockouts and lost sales; over-forecasting ties cash into slow-moving inventory, increases markdown risk, and limits flexibility to respond to new demand patterns. These trade-offs have become more severe as retail demand becomes increasingly shaped by digital channels and social influence (Khan, 2024; A. Rashid et al., 2024).

AI-enabled analytics tools are frequently presented as a solution to these challenges. Even relatively lightweight forecasting applications, integrated into point-of-sale systems or e-commerce dashboards, promise to transform historical transaction records into predictive signals. In principle, better forecasts should enable better replenishment timing, lower inventory costs, and improved service levels. In practice, performance outcomes vary sharply. Many SMEs adopt analytics tools yet continue to rely on intuition, treat model outputs as opaque, or apply forecasts inconsistently. Such patterns suggest that adoption metrics are insufficient for explaining operational outcomes. The relevant unit of analysis is capability: the extent to which SMEs can integrate AI forecasts into decision routines that are reliable, interpretable, and aligned with operational constraints (Baharudin, 2023; Kalisetty, 2024a).

Vietnam provides a strategically relevant setting for studying this capability gap. Vietnamese retail SMEs operate in a rapidly modernizing market that combines traditional storefront trade with expanding e-commerce. Competition is intense, consumer demand shifts quickly, and supply conditions can be uneven across regions. At the same time, many SMEs have begun digitizing sales records and experimenting with analytics tools through platform partnerships and affordable SaaS solutions. This creates an environment where AI capability is present in varying maturity levels, allowing examination of how capability translates into resilience and performance (Abdullah, 2023; Nayal et al., 2024).

The present study argues that AI-enabled forecasting contributes to performance through two complementary mechanisms: decision quality and inventory resilience. Decision quality refers to the extent to which replenishment decisions are timely, coherent, and aligned with both forecast signals and operational realities. High decision quality does not imply blind obedience to models; it implies the disciplined integration of quantitative signals with contextual judgment. Inventory resilience refers to the ability to maintain service continuity during demand or supply shocks by balancing stock availability, replenishment flexibility, and risk diversification (Dey et al., 2024; George, 2024). Resilience is increasingly relevant because shocks often occur without warning, and SMEs must respond quickly without overreacting.

A mechanism-based model is important because it helps explain why AI initiatives fail. When data is incomplete, when tools are unreliable, or when managers cannot interpret output, forecasts do not improve decisions. Poor decisions can even reduce resilience by causing overconfidence, excessive stocking, or reactive oscillation in replenishment orders (Ejjami, 2024; Ismaeil, 2024). When capability is mature, AI can improve operational control and reduce variability, enabling SMEs to sustain performance under volatility.

This study addresses three research questions: (1) whether AI-enabled forecasting capability is positively associated with operational performance; (2) whether decision quality and inventory resilience mediate this relationship; and (3) how these mechanisms inform practical guidance for SMEs and policymakers in ASEAN markets. The contribution lies in moving beyond technological adoption toward capability maturity and resilience pathways, providing a plausible causal account of how small retailers can use analytics to achieve robust performance rather than fragile optimization.

B. LITERATURE REVIEW

AI-Enabled Forecasting Capability and Operational Performance

AI-enabled forecasting capability should improve operational performance by reducing uncertainty and enabling more efficient replenishment. When SMEs can generate reliable signals, they can reduce stockout incidence, lower overstocks, and improve service consistency. Capability also supports coordination between sales and procurement by providing a shared reference point for planning (Jauhar et al., 2024; H. Rashid, 2024).

The use of analytics and AI in retail has been studied through information systems, operations management, and decision sciences. Early studies often emphasized technical accuracy of forecasting models, while more recent work recognizes that organizational routines determine whether forecasts translate into better outcomes. Small firms face distinct challenges: limited data quality, limited analytical expertise, and constrained capacity to redesign processes, AI benefits are contingent on capability maturity rather than on tool availability (Francis Onotole et al., 2022; Polo, 2024).

Capability theory provides a useful lens by conceptualizing technology-enabled advantage as the outcome of coordinated routines that combine resources, skills, and governance. AI-enabled forecasting capability can be defined as the ability to generate, interpret, and operationalize predictive demand signals consistently. It involves data readiness, tool reliability, and managerial interpretive competence. Data readiness includes clean transaction records and consistent product coding. Tool reliability includes stable dashboards, meaningful alerts, and error handling (Alshurideh et al., 2024; Ugwu et al., 2024). Interpretive competence includes the ability to understand uncertainty, detect outliers, and avoid overreacting to noise.

Performance effects are expected to be stronger when capability is operationalized as routines rather than as mere tool ownership. SMEs that integrate forecasts into ordering cycles and monitor outcomes systematically are more likely to realize benefits.

H1: AI-enabled demand forecasting capability is positively associated with operational performance.

Decision Quality as a Mediating Mechanism

Decision quality is a plausible mediator because AI capability creates value only when translated into actionable choices. Capability improves decision quality by providing structured evidence, reducing reliance on guesswork, and clarifying trade-offs. Interpretive competence allows managers to treat forecasts as probabilistic signals rather than deterministic rules, reducing overreaction to noise (Jackson et al., 2024; Olagunju, 2022).

Decision quality serves as a central mechanism connecting capability to performance. Decision quality in inventory planning reflects whether decisions are timely, coherent, and aligned with objectives such as service level, cashflow stability, and markdown risk. Forecasts can improve decisions by reducing uncertainty, yet they can also create false confidence if uncertainty is misunderstood. High-quality decisions incorporate model outputs while accounting for operational constraints (Goswami, 2022; Kalisetty, 2024b).

Inventory resilience extends performance logic by emphasizing robustness under shock. Resilient inventory systems maintain continuity during demand spikes and supply disruptions through flexible replenishment, diversified sourcing, and disciplined safety stock policies. AI capability can strengthen resilience by improving visibility and enabling earlier detection of shifts. Decision quality likely strengthens resilience by translating signals into actionable replenishment plans that reduce oscillation and avoid panic ordering (Akande & Enyejo, 2024; Chukwu et al., 2024).

Higher decision quality should improve operational performance by aligning replenishment timing with demand patterns, reducing oscillation in orders, and improving the match between inventory levels and cash constraints.

H2: AI-enabled forecasting capability is positively associated with decision quality.

H3: Decision quality is positively associated with operational performance.

H4: Decision quality mediates the relationship between AI capability and operational performance.

Inventory Resilience as a Complementary Mediator

Inventory resilience captures the ability to maintain service continuity under shock. AI capability can strengthen resilience by improving visibility into demand changes and enabling proactive replenishment adjustments. It can also support resilience by encouraging structured monitoring of lead times and supplier reliability (Modgil et al., 2022; Stewart, 2023).

Operational performance in retail SMEs can be conceptualized through service level stability, reduced stockouts, improved inventory turnover, and perceived profitability stability. These outcomes are influenced not only by forecast accuracy but also by how decisions are executed and how inventory buffers are managed. Accordingly, the present study develops a model in which AI capability influences performance directly and indirectly through decision quality and resilience (Onotole et al., 2023; Singh et al., 2024).

Resilience should improve performance by reducing stockouts during spikes and by preventing excessive markdowns when demand shifts. Decision quality is expected to support resilience because coherent decisions reduce panic ordering and improve safety stock calibration (Eyo-Udo, 2024; Filani et al., 2023).

H5: AI-enabled forecasting capability is positively associated with inventory resilience.

H6: Inventory resilience is positively associated with operational performance.

H7: Inventory resilience mediates the relationship between AI capability and operational performance.

H8: Decision quality is positively associated with inventory resilience.

C. METHOD

A quantitative explanatory design was employed to test direct and mediated relationships among AI-enabled forecasting capability, decision quality, inventory resilience, and operational performance. A cross-sectional survey approach was chosen because many retail SMEs do not maintain standardized operational KPIs that are easily comparable across firms, while managerial assessments can capture performance stability and service outcomes relative to competitors.

Data were collected from 455 Vietnamese retail SMEs across consumer goods, specialty retail, and small chain formats. Eligibility required that firms had used digital analytics tools for forecasting or replenishment planning for at least six months, ensuring exposure beyond initial experimentation. Respondents were owners, operations managers, or procurement leads responsible for inventory decisions. Recruitment was conducted through business associations, retail training networks, and platform partner communities.

AI capability was measured using indicators capturing data readiness, tool reliability, integration into ordering routines, and interpretive competence. Decision quality was measured through indicators of timeliness, coherence, and alignment with objectives. Inventory resilience measured buffer discipline, flexibility of replenishment, and ability to maintain service during shocks. Operational performance captured perceived stockout reduction, turnover improvement, service stability, and profitability stability. All items used five-point Likert scales. PLS-SEM was applied to assess measurement properties and structural relationships, with bootstrapping used for mediation inference. Participation was voluntary and anonymous.

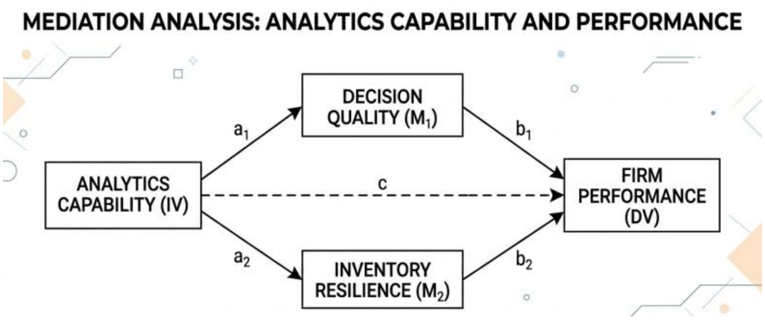

Figure 1. Mediation Analysis: Analytics Capability and Performance

D. RESULT AND DISCUSSION

Result

Measurement model assessment indicated acceptable reliability and validity across constructs. Respondents distinguished AI capability from decision quality, supporting the theoretical separation between having predictive routines and using them well. Decision quality and resilience were also empirically distinguishable, indicating that coherent planning and shock robustness represent complementary facets of operational maturity.

Structural evaluation supported the central proposition that AI-enabled forecasting capability is positively associated with operational performance. Capability also related positively to decision quality and inventory resilience. Decision quality and resilience each related positively to performance, consistent with the proposed mechanism logic.

Mediation analysis suggested that decision quality and inventory resilience transmit meaningful portions of the capability–performance relationship, while a direct association remains. This pattern indicates that capability improves performance partly by improving how decisions are made and partly by strengthening shock robustness, while also providing additional benefits such as improved coordination and visibility. Decision quality also related positively to resilience, supporting the interpretation that coherent planning strengthens robustness under volatility. Tables 1–3 summarize model adequacy, hypothesis support, and mechanism interpretations without emphasizing coefficient magnitudes.

Table 1. Measurement Model Summary

Construct	Internal Consistency	Convergent Validity	Discriminant Validity
AI Forecasting Capability	Established	Established	Confirmed
Decision Quality	Strong	Established	Confirmed
Inventory Resilience	Established	Established	Confirmed
Operational Performance	Established	Established	Confirmed

Source: data proceed

A micro-foundational interpretation treats forecasting capability as a joint production process between algorithmic output and managerial cognition, where performance depends less on whether a model is "accurate" in the abstract and more on whether decision-makers can translate probabilistic information into consistent operational choices. Forecasts arrive as distributions, not certainties, and the managerial task is to choose actions that are robust to variance, regime shifts, and measurement noise. Even highly predictive models can fail to improve outcomes when managers over-anchor on point estimates, ignore uncertainty bands, or treat anomaly signals as "errors" rather than as potential early warnings of structural change. In practice, these failures often arise from predictable cognitive patterns: overconfidence after short runs of success, myopic reaction to recent spikes, and confirmation bias when forecasts conflict with prior beliefs about customer behaviour.

Training that emphasises probabilistic thinking, scenario comparison, and structured post-action review can reduce these errors by making uncertainty legible and actionable, shifting attention from "What will happen?" to "What decisions perform acceptably across plausible futures?" Scenario comparison is particularly important because it discourages a single-forecast mindset and encourages managers to evaluate policy robustness, for example by comparing aggressive replenishment, conservative replenishment, and adaptive replenishment under high-volatility versus low-volatility demand. Post-action review further converts forecasting into a learning loop: managers evaluate not only forecast error but decision error, documenting what they assumed, what signals they ignored, and which constraints prevented execution, thereby building organisational memory that improves calibration over time.

Within this micro-foundational frame, inventory resilience can be conceptualised as the capacity to maintain service levels and financial viability while balancing three risks that pull in different directions: stockout risk, overstock risk, and disruption risk. Stockout risk manifests as lost sales, damaged reliability, and customer churn, especially in categories where substitution is limited or switching costs are low. Overstock risk appears as tied-up working capital, increased markdowns, shrinkage, and operational clutter, which is particularly punishing for SMEs with limited storage and weaker bargaining power. Disruption risk captures shocks that are not purely demand-driven, such as supplier delays, logistics bottlenecks, regulatory changes, or sudden channel shifts, all of which can render prior replenishment assumptions obsolete. AI capability can improve the balance among these risks by providing earlier signals, detecting leading indicators of demand change, and enabling differentiated safety stock policies across product categories rather than a one-size-fits-all buffer.

The key point is that resilience is not identical to holding "more inventory"; it is the quality of the policy that matters, including when to stock, what to stock, and how to adjust as signals evolve. Differentiated policies allow firms to treat fast movers, slow movers, seasonal items, and promotion-sensitive items as distinct classes with distinct service targets, review cycles, and reorder triggers. Decision quality then determines whether those policies remain stable rather than oscillating with short-term noise. When managers react too quickly to transient fluctuations, policies become erratic, producing a whiplash pattern of over-ordering followed by aggressive markdowns, which erodes trust in the forecasting system and encourages even more manual overrides. A disciplined governance mechanism, such as thresholds for action, escalation rules for anomalies, and clear ownership of parameter changes, helps prevent oscillation and preserves the benefits of signal-based adjustment.

Table 2. Hypotheses Testing Summary

Hypothesis	Relationship	Supported
H1	AI Capability → Operational Performance	Yes
H2	AI Capability → Decision Quality	Yes
H3	Decision Quality → Operational Performance	Yes
H4	Decision Quality mediates AI Capability → Performance	Partial
H5	AI Capability → Inventory Resilience	Yes
H6	Inventory Resilience → Operational Performance	Yes
H7	Inventory Resilience mediates AI Capability → Performance	Partial
H8	Decision Quality → Inventory Resilience	Yes

Source: data proceed

The SME context adds a constraint that materially changes how forecasting capability should be evaluated: limited working capital often forces trade-offs between inventory depth and liquidity that larger firms can absorb through better financing access, diversified product portfolios, and stronger supplier terms. For SMEs, a stockout is not merely a service failure; it can be a missed cashflow window that delays subsequent replenishment, producing cascading understock. Overstock is not merely an efficiency loss; it can threaten solvency by trapping cash in inventory that cannot be converted quickly without margin sacrifice. Forecasting capability can reduce the severity of this trade-off by improving turnover, reducing waste, and enabling more precise ordering, yet these benefits materialise only when decisions are disciplined and execution is aligned with the forecast. Discipline here means resisting the temptation to "buy certainty" by over-ordering when uncertainty increases, and instead using uncertainty as a trigger for contingency planning, such as negotiating flexible supplier arrangements, adjusting reorder frequency, or using partial replenishment strategies. This constraint also suggests a different interpretation of performance gains: for SMEs, the most meaningful gains may appear as stability gains rather than pure growth. Stability includes fewer liquidity crunches, smoother cash conversion cycles, reduced emergency replenishment costs, and more predictable margin outcomes. In other words, the value of forecasting capability can be measured in reduced variance and improved survivability, not only in higher average sales.

A deeper implication is that the payoff of forecasting tools is mediated by decision routines that convert forecasts into policy, and these routines must be compatible with the SME's operational bandwidth. If using the model requires high cognitive effort, continuous parameter tuning, or complex data engineering, SMEs may revert to heuristics and intuition, effectively nullifying the potential benefits. This is where an ecosystem perspective becomes decisive: platform partners can accelerate capability maturity by providing shared infrastructure that lowers the fixed costs of adoption and reduces the skill requirements for maintaining data readiness. Standardised product taxonomy is not a cosmetic feature; it is an enabling condition for learning, because inconsistent SKU naming, category drift, and ad hoc bundling break the continuity of training data and undermine signal quality. Automated data cleaning and reconciliation reduce the time managers spend fighting spreadsheets, making it more likely that forecasts are refreshed on schedule and comparable across time. Explainable forecasting dashboards increase interpretability by translating model outputs into actionable insights, such as which covariates are driving changes, which SKUs are at risk of stockout, and which anomalies require human review. Interpretability is not merely about transparency for its own sake; it helps build calibrated trust. When managers understand why a forecast changed, they are less likely to override it reflexively and more likely to treat it as a hypothesis to be tested against local knowledge. At the same time, explainability should be designed to support decisions rather than to overwhelm, prioritising a small number of "decision-relevant explanations" and surfacing uncertainty explicitly. The result is a reduction in the cognitive cost of disciplined decision-making, which is essential for SMEs with limited managerial time.

Decision quality, in this integrated view, is best understood as a capability that includes both cognitive skill and organisational process. Cognitive skill involves probabilistic reasoning, recognising regime changes, and avoiding common biases such as recency effects and overreaction to outliers. Organisational process involves embedding forecasting into routines, such as weekly demand reviews, exception-based escalation, and documented rules for safety stock adjustments. A useful way to conceptualise the interaction is to treat the algorithm as a sensor and the manager as a controller. Sensors can be precise, but control quality depends on how signals are filtered and how actions are damped to avoid instability. Without damping, a system can oscillate even with perfect sensing. In inventory contexts, damping is implemented through policy constraints, such as minimum order intervals, caps on week-to-week reorder changes, and guardrails triggered by uncertainty expansion. These guardrails prevent the system from "chasing noise," which is a common failure mode when managers treat every forecast update as a directive rather than as information.

The notion of disruption risk further clarifies why managerial cognition matters even when models are strong. Many disruptions do not resemble historical patterns, so models trained on stable periods may understate tail risk. Managers who rely solely on point forecasts may miss early warning signs embedded in anomaly detection outputs, such as unusual demand surges, channel migration, or supplier lead-time inflation. Proper interpretation of anomalies requires a different mindset from interpreting routine forecast error: anomalies should trigger diagnostic questions, not immediate replenishment changes. For example, a surge might reflect a promotional event, a competitor stockout, a social media trend, or data quality issues; each requires a different response. This is why training should include anomaly triage and scenario drills, not just statistical literacy. Post-action reviews then become the mechanism by which organisations convert disruptions into improved playbooks, refining how they distinguish between true signal and transient shock.

Table 3. Mechanism Summary for Interpreting the Results

Mechanism	**Interpretive Logic**	**Practical Meaning for Retail SMEs**
Capability → Decision Quality → Performance	Reliable signals and interpretive competence improve replenishment timing and coherence.	Fewer stockouts and overstocks, smoother ordering cycles, better turnover stability.
Capability → Resilience → Performance	Visibility and buffer discipline improve continuity under demand/supply shocks.	Service levels remain stable during spikes; markdown risk declines after shifts.
Decision Quality → Resilience	Coherent planning reduces oscillation and prevents panic ordering.	Safety stock and reorder points become more stable and aligned with risk.

Source: data proceed

From a strategic standpoint, forecasting capability should also be evaluated through its interaction with product strategy and channel strategy. Differentiated safety stock policies are easier to sustain when product assortments are rationalised and when categories are defined in ways that reflect demand behaviour rather than merchandising convenience. Overly broad assortments can dilute forecasting accuracy because sparse demand series become noisy, increasing uncertainty and encouraging manual overrides. Conversely, strategic assortment simplification can improve both model performance and execution discipline by reducing the number of decisions managers must make. Channel strategy matters because different channels carry different demand signals, lead times, and return patterns. Online channels may exhibit higher volatility and faster feedback loops, while offline channels may have more stable baselines but slower visibility into shifts. These differences suggest that channel complexity is not only a control variable but a potential moderator of the capability–decision quality relationship. SMEs operating in both offline and online environments face more volatile and multi-source demand, making forecasting signals more valuable, yet also more difficult to interpret because the same SKU can exhibit different patterns across channels and because promotions, fulfilment constraints, and platform algorithms can amplify noise. In such settings, decision routines must explicitly allocate responsibility for channel attribution, define how forecasts are combined or separated, and specify which channel signals trigger replenishment changes.

This logic motivates a concrete research extension: testing whether channel complexity moderates the marginal payoff of forecasting capability and whether decision quality amplifies or attenuates this effect. A multi-group approach could compare single-channel SMEs to omni-channel SMEs, examining whether forecasting capability yields higher improvements in service level stability, markdown reduction, or cash conversion predictability under higher demand volatility. The key hypothesis is not simply "omni-channel benefits more," but "omni-channel benefits more when decision routines prevent oscillation and when dashboards support attribution and uncertainty interpretation." A complementary analysis could test whether the effect differs by category, for example essentials versus discretionary, high-frequency versus low-frequency items, and promotion-driven versus baseline-driven demand. Such segmentation would strengthen causal interpretation by showing that capability is not uniformly valuable, but contingent on demand structure and managerial capacity.

Forecasting capability is not a technology variable; it is an organisational capability that emerges from the fit between model outputs, managerial cognition, and execution routines under capital constraints. Inventory resilience is achieved by balancing stockout, overstock, and disruption risks through differentiated policies that are maintained with disciplined decision-making rather than reactive oscillation. For retail SMEs, the most defensible performance story is often stability, not only growth, because working-capital constraints make volatility itself a threat to survival. Platform ecosystems can accelerate maturation by lowering data readiness costs and increasing interpretability, enabling SMEs to build sustainable decision routines. Future work should focus on boundary conditions, especially channel complexity, and use multi-group analysis to identify where forecasting capability produces the highest payoff and where managerial decision quality is most essential for translating algorithmic output into resilient inventory performance.

Discussion

The findings support the view that AI analytics create value for retail SMEs when treated as a capability rather than as a software purchase. AI-enabled forecasting capability is positively associated with operational performance, yet the mechanism pattern indicates that benefits arise through decision quality and inventory resilience. This clarifies why many AI initiatives disappoint: forecasting output does not improve performance unless it changes how decisions are made and how inventory buffers are governed.

Decision quality emerges as a central pathway because inventory performance is ultimately determined by choices regarding what to order, when to order, and how to respond to uncertainty. Capability improves decision quality by providing structured evidence, reducing reliance on guesswork, and enabling disciplined learning. Interpretive competence is particularly important because forecasts are probabilistic. Managers who treat model output as deterministic can overreact to noise, creating oscillations that increase both stockout and overstock risk. Capability maturity reduces this behavior by encouraging calibration and post-action review (Goswami, 2022; Modgil et al., 2022).

Inventory resilience complements decision quality by emphasizing robustness under shock. Retail SMEs face disruptions that cannot be fully predicted, including supply delays, sudden demand spikes during promotions, and social-media-driven trend shifts. Capability supports resilience by improving visibility and enabling earlier adjustments, while decision quality supports resilience by preventing panic ordering and stabilizing safety stock policies. This interaction suggests that resilience is not only about holding more inventory; it is about holding and moving inventory intelligently under uncertainty.

A Vietnam-specific interpretation highlights rapid retail modernization and the coexistence of offline and online channels. SMEs that digitize sales data and use forecasting tools can coordinate replenishment across channels more effectively, reducing the risk that online demand drains offline stock unexpectedly. At the same time, data quality challenges remain common, including inconsistent product coding and missing transactions, which can undermine forecasts (Akande & Enyejo, 2024; Alshurideh et al., 2024). The results imply that data governance and routine discipline are as important as model sophistication.

An ASEAN comparative lens suggests that the capability–decision–resilience architecture is likely to generalize, while ecosystem maturity shapes feasibility. Indonesia's retail SMEs face similar volatility and could benefit from capability development, though data fragmentation and varied infrastructure may slow maturity. Thailand's more mature digital payments and retail analytics ecosystems may provide richer data footprints, potentially strengthening capability effects. The Philippines' dispersed geography and supply variability may make resilience especially valuable, increasing the performance payoff of disciplined buffer governance. Across these contexts, the consistent theme is that analytics must be embedded in routines and supported by managerial learning, not treated as a one-time tool deployment.

Managerial implications emphasize capability building steps that are feasible for SMEs. First, data readiness should be prioritized through consistent product coding, basic transaction completeness, and routine error checks. Second, decision routines should be standardized with regular review cycles that compare forecast signals to outcomes, enabling calibration. Third, resilience policies should be explicit, including thresholds for safety stock, supplier diversification practices, and contingency plans for promotion-driven spikes. Tool vendors and platform partners can support this process by providing explainable outputs and simple scenario tools rather than complex black-box models (Ejjami, 2024; H. Rashid, 2024).

Policy implications extend to SME digitalization support. Training programs that combine basic analytics literacy with inventory governance can help SMEs convert digital tools into performance. Incentives that encourage digital record-keeping can strengthen data readiness and reduce capability gaps. As ASEAN economies pursue AI adoption agendas, the evidence suggests that capability maturity—data, interpretation, and governance—determines whether AI produces robust productivity gains. Limitations suggest future research. Cross-sectional design restricts temporal inference, and longitudinal studies could examine how capability maturity evolves and how resilience benefits appear during shock periods. Objective operational data, such as stockout rates and turnover, could complement subjective assessments. Future work could also explore sectoral differences and examine whether supply complexity moderates the capability–resilience relationship.

E. CONCLUSION

This study demonstrates that AI-enabled demand forecasting capability is positively associated with operational performance among Vietnamese retail SMEs, with decision quality and inventory resilience operating as complementary mediators. Capability improves performance partly by strengthening planning coherence and partly by improving robustness under demand and supply volatility. Decision quality also supports resilience, indicating that disciplined choices and stable routines reduce panic ordering and improve buffer governance. For SME managers, the findings suggest that analytics value depends on data readiness and interpretive competence, not only on tool access. For policymakers and platform partners, the results highlight the importance of supporting digital record-keeping and managerial training that converts forecasts into resilient actions. As ASEAN markets continue to digitalize retail, capability maturity becomes a central determinant of whether AI contributes to sustainable operational improvement.

REFERENCES

Abdullah, A. F. Bin. (2023). AI-Enabled Demand Forecasting in SAP: Machine Learning Models for Supply Chain Accuracy. *International Journal of Research and Applied Innovations*, *6*(5), 9501–9504.

Akande, S. A., & Enyejo, J. O. (2024). Leveraging predictive analytics to improve demand forecasting and inventory management in healthcare supply chains. *International Journal of Scientific Research in Science, Engineering and Technology*, *11*(2).

Alshurideh, M. T., El Khatib, M., Al Kurdi, B., Nawaiseh, A. K., Hamadneh, S., Al-Sulaiti, K., Alrawabdeh, W. A., Alshurideh, A., Shwedeh, F., & Alzoubi, H. M. (2024). Exploring the Impact of AI-Based Technology on Supply Chain Efficiency, with Mediator Role of Smart Inventory Management Practices. *International Scientific Conference Management and Engineering*, 55–63.

Baharudin, H. (2023). AI in E-Commerce Warehouse Management: Enhancing Operational Efficiency, Ensuring Inventory Precision, and Strengthening Security Measures. *Ensuring Inventory Precision, and Strengthening Security Measures (October 24, 2023)*.

Chukwu, N., Yufenyuy, S., Ejiofor, E., Ekweli, D., Ogunleye, O., Clement, T., Obunadike, C., Adeniji, S., Elom, E., & Obunadike, C. (2024). Resilient chain: AI-enhanced supply chain security and efficiency integration. *International Journal of Scientific and Management Research*, *7*(03), 46–65.

Dey, P. K., Chowdhury, S., Abadie, A., Vann Yaroson, E., & Sarkar, S. (2024). Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small-and medium-sized enterprises. *International Journal of Production Research*, *62*(15), 5417–5456.

Ejjami, R. (2024). Optimizing in-store logistics: How AI enhances inventory management and space utilization. *Journal of Next-Generation Research 5.0*.

Eyo-Udo, N. (2024). Leveraging artificial intelligence for enhanced supply chain optimization. *Open Access Research Journal of Multidisciplinary Studies*, *7*(2), 1–15.

Filani, O. M., Olajide, J. O., & Osho, G. O. (2023). Artificial intelligence in demand forecasting and inventory optimization. *Journal of Applied Research in Technology and Innovation. Https://Doi. Org/10.62225/2583049x*, *6*.

Francis Onotole, E., Ogunyankinnu, T., Adeoye, Y., Osunkanmibi, A. A., Aipoh, G., & Egbemhenghe, J. (2022). The role of generative AI in developing new supply chain strategies-future trends and innovations. *International Journal of Supply Chain Management*, *11*(4), 325–338.

George, A. S. (2024). AI-enabled intelligent manufacturing: A path to increased productivity, quality, and insights. *Partners Universal Innovative Research Publication*, *2*(4), 50–63.

Goswami, D. (2022). Harnessing ai-driven business intelligence from customer data. *Review of Applied Science and Technology*, *1*(03), 10–63125.

Ismaeil, M. K. A. (2024). The role and impact of artificial intelligence on supply chain management: Efficiency, challenges, and strategic implementation. *Journal of Ecohumanism*, *3*(4), 89–106.

Jackson, I., Ivanov, D., Dolgui, A., & Namdar, J. (2024). Generative artificial intelligence in supply chain and operations management: a capability-based framework for analysis and implementation. *International Journal of Production Research*, *62*(17), 6120–6145.

Jauhar, S. K., Jani, S. M., Kamble, S. S., Pratap, S., Belhadi, A., & Gupta, S. (2024). How to use no-code artificial intelligence to predict and minimize the inventory distortions for resilient supply chains. *International Journal of Production Research*, *62*(15), 5510–5534.

Kalisetty, S. (2024a). Agentic AI and predictive analytics: Revolutionizing retail supply chain management for next-gen resilience and efficiency. *Available at SSRN 5231377*.

Khan, M. O. (2024). Transforming Supply Chains with AI: Enhancing Sustainability and Manufacturing Resilience. *Unpublished. Available at: Https://Doi. Org/10.13140/RG*, *2*(15436.83844).

Modgil, S., Singh, R. K., & Hannibal, C. (2022). Artificial intelligence for supply chain resilience: learning from Covid-19. *The International Journal of Logistics Management*, *33*(4), 1246–1268.

Nayal, K., Raut, R. D., Kumar, M., Paul, S. K., & Narkhede, B. E. (2024). Role of artificial intelligence capability in the interrelation between manufacturing strategies and operational resilience. *Global Journal of Flexible Systems Management*, *25*(1), 137–162.

Olagunju, E. (2022). Integrating AI-driven demand forecasting with cost-efficiency models in biopharmaceutical distribution systems. *Int J Eng Technol Res Manag*.

Onotole, E. F., Ogunyankinnu, T., Osunkanmibi, A. A., Adeoye, Y., Ukatu, C. E., & Ajayi, O. A. (2023). AI-driven optimization for vendor-managed inventory in dynamic supply chains. *Operations Research Letters*, *51*(4), 445–462.

Polo, L. (2024). Revolutionizing sales and operations planning with artificial intelligence: Insights and results. *International Journal For Multidisciplinary Research*, *6*(6).

Rashid, A., Kazi, A. K., & Ramish, M. S. (2024). Impact of Artificial Intelligence on Supply Chain Performance: Mediation Role of Supply Chain Resilience. *Pakistan Social Sciences Review*, *8*(4), 408–418.

Rashid, H. (2024). Designing cost-effective, AI-powered demand forecasting models for the manufacturing sector. *Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-E252. DOI: Doi. Org/10.47363/JAICC/2024 (3) E252 J Arti Inte & Cloud Comp*, *3*(1), 2–5.

Singh, R. K., Modgil, S., & Shore, A. (2024). Building artificial intelligence enabled resilient supply chain: a multi-method approach. *Journal of Enterprise Information Management*, *37*(2), 414–436.

Stewart, O. (2023). AI-powered supply chain optimization: enhancing resilience through predictive analytics. *International Journal of AI, BigData, Computational and Management Studies*, *4*(2), 9–20.

Ugwu, O. I., Clarksville, T. N., Hassan, O. F., Clarksville, T. N., Sanusi, M. A., Odukoya, O., & Onasanya, T. (2024). Artificial intelligence in healthcare supply chains: Enhancing resilience and reducing waste. *Int J Adv Res Ideas Innov Technol*, *10*, 203–217.