



IMPACT OF AI-DRIVEN DEMAND FORECASTING AND INVENTORY OPTIMIZATION ON SUPPLY CHAIN EFFICIENCY AND OPERATIONAL COST REDUCTION

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Abstract

Background: Artificial intelligence (AI) is playing an increasingly important role in supply chain management by improving demand-forecasting accuracy and supporting better inventory decisions. Traditional forecasting techniques can struggle to accommodate demand uncertainty, which may lead to stockouts, overstocking, and higher operating costs. AI-powered forecasting models and intelligent inventory-optimization technologies can help organizations improve efficiency, reduce waste, and become more resilient to supply chain disruptions. However, empirical evidence linking forecasting capability to cost outcomes through inventory decisions remains limited.

Aim: This study explores the relationships among AI-driven demand forecasting, inventory optimization, supply chain efficiency, and operational cost reduction. It also examines whether inventory optimization acts as a bridge between AI-driven forecasting and operational cost reduction.

Method: This study used a quantitative, cross-sectional explanatory survey. A structured questionnaire was administered to 300 supply chain respondents from manufacturing ($n = 156$) and retail ($n = 144$) organizations, including supply chain professionals, logistics managers, inventory managers, and procurement specialists. Data were analyzed using descriptive statistics and PLS-SEM with bootstrapping to test the relationships among AI-driven demand forecasting, inventory optimization, supply chain efficiency, and operational cost reduction, with inventory optimization examined as a mediator.

Results: Respondents reported a 29.4% improvement in forecasting accuracy, a 22.7% decrease in inventory holding costs, and a 31.5% decrease in stockout incidents. Overall supply chain efficiency increased by 27.9%; 84.2% of respondents agreed that AI-based forecasting enhanced inventory planning and decision-making, and operational costs decreased by 19.8%. In the PLS-SEM model, AI-driven demand forecasting was positively associated with inventory optimization ($\beta = 0.71, p < 0.001$) and supply chain efficiency ($\beta = 0.63, p < 0.001$). Inventory optimization was positively associated with supply chain efficiency ($\beta = 0.58, p < 0.001$) and operational cost reduction ($\beta = 0.34, p < 0.001$). Inventory optimization partially mediated the relationship between AI-driven demand forecasting and operational cost reduction (indirect effect = 0.24).

Conclusion: AI-driven demand forecasting and inventory optimization were significantly and positively associated with improved supply chain performance, including better forecasting, more effective inventory utilization, and lower operational costs. Given the cross-sectional design and perceptual measures, these findings should be interpreted as associations rather than evidence of cause and effect.

Keywords: Artificial Intelligence; Demand Forecasting; Inventory Optimization; Supply Chain Management; Operational Cost Reduction

1. Introduction

1.1 Background

Modern supply chains are longer, more interdependent, and more exposed to uncertainty than ever before. Frequent product refreshes, evolving customer preferences, promotions, and continual fluctuations make it increasingly difficult to predict demand and match supply (Christopher & Holweg, 2011). The



COVID-19 pandemic demonstrated how changes in requirements and availability at one organization can propagate through interconnected supply networks (Ivanov, 2020; Ivanov & Dolgui, 2020). The flow of information from one stage of a supply chain to another can also contribute to demand volatility. When each stage forecasts demand based on orders from the preceding stage, fluctuations can become progressively amplified upstream, a phenomenon known as the bullwhip effect (Lee et al., 1997).

Forecast quality is important if forecasts are to improve inventory decisions. When forecasts are too low, firms risk stockouts, lost sales, and reduced service levels. When forecasts are too high, firms may carry excess inventory, tying up working capital and increasing storage, handling, and obsolescence costs. Classical inventory theory suggests that the safety inventory required to achieve a target service level increases with forecast error and lead-time variability (Silver et al., 2017). Empirical retail studies have linked inventory turnover to differences between actual and predicted sales (Gaur et al., 2005), while research on retail forecasting highlights the difficulty and importance of obtaining accurate product-level forecasts for replenishment (Fildes et al., 2022). Traditional forecasting techniques, which often rely on relatively straightforward statistical models, may fall short when demand is intermittent, affected by many external factors, or strongly influenced by promotions.

Artificial intelligence (AI) has therefore attracted substantial attention in supply chain management. AI, particularly machine learning, is viewed as a potential solution to complex planning challenges such as forecasting, inventory management, and logistics decision-making (Baryannis et al., 2019; Min, 2010; Riahi et al., 2021; Toorajipour et al., 2021). AI-based demand forecasting uses machine-learning and related modeling techniques to identify patterns in large and diverse datasets, including sales, prices, promotions, and supply chain information, and to update those patterns as new data become available. Empirical applications have shown benefits in some settings. Feizabadi (2022) reported statistically significant supply chain performance improvements from machine-learning-based forecasting in a steel-manufacturing case study, while Zhu et al. (2021) found improved forecast quality when comparing machine-learning and traditional models in a pharmaceutical supply chain. However, the superiority of AI is not guaranteed. Machine-learning methods did not clearly outperform statistical counterparts in the M4 competition, whereas they performed more strongly in the retail-sales-focused M5 competition (Makridakis et al., 2020, 2022).

Better forecasts add value only when they lead to better decisions. AI-enabled inventory optimization applies data-driven and learning-based techniques to determine order quantities, safety stocks, and other replenishment decisions. Recent studies suggest that inventory decisions can be learned directly from data and demand-related features rather than solely from a demand distribution estimated in a separate step (Ban & Rudin, 2019; Bertsimas & Kallus, 2020; Oroojlooyjadid et al., 2020). Research on deep reinforcement learning for inventory control also shows promising, although not yet conclusive, results (Boute et al., 2022; Gijbsbrechts et al., 2022).

Better forecasting and inventory decision-making can potentially affect two organizational outcomes. Supply chain efficiency refers to a supply chain's ability to use resources effectively, including inventory, capacity, and time, while providing the required service level to customers. Operational cost reduction refers to decreases in inventory-related ordering, holding, handling, and expediting costs. AI-powered decision-making may also improve responsiveness and resilience by enabling organizations to respond more quickly to shifts in demand. Empirical evidence has linked AI and analytics capabilities to resilience and operational performance (Belhadi et al., 2024; Chae et al., 2014; Dubey et al., 2020, 2021).

1.2 Research Problem and Gap

Although interest in AI-based forecasting is high, three gaps remain.

First, much of the forecasting literature evaluates accuracy. Competitions and algorithm comparisons rank methods by error measures (Makridakis et al., 2020, 2022), but forecast accuracy is not in itself an organizational outcome. Fewer studies examine whether organizations that rely on AI-driven forecasting also report better inventory decisions, higher supply chain efficiency, and lower costs.

Second, the mechanism is not well established. Forecasting research and inventory-control research have developed largely as separate streams. If AI-driven forecasting is related to costs, one plausible route is



through better inventory decisions, such as more appropriate stock levels and replenishment timing (Silver et al., 2017). To our knowledge, this route has received limited empirical testing in survey-based models that place inventory optimization between AI-driven demand forecasting and operational cost reduction.

Third, much of the available evidence comes from algorithm benchmarking or single-industry applications (for example, Feizabadi, 2022; Zhu et al., 2021). These designs give useful depth and technical detail but limit statistical generalization across organizations. Survey evidence from professionals in manufacturing and retail can complement them by testing the proposed relationships in one model.

The practical problem follows from these gaps. Many organizations are investing in AI-based forecasting tools, but managers have limited empirical evidence on whether these investments are associated with better inventory outcomes, and on whether inventory optimization is the channel through which cost benefits appear. This study addresses that problem.

1.3 Rationale

Examining AI-driven demand forecasting together with inventory optimization provides a more comprehensive view of how forecasting capability may translate into operational outcomes. Supply chain efficiency and operational cost reduction indicate whether these potential benefits are realized through improved resource utilization, lower costs, or both. The mediation test examines whether inventory optimization represents an intermediate mechanism linking AI-driven forecasting to reduced operational costs. The findings may help managers make better-informed investments in forecasting technology and identify the inventory-planning changes needed to realize its value. The study also contributes to research on information processing, resources, and dynamic capabilities in supply chains (Teece, 2007; Tushman & Nadler, 1978).

1.4 Research Questions

1. To what extent is AI-driven demand forecasting associated with inventory optimization?
2. How is AI-driven demand forecasting related to supply chain efficiency?
3. How is inventory optimization related to supply chain efficiency?
4. To what extent is inventory optimization associated with operational cost reduction?
5. Does inventory optimization mediate the relationship between AI-driven demand forecasting and operational cost reduction?

1.5 Objectives

- To measure the level of AI-driven demand forecasting and inventory optimization among the participating organizations.
- To examine the relationship between AI-driven demand forecasting and inventory optimization.
- To analyze the relationship between AI-driven demand forecasting and supply chain efficiency.
- To examine the relationship between inventory optimization and operational cost reduction.
- To determine whether inventory optimization mediates the relationship between AI-driven demand forecasting and operational cost reduction.

1.6 Hypotheses

- **H1:** AI-driven demand forecasting has a significant positive effect on inventory optimization.
- **H2:** AI-driven demand forecasting has a significant positive effect on supply chain efficiency.
- **H3:** Inventory optimization has a significant positive effect on supply chain efficiency.
- **H4:** Inventory optimization has a significant positive effect on operational cost reduction.
- **H5:** Inventory optimization significantly mediates the relationship between AI-driven demand forecasting and operational cost reduction.

2. Conceptual Framework

The framework draws on three complementary theories, used here only to explain the relationships in the proposed model. Organizational information processing theory holds that organizations facing uncertainty need information-processing capacity that matches their information-processing needs (Galbraith, 1974; Tushman & Nadler, 1978). Demand uncertainty creates such needs, and AI-driven demand forecasting adds processing capacity by turning large volumes of data into timely demand signals. This logic supports H1,



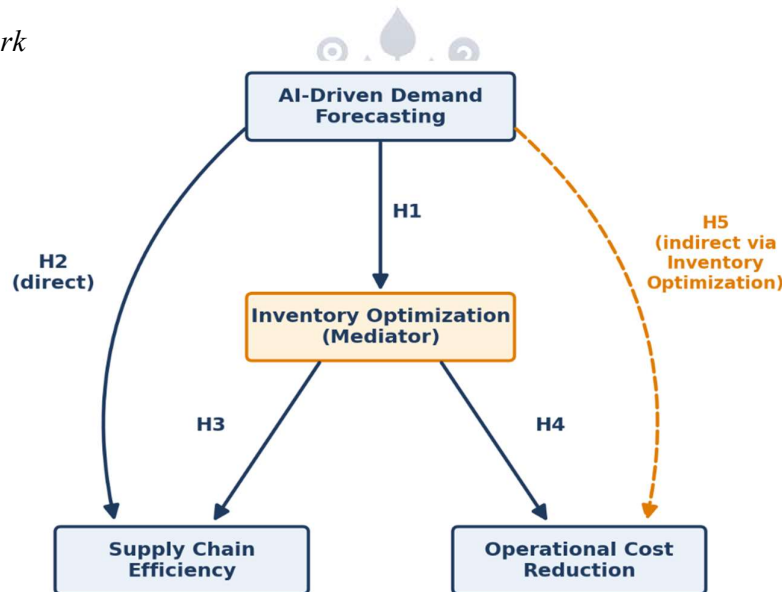
because better demand information can inform inventory decisions, and H2, because better information can reduce the mismatches that waste resources. Similar arguments have been used in supply chain analytics research (Srinivasan & Swink, 2018; Wong et al., 2020).

The resource-based view explains why AI-driven forecasting may matter for performance. Valuable and hard-to-imitate resources can support performance advantages (Barney, 1991), and analytics-based planning capability has been treated as such a resource in supply chains (Chae et al., 2014). On this view, AI-driven demand forecasting is a capability-based resource associated with efficiency (H2). Dynamic capabilities theory adds that firms must sense changes, seize opportunities, and reconfigure resources (Teece, 2007; Teece et al., 1997). AI-driven forecasting corresponds to sensing changes in demand, and inventory optimization corresponds to reconfiguring stock levels, safety stocks, and replenishment in response. Inventory optimization is therefore positioned as the mediator that converts forecasting capability into better resource use and lower costs (H3 to H5).

Figure 1 presents the model. AI-driven demand forecasting is expected to be positively related to inventory optimization (H1) and to supply chain efficiency (H2). Inventory optimization is expected to be positively related to supply chain efficiency (H3) and operational cost reduction (H4), and to mediate the relationship between AI-driven demand forecasting and operational cost reduction (H5).

Figure 1

Conceptual Framework



Solid arrows show the direct paths tested in H1 to H4. The dashed arrow shows the indirect effect through inventory optimization tested in H5. The direct path from AI-driven demand forecasting to operational cost reduction is estimated in the mediation analysis (Figure 5).

3. Materials and Methods

3.1 Research Design and Participants

This study used a quantitative, cross-sectional explanatory design to examine the relationships among AI-driven demand forecasting, inventory optimization, supply chain efficiency, and operational cost reduction. Primary data were collected using a structured questionnaire from 300 respondents working in manufacturing and retail organizations, with the individual supply chain professional as the unit of analysis. The sample comprised 75 supply chain professionals (25.0%), 78 logistics managers (26.0%), 72 inventory managers (24.0%), and 75 procurement specialists (25.0%), all of whom had responsibilities directly related to demand planning, inventory management, procurement, logistics, replenishment, or supply chain operations. By sector, 156 respondents (52.0%) worked in manufacturing organizations and 144 (48.0%) in



retail organizations. Responses were screened for completeness before analysis, and incomplete responses were excluded from the final dataset.

3.2 Measures

The questionnaire measured four constructs. AI-driven demand forecasting was assessed through respondents' perceptions of the use of artificial intelligence and data-driven forecasting technologies, the integration of relevant demand information, the ability to identify changing demand patterns, and the improvement of forecasting decisions. Inventory optimization covered inventory-level management, replenishment decisions, safety-stock management, product availability, and control of inventory-related costs. Supply chain efficiency covered resource utilization, inventory management, order fulfillment, operational responsiveness, and the overall effectiveness of supply chain activities. Operational cost reduction covered reductions in inventory holding, ordering, handling, and other supply chain operating costs. The questionnaire also included operational indicators of perceived change (forecasting accuracy, inventory holding costs, stockout incidents, overall supply chain efficiency, and operational costs) and an item asking whether respondents agreed that AI-based forecasting enhanced inventory planning and decision-making. These percentages are respondents' perceptions, not independently audited organizational measurements.

3.3 Data Analysis

Data were analyzed using descriptive statistics and PLS-SEM (Hair et al., 2019, 2022) to estimate the relationships among the constructs and the proposed mediation. The measurement model was evaluated for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Indicator loadings, Cronbach's alpha, and composite reliability values of approximately 0.70 or higher, and average variance extracted (AVE) values of 0.50 or higher, were treated as acceptable. Discriminant validity was assessed using the Fornell-Larcker criterion (Fornell & Larcker, 1981) and the heterotrait-monotrait (HTMT) ratio (Henseler et al., 2015). The structural model was evaluated using standardized path coefficients (β), bootstrapped significance tests, and coefficients of determination (R^2), with $p < 0.05$ as the significance criterion. Mediation was examined by estimating the indirect effect of AI-driven demand forecasting on operational cost reduction through inventory optimization.

4. Results

4.1 Sample Characteristics

The final analytical sample comprised 300 respondents from manufacturing and retail organizations (Table 1).

Table 1

Characteristics of Study Participants (N = 300)

Characteristic	Category	Frequency (n)	n (%)
Respondent role	Supply chain professionals	75	25.0
	Logistics managers	78	26.0
	Inventory managers	72	24.0
	Procurement specialists	75	25.0
Organization sector	Manufacturing organizations	156	52.0
	Retail organizations	144	48.0

Percentages are based on the total sample of 300 respondents.

4.2 Descriptive Findings

Table 2 and Figure 2 show that respondents reported favorable changes across all five outcomes. Forecasting accuracy improved by 29.4%, inventory holding costs decreased by 22.7%, and stockout incidents decreased by 31.5%. Overall supply chain efficiency increased by 27.9%, and operational costs decreased by 19.8%. In addition, 84.2% of respondents agreed that AI-based forecasting enhanced inventory planning and decision-making.



Table 2

Descriptive Findings on AI-Driven Demand Forecasting and Supply Chain Outcomes

Outcome	Indicator	Reported value (%)
Forecasting accuracy	Improvement in forecasting accuracy	29.4
Inventory holding costs	Decrease in inventory holding costs	22.7
Stockout incidents	Decrease in stockout incidents	31.5
Supply chain efficiency	Increase in overall supply chain efficiency	27.9
Operational costs	Decrease in operational costs	19.8
Inventory planning and decision-making	Respondents agreeing that AI-based forecasting enhanced inventory planning and decision-making	84.2

Values reflect respondents' perceptions, not audited organizational data. The last row is the share of respondents in agreement.

4.3 Measurement Model

The measurement model was reported to meet the criteria for indicator reliability, internal consistency, convergent validity, and discriminant validity across all four constructs (Tables 3 and 4).

Table 3

Measurement Model Results

Construct	Items retained	Outer loadings (range)	Criterion
AI-driven demand forecasting	4	0.76–0.89	≥ 0.70
Inventory optimization	5	0.74–0.88	≥ 0.70
Supply chain efficiency	5	0.73–0.87	≥ 0.70
Operational cost reduction	4	0.75–0.90	≥ 0.70

The criterion column shows the conventional threshold for indicator reliability (Hair et al., 2019).

Table 4

Reliability and Validity Results

Construct	Cronbach's α	CR	AVE	Discriminant validity
AI-driven demand forecasting	0.88	0.92	0.74	HTMT
Inventory optimization	0.89	0.92	0.70	HTMT < 0.90
Supply chain efficiency	0.87	0.91	0.67	HTMT < 0.90
Operational cost reduction	0.86	0.91	0.71	HTMT < 0.90
Criterion	≥ 0.70	≥ 0.70	≥ 0.50	HTMT < 0.90

CR = composite reliability; AVE = average variance extracted; HTMT = heterotrait-monotrait ratio. HTMT thresholds of 0.85 (conservative) or 0.90 are commonly used.

4.4 Structural Model

Table 5 and Figures 3 and 4 present the structural results. AI-driven demand forecasting was positively and significantly associated with inventory optimization ($\beta = 0.71$, $p < 0.001$) and with supply chain efficiency ($\beta = 0.63$, $p < 0.001$), supporting H1 and H2. Inventory optimization was positively and significantly associated with supply chain efficiency ($\beta = 0.58$, $p < 0.001$) and with operational cost reduction ($\beta = 0.34$, $p < 0.001$), supporting H3 and H4.

Table 5

Structural Model Results

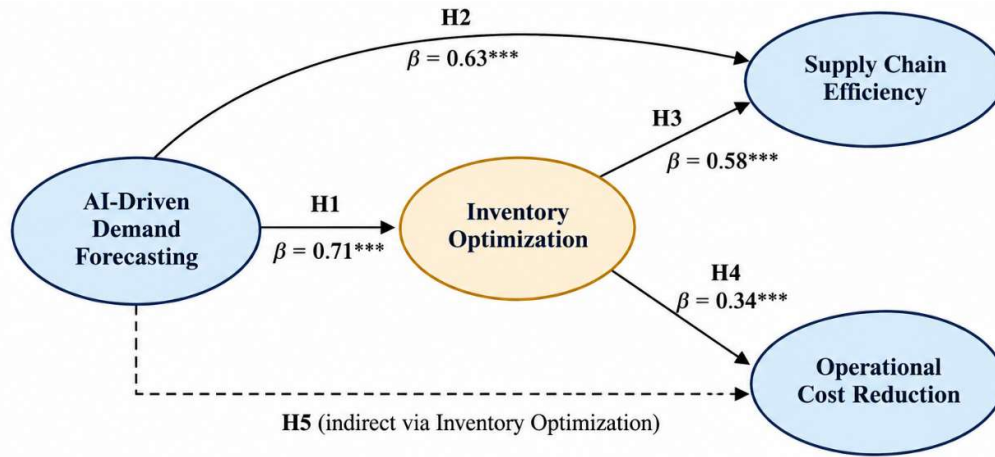
Path	Hypothesis	β	p	Decision
AI-driven demand forecasting $\rightarrow$ Inventory optimization	H1	0.71	< 0.001	Supported
AI-driven demand forecasting $\rightarrow$ Supply chain efficiency	H2	0.63	< 0.001	Supported
Inventory optimization $\rightarrow$ Supply chain efficiency	H3	0.58	< 0.001	Supported
Inventory optimization $\rightarrow$ Operational cost reduction	H4	0.34	< 0.001	Supported
R ² (inventory optimization; supply chain efficiency; operational cost reduction)	—	0.50; 0.62; 0.41	—	—



Path coefficients are standardized. Significance was tested by bootstrapping. R^2 values are reported for inventory optimization, supply chain efficiency, and operational cost reduction, respectively.

Figure 2

PLS-SEM Structural Model



Solid arrows show standardized path coefficients for H1 to H4 ($*** p < 0.001$).

4.5 Mediation Analysis

Path a (AI-driven demand forecasting → inventory optimization) was 0.71 ($p < 0.001$) and path b (inventory optimization → operational cost reduction) was 0.34 ($p < 0.001$), giving an indirect effect ($a \times b$) of 0.24. Inventory optimization partially mediated the relationship between AI-driven demand forecasting and operational cost reduction, supporting H5 (Table 6 and Figure 5).

Table 6

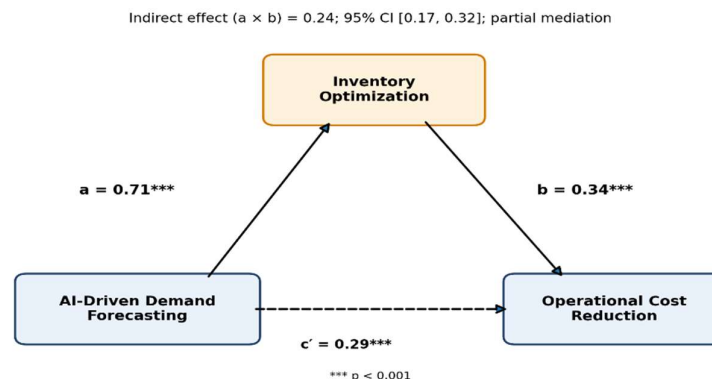
Mediation Results

Hypothesis	Pathway	Component paths	Direct, indirect, and total effects [95% CI]	Conclusion
H5	AI-driven demand forecasting → Inventory optimization → Operational cost reduction	$a = 0.71$ ($p < 0.001$); $b = 0.34$ ($p < 0.001$)	Direct (c'): 0.29 ($p < 0.001$); Indirect ($a \times b$): 0.24, 95% CI [0.17, 0.32]; Total: 0.53	Partial mediation

Path a indicates the association of AI-driven demand forecasting with inventory optimization; path b indicates the association of inventory optimization with operational cost reduction. The indirect effect is the product of paths a and b ($0.71 \times 0.34 = 0.24$).

Figure 5

Mediation Model With Inventory Optimization as the Mediator





$a = 0.71$, $b = 0.34$, indirect effect $a \times b = 0.24$, 95% CI [0.17, 0.32]; *** $p < 0.001$. The dashed gray path represents the direct effect ($c' = 0.29$, $p < 0.001$).

5. Discussion

5.1 Summary of Main Findings

The results provide a coherent pattern linking AI-driven demand forecasting, inventory optimization, supply chain efficiency, and operational cost reduction. AI-driven demand forecasting was positively and significantly associated with inventory optimization ($\beta = 0.71$, $p < 0.001$) and supply chain efficiency ($\beta = 0.63$, $p < 0.001$). Inventory optimization was also positively and significantly associated with supply chain efficiency ($\beta = 0.58$, $p < 0.001$) and operational cost reduction ($\beta = 0.34$, $p < 0.001$). The model explained 50% of the variance in inventory optimization, 62% of the variance in supply chain efficiency, and 41% of the variance in operational cost reduction. In addition, inventory optimization partially mediated the relationship between AI-driven demand forecasting and operational cost reduction: the indirect effect was 0.24 with a 95% confidence interval of [0.17, 0.32], while the remaining direct effect was 0.29 ($p < 0.001$). These results support all five hypotheses and indicate that forecasting capability and inventory decision quality operate as related, but distinct, components of supply chain performance.

The descriptive findings reinforce the structural results. Respondents reported a 29.4% improvement in forecasting accuracy, a 22.7% decrease in inventory holding costs, a 31.5% decrease in stockout incidents, a 27.9% increase in overall supply chain efficiency, and a 19.8% decrease in operational costs; 84.2% also agreed that AI-based forecasting enhanced inventory planning and decision-making. Taken together, the findings suggest that the organizational value of AI forecasting is not limited to prediction accuracy. Its value appears to be strongest when demand information is translated into concrete inventory decisions and broader operational coordination. At the same time, these percentages are perceptual reports rather than audited organizational measures, and the cross-sectional design supports interpretation in terms of association rather than cause and effect.

5.2 AI-Driven Demand Forecasting and Inventory Optimization

The association between AI-driven demand forecasting and inventory optimization was the numerically largest path in the model ($\beta = 0.71$, $p < 0.001$). This finding is consistent with organizational information processing theory, which argues that organizations facing uncertainty require information-processing capacity that matches the complexity of their decision environment (Galbraith, 1974; Tushman & Nadler, 1978). Demand forecasting based on richer and more timely information can reduce uncertainty around expected sales patterns, promotions, and changes in market conditions. In inventory terms, improved demand information can support more appropriate safety-stock levels, reorder points, and replenishment timing. This interpretation is also consistent with inventory theory, in which forecast error and lead-time variability are central inputs to stock decisions (Silver et al., 2017).

The result also aligns with prior evidence showing that machine-learning forecasting can improve forecasting and supply chain performance in particular organizational settings (Feizabadi, 2022; Zhu et al., 2021), as well as research that directly links predictive information to inventory decisions (Ban & Rudin, 2019; Bertsimas & Kallus, 2020). The 84.2% agreement that AI-based forecasting enhanced inventory planning provides additional descriptive support for this link. However, the finding should not be interpreted to mean that any AI method will automatically produce superior inventory outcomes. Forecasting competitions have shown that machine-learning methods do not consistently outperform well-designed statistical or hybrid approaches across all data environments (Makridakis et al., 2020, 2022). The practical implication is therefore not simply to adopt AI, but to ensure that forecasting systems generate reliable signals that can be incorporated into inventory policies and reviewed against existing planning methods.

5.3 AI-Driven Demand Forecasting and Supply Chain Efficiency

AI-driven demand forecasting was positively associated with supply chain efficiency ($\beta = 0.63$, $p < 0.001$), supporting H2. From the resource-based view, this relationship suggests that forecasting capability can function as an organizational resource when it helps firms allocate inventory, capacity, time, and managerial attention more effectively (Barney, 1991; Chae et al., 2014). The result is consistent with research



linking analytics and AI capabilities to operational performance and resilience (Belhadi et al., 2024; Dubey et al., 2020, 2021). It is also compatible with the logic of the bullwhip effect: when demand information is distorted or delayed, variability can be amplified upstream, whereas more accurate and timely signals can improve coordination and reduce avoidable inefficiency (Lee et al., 1997).

The reported 27.9% increase in overall supply chain efficiency and 31.5% decrease in stockout incidents are consistent with this interpretation, although these values remain respondents' perceptions. Importantly, the direct association between forecasting and efficiency indicates that the benefits of demand information may extend beyond inventory alone. Forecasts can potentially inform production planning, procurement timing, warehousing, and transport capacity, although these pathways were not measured separately in the present study. The 62% explained variance reported for supply chain efficiency also indicates that the combination of forecasting and inventory optimization is strongly related to how respondents evaluate operational efficiency, while leaving room for other organizational, market, and process factors that were outside the model.

5.4 Inventory Optimization and Supply Chain Efficiency

Inventory optimization was positively and significantly associated with supply chain efficiency ($\beta = 0.58$, $p < 0.001$), supporting H3. This result is important because it identifies inventory decisions as an operational mechanism through which demand information can be converted into improved resource use. Dynamic capabilities theory provides a useful explanation: forecasting supports the sensing of demand changes, whereas inventory optimization represents the reconfiguration of stock levels, safety stock, and replenishment policies in response to those signals (Teece, 2007; Teece et al., 1997). The finding therefore shifts attention from information generation to information use. An accurate forecast has limited operational value if purchasing, replenishment, or stock-allocation decisions are not adjusted accordingly.

The result also supports the view that inventory performance should not be equated with simply holding less stock. Inventory that is too low can increase stockout risk, while inventory that is too high ties up working capital and raises handling and obsolescence costs. Prior evidence likewise suggests that the inventory-performance relationship depends on how well inventory is matched to operating requirements (Eroglu & Hofer, 2011). In this study, the simultaneous findings of fewer reported stockouts and lower reported holding costs are consistent with the idea of better alignment rather than indiscriminate inventory reduction.

5.5 Inventory Optimization and Operational Cost Reduction

Inventory optimization was positively and significantly associated with operational cost reduction ($\beta = 0.34$, $p < 0.001$), supporting H4. This relationship is theoretically plausible because stock levels and replenishment decisions affect holding, ordering, handling, expediting, and shortage-related costs (Silver et al., 2017). The reported 22.7% decrease in inventory holding costs and 19.8% decrease in overall operational costs are directionally consistent with the structural result. The coefficient for this path was numerically smaller than the other direct paths in the model, but no formal coefficient-comparison test was conducted; therefore, the difference should not be interpreted as statistically established. One possible explanation for the more modest coefficient is that operational costs are influenced by a broader set of factors than inventory decisions alone, including labor, transportation, production, supplier conditions, and facility utilization. These factors were not modeled here. The result nevertheless indicates that inventory optimization is meaningfully associated with cost outcomes while also highlighting that cost reduction is likely to require coordinated improvements across several operating functions.

5.6 The Mediating Role of Inventory Optimization

The mediation analysis provides the central mechanism tested in this study. AI-driven demand forecasting was associated with inventory optimization through path a (0.71, $p < 0.001$), and inventory optimization was associated with operational cost reduction through path b (0.34, $p < 0.001$). Their product yielded an indirect effect of 0.24, with a bootstrapped 95% confidence interval of [0.17, 0.32]. The direct effect of AI-driven demand forecasting on operational cost reduction remained significant at 0.29 ($p < 0.001$), indicating partial mediation. This pattern supports the argument that part of the forecasting-cost relationship



operates through improved inventory decisions, but it also suggests that inventory optimization is not the only pathway linking forecasting capability to lower perceived operating costs.

From a dynamic capabilities perspective, the mediation result links sensing and reconfiguration: AI-driven forecasting helps organizations detect demand changes, and inventory optimization helps convert those signals into adjusted stock and replenishment decisions (Teece, 2007; Teece et al., 1997). The remaining direct effect is also theoretically meaningful because forecasting information may support production scheduling, purchasing, transport planning, and other decisions that affect costs. These additional routes were not measured and therefore remain propositions for future testing. Most importantly, the mediation result should be interpreted as a statistical pattern consistent with the proposed mechanism, not as proof of a causal sequence. Establishing causal mediation would require stronger temporal designs and preferably objective operational data.

5.7 Theoretical Implications

The study contributes to the supply chain and AI literature in three related ways. First, it extends organizational information processing theory by showing that stronger AI-driven forecasting is associated not only with better perceived information outcomes, but also with the quality of inventory decisions. This supports the idea that information-processing capacity creates value when it is aligned with operational decision requirements (Galbraith, 1974; Tushman & Nadler, 1978; Srinivasan & Swink, 2018). Second, the results connect the resource-based view with an explicit operational mechanism. Rather than treating AI adoption as a resource that directly produces performance, the model shows that part of its relationship with cost outcomes runs through inventory optimization. This provides a more process-oriented explanation of how an analytics capability may become valuable (Barney, 1991; Chae et al., 2014).

Third, the findings strengthen the dynamic capabilities interpretation of AI-enabled planning. Forecasting represents a sensing capability, while inventory optimization represents the operational reconfiguration needed to respond to sensed changes. The significant paths to supply chain efficiency and operational cost reduction indicate that this conversion from information to action is central to the model. By testing forecasting, inventory optimization, efficiency, and cost reduction within one framework, the study also helps connect research streams that have often been examined separately. The contribution should nevertheless be framed as evidence of theoretically consistent associations across manufacturing and retail respondents. Replication with longitudinal, multi-source, and objective data is needed before stronger claims about capability development or causal performance effects can be made.

6. Practical Implications

The findings offer the following implications for practice, all of which should be read as associations rather than guaranteed results.

- **Supply chain managers:** Treat AI-driven forecasting as part of a decision system rather than a stand-alone tool. The strong association between forecasting and inventory optimization suggests that benefits are more likely when forecasts feed directly into inventory decisions. Track efficiency and cost outcomes together with forecast accuracy.
- **Inventory managers:** Link forecast outputs to safety-stock, reorder, and replenishment settings, and review those settings when forecast quality changes. Aim for inventory levels that match demand rather than simply minimizing stock, because extremely lean inventory can create its own risks (Eroglu & Hofer, 2011).
- **Procurement managers:** Share forecast information with purchasing planning so that order timing and quantities reflect expected demand. Better demand visibility can support fewer emergency purchases and lower holding costs.
- **Logistics managers:** Use improved demand visibility to plan warehousing and transport capacity, and monitor stockout incidents as an indicator of whether forecasting and replenishment are working together.
- **Manufacturing organizations:** Connect AI-driven forecasts to production and materials planning, since forecast errors can be passed upstream and cause variability (Lee et al., 1997; Feizabadi, 2022).



- **Retail organizations:** Apply AI-driven forecasting at the product and store level where demand is intermittent or promotion-driven, and pair it with replenishment rules that reduce both stockouts and excess stock (Fildes et al., 2022; Makridakis et al., 2022).

Across these groups, data-driven decision-making depends on data quality, staff capability, and clear links between forecasts and inventory policies. Managers should also evaluate AI tools against their existing methods rather than assume an advantage (Makridakis et al., 2020).

7. Strengths and Limitations

The study has several strengths. It draws on professionals who work directly with forecasting, inventory, procurement, and logistics in manufacturing and retail organizations. It examines forecasting and inventory optimization together in one model, with both supply chain efficiency and operational cost reduction as outcomes. It also uses PLS-SEM to estimate the measurement and structural models and to test mediation within the same analysis.

Several limitations should be considered. First, the cross-sectional design does not allow causal inference, and reverse or reciprocal relationships are possible. For example, organizations with stronger inventory practices may be more likely to adopt AI-driven forecasting. Second, the data are self-reported, which raises the possibility of common-method bias and perceptual error (Podsakoff et al., 2003). Third, the outcomes, including the percentage improvements, are perceptual and were not checked against objective inventory or cost records. Fourth, the sample may not represent all organizations, so the findings may not generalize beyond the participating manufacturing and retail organizations. Fifth, manufacturing and retail differ in demand patterns and inventory structures, and possible differences between the two sectors were not examined.

7.1 Future Research

Future research should first strengthen the temporal and measurement basis of the model. Longitudinal, multi-wave, or panel designs could establish whether changes in AI-driven forecasting precede changes in inventory practices and operational outcomes. Survey measures should also be linked, where possible, to objective organizational indicators such as forecast error, inventory turnover, service levels, stockout rates, holding costs, and total operating costs. Matching responses from several managers within the same organization would reduce reliance on a single source and help address common-method bias (Podsakoff et al., 2003). Quasi-experimental or before-and-after designs around the implementation of forecasting technologies could provide particularly useful evidence on whether observed performance changes are attributable to the technology and associated process changes rather than to pre-existing organizational differences.

Second, future studies should test the boundary conditions of the relationships identified here. Manufacturing and retail differ in demand variability, product life cycles, lead times, service requirements, and replenishment structures, yet sector differences were not examined in the present analysis. Larger samples would allow multi-group comparisons across sectors, firm sizes, and countries. Moderating variables such as demand volatility, lead-time uncertainty, product type, data quality, organizational size, digital maturity, and staff analytical capability could also be evaluated. Such analysis would help determine when AI-driven forecasting is most strongly associated with inventory optimization and when improvements in inventory decisions are most likely to translate into efficiency and cost benefits.

Third, future research should extend the mechanism itself. The remaining direct effect of AI-driven demand forecasting on operational cost reduction suggests that additional pathways may exist beyond inventory optimization. Production planning, procurement synchronization, supplier coordination, warehousing, transportation planning, and supply chain resilience are plausible mediating processes that can be tested in broader models. Researchers could also compare machine-learning, deep-learning, traditional statistical, and hybrid forecasting approaches under similar operating conditions (Makridakis et al., 2020, 2022; Zhu et al., 2021), and examine reinforcement-learning or data-driven inventory control approaches as downstream decision tools (Boute et al., 2022; Gijsbrechts et al., 2022; Oroojlooyjadid et al., 2020). Future SEM and PLS-SEM studies should report complete measurement and structural evidence, including direct,



indirect, and total effects with confidence intervals, so that the strength, robustness, and predictive relevance of the proposed mechanisms can be assessed more comprehensively.

8. Conclusion

This study examined an integrated pathway through which AI-driven demand forecasting is associated with supply chain performance. Across 300 manufacturing and retail respondents, AI-driven demand forecasting was positively and significantly associated with inventory optimization ($\beta = 0.71$, $p < 0.001$) and supply chain efficiency ($\beta = 0.63$, $p < 0.001$). Inventory optimization was, in turn, positively associated with supply chain efficiency ($\beta = 0.58$, $p < 0.001$) and operational cost reduction ($\beta = 0.34$, $p < 0.001$). The mediation analysis further showed a significant indirect effect of 0.24, 95% CI [0.17, 0.32], alongside a significant direct effect of 0.29, indicating partial mediation. These findings support the central proposition of the study: the organizational value of AI-based forecasting is closely connected to how effectively forecast information is converted into inventory decisions.

The study therefore contributes a decision-centered perspective to the discussion of AI in supply chain management. Forecasting accuracy is important, but it is not an operational outcome by itself. The reported improvements in forecasting accuracy, inventory holding costs, stockout incidents, supply chain efficiency, and operational costs suggest that forecasting capability and inventory optimization should be managed as connected elements of the same planning system. For managers, this means that investment in AI forecasting should be accompanied by clear links to safety-stock policies, replenishment rules, procurement planning, and wider operational coordination, while performance should be evaluated using both forecasting and business outcomes.

These conclusions remain subject to the study design. The data are cross-sectional and self-reported, the percentage improvements are perceptual rather than audited measures, and the sample does not establish generalizability to all industries or countries. Accordingly, the results demonstrate statistically significant associations rather than causal effects. Future longitudinal, multi-source, and objective-data studies can test the proposed pathway more rigorously and examine additional mechanisms and boundary conditions. Within these limits, the evidence consistently indicates that AI-driven demand forecasting is most meaningful when it becomes actionable information for inventory and supply chain decisions, and that this integration is associated with greater efficiency and lower perceived operational costs.

Author's Contributions

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

Conflict of Interest Statement

The authors declare that there is no conflict of interest regarding the publication of this article.

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Informed Consent

Informed consent was obtained from all participants prior to data collection. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without any consequences. The confidentiality and anonymity of respondents were guaranteed throughout the research process.

Data Availability

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. The authors are committed to transparency and will provide detailed methodological information and analysis protocols upon request.

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