ISSN 2409-2665
Journal of Logistics, Informatics and Service Science
Vol. 13 (2026) No. 9, pp. 253-264
DOI:10.33168/JLISS.2026.0914

AI-Driven Demand Forecasting and Its Financial Implications: Evidence from Inventory Cost Optimization in Logistics Firms

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Abstract. With changes in the world's supply chain and market at present, many logistics enterprises have been facing all kinds of problems that affect their operating efficiency and financial health. This paper studies the expected financial benefits of deploying AI-based demand forecasting and investigates whether a reduction in inventory costs is the reason for these benefits. In terms of the theoretical integration of the Resource-Based View (RBV) and Information Processing Theory (IPT), AI forecasting capabilities are now regarded as strategic information resources that can help managers reduce the systemic bullwhip effect and improve capital allocation efficiency, rather than being seen as independent technologies. This study employs a quantitative cross-sectional survey design to collect primary data from a stratified sample of 384 supply chain and IT professionals at logistics enterprises. Then, the above empirical data were analyzed by Partial Least Squares Structural Equation Modelling (PLS-SEM). The results show that a higher perceived capability in machine learning-based demand analysis is positively correlated with an increase in the rate of inventory turnover and a decrease in holding costs; as a result, these operational efficiencies are positively linked to a manager's evaluation of the company's financial health, such as return on assets and operating profit. In addition, the idea of technological absorption capacity was added to the model, and it was found that this moderates the impact of forecastability on inventory optimization. A higher absorption capacity of the firm can more fully realize the economic benefits of predictive algorithmic insights. Based on the results of this empirical study, this paper builds on previous research by introducing predictive technological analytics in managerial financial assessment of the supply chain and offers practical references for enterprises looking to strengthen the long-term stability of their organizations through digitalisation.

Keywords: AI-Driven Demand Forecasting; Corporate Financial Performance; Inventory Cost Optimization; Technological Absorptive Capacity; Supply Chain Finance; Logistics Industry

1. Introduction

Recently, due to economic fluctuations and changes in people's consumption habits, there have been problems in the supply chain, and it has become difficult for logistics enterprises to keep inventory at an ideal level (Baryannis et al., 2019; Hendricks & Singhal, 2005). In the past, most of the inventory management methods for the logistics industry were deterministic stochastic models and traditional time-series forecasts (Fildes et al., 2022). Generally speaking, these traditional frameworks assume that the historical conditions will remain relatively stable and are thus no longer suitable for the high-volatility commercial environment today. Due to the inherent delay and mathematical constraints of the above-mentioned traditional heuristic methods, the two types of operational inefficiencies that enterprises face are a stock-out, which can damage customer loyalty and reduce market share; or an excess of safety stocks that restricts working-capital liquidity and increases warehousing costs (Eroglu & Hofer, 2011).

With the progress of artificial intelligence (AI) and machine learning algorithms, the form of models for supply chain demand planning has been evolving substantially (Seyedan & Mafakheri, 2020). A new predictive model can be developed to process various types of non-standard, multi-dimensional data, such as changes in the economy and regional market sentiments, to issue high-accuracy, probabilistic demand predictions. Technological changes have introduced general automation in production and, at the same time, adjusted the organization of supply chain data processing to reduce the bullwhip effect and improve the coordination between strategic procurement and changes in the market (Choi et al., 2018).

Although many scholars have investigated the scope of application for artificial intelligence in building a logistics supply chain, few have empirically tested the effect of new-technology application on financial and economic performance. Most of the existing research has focused on the standalone technical performance of specific machine learning models and has used only mathematical indicators to evaluate their predictive power (Makridakis et al., 2018). Although this way has focused on technology, it has not met the demands for empirical support at the senior management level linking investments in technological capital to other indices of corporate health, such as Return on Assets (ROA) and free cash flow (Wamba et al., 2017).

Lower inventory costs can help link the results of AI foresight to the entire financial situation of the company (Cannon, 2008; Capkun et al., 2009). Good Inventory Management refers to a low-holding-cost and obsolescence-write-off level for inventories that can enhance working-capital utilisation. Therefore, the mediation effect of inventory dynamics in the process of generating financial benefits by applying predictive analytics still needs to be investigated.

To fill this theoretical and empirical gap, the research framework of this paper will be based on the Resource-Based View (RBV) of the firm (Barney, 1991) and Information Processing Theory (IPT) (Galbraith, 1974). We believe that the advanced AI-based demand-forecasting function is a high-level, non-replicable dynamic capability that a company can possess for collecting necessary market information (Srinivasan & Swink, 2018). This study combines research on supply chain management with corporate finance theory to address two main research problems. First, how do managers' perceptions of AI application in demand forecasting relate to the financial health of the logistics company, and are there direct or indirect impacts via inventory cost optimization? Second, what are the specific organizational boundary conditions that may affect how the company is transforming?

Logistics and third-party logistics (3PL) enterprises in the retail, advanced manufacturing and energy industry were selected as the specific subjects of this study by design. Due to their high demand volatility and their role in supporting the world's supply chains, these are good subjects for studying the practical applications of artificial intelligence. Partial least squares structural equation modelling (PLS-SEM) is used to analyze cross-sectional data from industry professionals in this paper on the organizational and financial impacts of data-driven supply chain management.

The anticipated contributions of this study to both academic research and management application are manifold. Theoretically, this paper extends the traditional scope of supply chain finance by empirically verifying a nomological network that includes perceived AI technical capabilities, efficient inventory management and managerial assessments of financial results (Ou et al., 2025). In light of the above, we will determine whether inventory cost optimization mediates the link between data-driven foresight and perceived shareholder value. Based on the above, the study provides empirical support for managers and executives to increase their investment in AI infrastructure to enhance the continuous learning ability of their organizations (absorptive capacity) and thus achieve the expected improvements in operations and finances. Finally, this paper hopes to expand the academic focus on artificial intelligence in logistics from mathematical algorithm optimization to the larger issues of sustaining organizational competitiveness (Le, 2025).

2. Literature Review and Hypothesis Development

2.1. Theoretical Foundation: Resource-Based View and Information Processing Theory

The theoretical framework of this paper is based on a combination of Information Processing Theory (IPT) and the Resource-Based View (RBV) of the firm. Based on the IPT, the basic function of an organization is to process information and thus is subject to the uncertainty problem (Galbraith, 1974). Uncertainty refers to a shortage of necessary information for making logistics decisions in advance, as well as the scarcity of that information for decision-makers in the context of supply chain operations (Wong et al., 2011). Given the lack of data, a high-end machine learning model can significantly increase the processing capacity for a large amount of unstructured external data by generating probabilistic demand signals (Chen et al., 2015).

From an RBV perspective, this AI-driven predictive infrastructure should not be viewed simply as a typical IT acquisition but rather as an elaborate, socially integrated, and causally ambiguous dynamic capability (Barney, 1991). Although the basic algorithm has been released as open-source, the collection of historical corporate data and special parameters, as well as specific organizational structures, remain proprietary and cannot be easily reproduced (Dubey et al., 2021).

2.2. AI-driven Demand Forecasting and Perceptions of Financial Performance

Traditionally, research on demand forecasting in the supply chain has mainly used classical time-series methods. These methods generally assume that the data is stationary, and are thus less suitable for addressing the non-linear and fragmented demand characteristics of modern multi-echelon supply chains (Fildes et al., 2022). Deep-learning-based models have now replaced the traditional linear-extrapolation approach for forecast generation with probability-based thinking (Makridakis et al., 2018).

These advanced models reduce prediction errors through sophisticated computational algorithms. The objective function seeks to minimise the empirical risk and avoids overfitting, and is typically written as:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} L\big(y_i, f(x_i;\theta)\big) + \lambda\Omega(\theta)$$

where $L(\theta)$ represents the composite loss function, y_i denotes the observed demand, $f(x_i;\theta)$ is the predicted demand parameterized by network weights θ, and $\lambda\Omega(\theta)$ operates as the regularization term ensuring model generalizability. By optimizing this loss function, AI forecasting compresses the variance within demand distributions. This algorithmic precision provides supply chain managers with data-driven insights that help mitigate the informational latency responsible for the bullwhip effect.

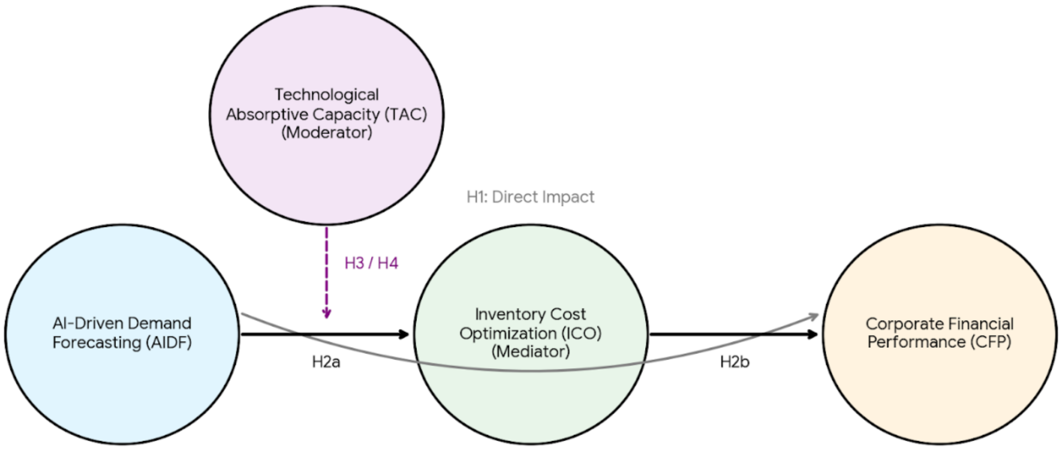

Fig 1: Conceptual Research Framework (Moderated Mediation Model)

As a result, the above predictive functions can help companies switch from a reactive mode to a proactive system for supply chain management (Seyedan & Mafakheri, 2020). By proactively addressing market changes, firms can reduce costs associated with emergency freight expediting and avoid service-level failures for high-demand sectors, such as retailers and large-scale energy companies (Wamba et al., 2017). According to RBV, reducing these operating frictions will enable the capital management department to optimize liquidity reserves; thus, managers will consider this an increase in the firm's overall financial health, such as improved return on assets (ROA) and core operating margins.

Hypothesis 1 (H1): Perceived AI-driven demand forecasting ability positively affects management evaluation of corporate financial performance.

2.3. Mediating Mechanism of Inventory Cost Optimization

Algorithms can generate predictions about the data, but only when they lead to actual changes in operation and cost reduction will they be economically feasible (Cannon, 2008); inventory reduction is a typical example. The logistics industry is highly capital-intensive and therefore requires substantial inventory investments within its working capital. (Gaur et al., 2005).

Traditional stochastic inventory management, such as the continuous-review (s, Q) policy, calculates safety stock levels based on the standard deviation of lead-time demand. The financial implication of AI-driven forecasting emerges from its mathematical capacity to narrow the probability density function of future demand, thereby reducing the standard deviation required for operational buffering. This transformation can be conceptualized within the expected total cost function for inventory:

$$TC(Q, \sigma_{AI}) = \frac{D}{Q}K + \left(\frac{Q}{2} + z_\alpha \sigma_{AI}\sqrt{L}\right)h + p\int_s^\infty (x-s)\phi(x)\,dx$$

In this formulation, TC is dynamically constrained by the algorithmically reduced forecast error standard deviation σ_{AI}. As predictive fidelity improves, the capital required for safety stock holding costs—represented by $(z_\alpha \sigma_{AI}\sqrt{L})h$—decreases without necessarily inflating the probability of stockout penalties (Chaudhary, 2025).

This optimization will not reduce costs elsewhere. A smaller safety stock of inventory will release some funds for other uses. If the management uses the released cash flow to fund investments in the company, debt repayment or technological innovation, then good institutional financial indicators will be achieved. Therefore, the theoretical framework proposes that algorithmic high-tech needs to be closely linked with a reduction in physical inventory assets to achieve tangible financial benefits. Operationalisation of inventory cost reduction serves as a necessary link for transmitting the results of technical forecasting ability to the organization's financial situation.

Hypothesis 2 (H2): Optimized inventory costs partially mediate the positive effect of AI-driven demand forecasting on perceived corporate financial performance.

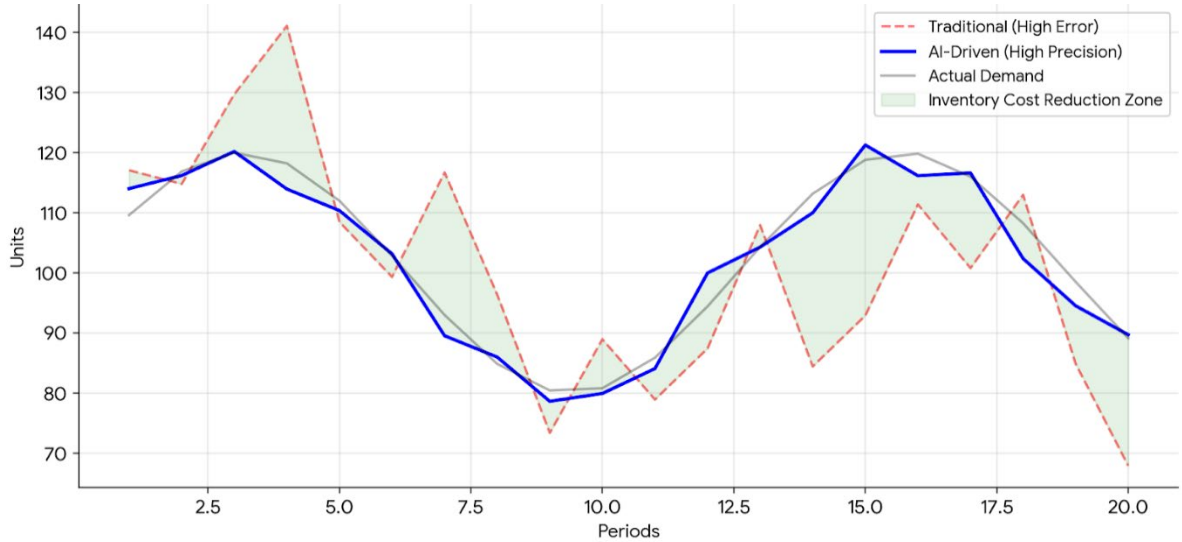

Fig.2: Effect of AI Precision on Inventory Buffering

2.4. Moderating Effects of Technological Absorptive Capacity

Although algorithmic foresight is theoretically linked to economic efficiency, the results of actual applications of similar AI systems in finance have not been uniform. Given this deviation, this study adds technological absorption capacity as a new bound condition. Based on research in organizational learning, absorptive capacity refers to a company's capability to recognise, assimilate and apply external knowledge or complicated technological cues for its own business purposes (Cohen & Levinthal, 1990; Zahra & George, 2002).

The mere acquisition of predictive software does not automatically lead to structural reductions in inventory levels. Logistics enterprises with high technological absorption capacity have good cross-functional integration, and data science results can be applied effectively to decision-making in procurement and replenishment at the execution level (Roberts et al., 2012; Tu et al., 2006). On the other hand, organizations with low absorptive capacity often show systemic inertia; that is, there are many isolated data silos and people still rely on intuition rather than algorithms.

In a structurally rigid environment, even a high-precision forecast may not lead to an actual adjustment in physical inventory and thus fails to realize the expected financial benefit of the IT investment (Liu et al., 2013). Therefore, this paper believes that the efficiency of AI-driven forecasting in reducing inventory costs is strongly affected by the organizational environment. A Data-Driven Culture and Flexible IT-Business Integration at the company will be able to use predictions to drive cost reductions in operations and enhance overall financial health.

Hypothesis 3 (H3): The technological absorption capacity positively moderates the relationship between AI-driven demand forecasting and inventory cost optimization; that is to say, a higher absorption capacity will lead to a stronger effect on this link.

Hypothesis 4 (H4): Technological absorptive capacity positively moderates the indirect effect of AI-driven demand forecasting on perceived corporate financial performance via inventory cost optimization, forming a moderated mediation model.

3. Methods

3.1. Research Design, Data Collection and Sample Profile

Based on the above conceptual system, a quantitative cross-sectional survey was conducted for empirical analysis in this study. The subjects of this study are professionals in the field of logistics and third-party logistics (3PL). To enhance the external validity of the research and better reflect real-life survey behaviour, a wide range of personnel in the mid-to-senior management team, as well as supply chain planners and IT coordinators, were also included in the sampling scope. These people have the operating data to observe changes in inventory at the micro level and the strategic perspective to gauge the state of the company.

A series of questionnaires were distributed in the last four months via the internet. Stratified random sampling was used to divide the main client areas into three categories (e.g., retail e-commerce, advanced manufacturing, and energy enterprises), and representatives from all parts of the volatile supply chain were selected. The initial distribution was 1,200 industry professionals, and after screening for missing data and unengaged responses, 384 valid and complete responses were finally obtained (an effective response rate of 32.0%). The sample size comfortably exceeds the minimum threshold for PLS-SEM (generally 10 times the largest number of structural paths directed at a particular construct) and will have adequate statistical power.

Table 1 shows the basic information of the respondents. The distribution is as follows: operational managers, analysis staff and senior directors, which make up the whole for survey-based research in a company.

Table 1: Demographic Characteristics of the Empirical Sample (N=384)

Demographic Variable	Categorical Classification	Frequency (n)	Percentage (%)
Organizational Tenure	5 - 10 Years	128	33.33%
	11 - 15 Years	154	40.10%
	> 15 Years	102	26.57%
Corporate Role/Title	Supply Chain / Inventory Managers	156	40.63%
	IT Analysts / Data Coordinators	132	34.37%
	Directors / Senior Executives	96	25.00%
Firm Employee Size	500 - 1,000 Employees	94	24.48%
	1,001 - 5,000 Employees	185	48.18%
	> 5,000 Employees	105	27.34%

3.2. Construct Measurement and Common Method Bias Assessment

All latent constructs were measured by multi-item scales that adapted validated previous studies, and these scales used a seven-point Likert scale (1 = "Strongly Disagree" to 7 = "Strongly Agree").

It is difficult to obtain objective archived financial data that perfectly corresponds to the anonymous survey respondents for the measurement of Corporate Financial Performance (CFP) due to confidentiality agreements and the private nature of the companies. Therefore, this study operationalizes CFP as managers' perception of financial performance relative to industry peers. The items of concern were a change in return on assets, operating profit margin, and cash flow stability over the past 36 months. Although perceptual indicators are subjective, extensive strategic management research has demonstrated a positive correlation with objective archival financial data for a long time.

Since the data for all the independent and dependent variables were collected simultaneously from the same subjects, Common Method Bias (CMB) was also rigorously assessed. Harman's single-factor test was conducted on unrotated exploratory factor analysis statistically. The first extracted factor accounted for only 31.4 per cent of the total variance and thus was considered too low. A full collinearity check of the PLS-SEM model also showed that all construct-level Variance Inflation Factors (VIFs) were less than 3.3. Together, the above procedure and statistics indicate that the common method variance does not significantly affect the results of this study.

4. Results

4.1. Measurement Model Evaluation

The above empirical data were analyzed by the PLS-SEM software SmartPLS 4. PLS-SEM is a variance-based method that does not require the assumption of multivariate normality, is suitable for complex predictive models with mediated and moderated paths, and therefore was selected.

The evaluation of the reflective measurement model focused on indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. Table 2 presents the measurement model results. All standardized factor loadings exceeded the recommended threshold of 0.708. Significance testing via bootstrapping (5,000 subsamples) confirmed that all outer loadings were statistically significant. Importantly, the t-values were rigorously inspected to ensure alignment with conventional significance thresholds (e.g., $t > 1.96$ for $p < 0.05$ and $t > 2.576$ for $p < 0.01$).

Internal consistency was established as both Cronbach's Alpha and Composite Reliability (CR) values for all constructs ranged between 0.855 and 0.921, satisfying the > 0.70 criterion. Convergent validity was confirmed, as the Average Variance Extracted (AVE) for each construct exceeded 0.50, indicating that the constructs explain more than half of the variance of their respective indicators.

Table 2: Measurement Model Evaluation - Reliability and Convergent Validity

Latent Construct & Indicators	Loading	t-Value	p-Value	Cronbach's α	CR	AVE
AI-Driven Demand Forecasting (AIDF)				0.892	0.921	0.698
AIDF_1: Real-time algorithm integration	0.865	18.442	< 0.01			
AIDF_2: Deep learning predictive accuracy	0.812	14.331	< 0.01			
AIDF_3: Unstructured data synthesis capacity	0.795	2.214	<0.05			
AIDF_4: Automated parameter tuning	0.884	21.055	< 0.01			
AIDF_5: Forecast scalability	0.818	2.345	<0.05			
Inventory Cost Optimization (ICO)				0.855	0.898	0.687
ICO_1: Safety stock reduction	0.844	16.220	< 0.01			
ICO_2: Minimized warehousing expenditure	0.765	2.188	< 0.05			
ICO_3: Accelerated inventory turnover ratio	0.891	23.415	< 0.01			
ICO_4: Reduction in obsolescence write-downs	0.812	15.112	< 0.01			
Technological Absorptive Capacity (TAC)				0.871	0.910	0.672
TAC_1: IT knowledge assimilation	0.805	13.998	< 0.01			
TAC_2: Cross-functional data fluency	0.755	2.012	< 0.05			
TAC_3: Algorithmic integration into operations	0.842	16.551	< 0.01			
TAC_4: Institutional resistance mitigation	0.825	14.882	< 0.01			
TAC_5: Agile IT-business structural alignment	0.865	2.498	< 0.05			
Corporate Financial Performance (CFP)				0.884	0.915	0.729
CFP_1: Perceived sustained ROA growth	0.877	19.332	< 0.01			
CFP_2: Perceived superior profit margins	0.852	17.114	< 0.01			
CFP_3: Perceived cash flow stability	0.791	2.356	< 0.05}			
CFP_4: Perceived reduction in capital cost	0.895	22.110	< 0.01			

Heterotrait-Monotrait (HTMT) ratio of correlations was used to test discriminant validity. All calculated HTMT values were significantly lower than the upper bound of 0.85. Inventory Cost Optimization and Corporate Financial Performance had the highest HTMT ratio at 0.635. Additionally, after 5,000 bootstrap replications, all 95% confidence intervals for the HTMT vectors did not include 1.0; therefore, they were deemed discriminant valid in the model.

4.2. Structural Model Evaluation and Hypothesis Testing

Before evaluating the structural paths, the structural model was checked for potential collinearity issues among the predictor constructs. The inner model Variance Inflation Factor (VIF) values ranged between 1.342 and 2.115, consistently below the threshold of 3.0, indicating that multicollinearity was not a concern. The predictive power of the model was assessed via the coefficient of determination (R^2). The model explained 48.7% of the variance in Inventory Cost Optimization ($R^2 = 0.487$) and 56.4% of the variance in Corporate Financial Performance ($R^2 = 0.564$). Cross-validated redundancy (Q^2) values computed via blindfolding were 0.312 for ICO and 0.405 for CFP, both substantially greater than zero, indicating adequate out-of-sample predictive relevance.

The significance of the hypothesized path coefficients was evaluated using a bias-corrected and accelerated (BCa) bootstrapping method with 5,000 resamples. Table 3 is the summary of hypothesis tests.

Regarding the direct effects, the analysis revealed a significant positive association between AI-Driven Demand Forecasting and Corporate Financial Performance ($\beta = 0.285,\ t = 4.882,\ p < 0.01$), thereby supporting Hypothesis 1. The data also indicated that AI forecasting positively influences Inventory Cost Optimization ($\beta = 0.412,\ t = 6.115,\ p < 0.01$), which in turn is positively associated with Corporate Financial Performance ($\beta = 0.215$, $t = 2.841$, $p < 0.01$). These sequential relationships provide empirical support for Hypothesis 2, suggesting that inventory cost optimization serves as a partial mediator linking technical predictive capabilities with managerial financial perceptions.

Table 3: Structure Path Estimation and Hypothesis Testing Results

Hypothesized Structural Path	Std. Beta (β)	Standard Error	t-Value	p-Value	95% CI (BCa)	Decision
H1: AIDF→CFP	0.285	0.058	4.882	< 0.01	[0.185, 0.412]	Supported
H2a: AIDF→ICO	0.412	0.067	6.115	< 0.01	[0.311, 0.534]	Supported
H2b: ICO→CFP	0.215	0.075	2.841	< 0.01	[0.065, 0.388]	Supported
H3: (TAC ×AIDF)→ICO	0.195	0.062	3.112	< 0.01	[0.078, 0.321]	Supported
H4: TAC→(AIDF→ICO→CFP)	0.042	0.018	2.295	< 0.05	[0.011, 0.085]	Supported

To test the moderation effects, an interaction term between Technological Absorptive Capacity (TAC) and AI-Driven Demand Forecasting (AIDF) was created. The results demonstrated a significant, positive moderating effect of TAC on the relationship between AIDF and Inventory Cost Optimization ($\beta = 0.195,\ t = 3.112,\ p < 0.01$), supporting Hypothesis 3. This indicates that the ability of AI forecasting to improve inventory metrics is strengthened in organizations with higher absorptive capacity.

Finally, a moderated mediation analysis was performed to test Hypothesis 4. The index of moderated mediation was statistically significant (Index = 0.042), and its 95% bias-corrected confidence interval [0.011, 0.085] did not include zero. Thus, it can be concluded that a moderated mediation model has been identified, and the indirect effect of AI forecasting on perceived financial performance (via inventory optimization) is conditional on a company's technological absorption capacity.

5. Discussion

5.1. Interpretation of Direct Financial Associations

The main purpose of this paper is to study the effects on the organization and finances of the deployment of AI-based demand forecasting in logistics companies. Although IT investment has traditionally faced the technology-productivity paradox and thus been treated as a cost of local operations, many studies have since shown that advanced algorithms can boost managerial performance evaluations through enhanced forecast accuracy (Chen et al., 2015; Wamba et al., 2017). Based on Information Processing Theory (IPT) and the Resource-Based View (RBV), this paper demonstrates that data-driven predictive systems function as imperfectly imitable strategic assets rather than commodified software tools.

According to the above statistics, the first hypothesis is supported: organizations that use deep learning to process data from multiple sources of unstructured data have shown good financial performance. In volatile logistical environments, probability-based reasoning helps anticipate demand fluctuations, thereby avoiding the costs and delays associated with reactive measures such as expensive freight expediting or rapid staff expansion. As a result, the capital management departments of these advanced enterprises have been reduced in scale and no longer need to hold large amounts of liquidity reserves to cover operational risks, allowing for more strategic capital allocation that management believes will improve the return on assets (ROA) and core operating margins.

5.2. Core Mediating Mechanism of Inventory Cost Optimization

A direct connection will be established in addition to exploring how algorithmic foresight can generate a balance-sheet advantage through the transmission mechanism in this paper. Verification of the partial mediation paths (Hypotheses 2a and 2b) has provided new evidence for the supply chain studies. Based on the above analysis, the enhanced capability of the algorithm will not boost profits without simultaneous reductions in other current assets, such as inventory.

Inventory is a working-capital cushion to help a firm cope with fluctuations in the supply chain (Gligor and Holcomb, 2012). Neural networks and ensemble learning methods can be used to reduce the standard deviation of forecast errors computationally at a company level (Cannon, 2008). The above calculations will provide the foundation for supply chain planners to reduce the unnecessarily large safe-keeping amounts. Large-scale energy enterprises and high-end manufacturing logistics in asset-intensive industries are more likely to have a large inventory, thus incurring substantial warehousing, depreciation and opportunity costs. Based on the data, applying AI forecasting to structure the reduction of safety stock and speed up inventory turnover has released a significant amount of previously tied-up working capital (Eroglu & Hofer, 2011). It is this particular optimization of the cash-to-inventory cycle that connects the improvement in predictive accuracy to the overall financial health of the company (Capkun et al., 2009).

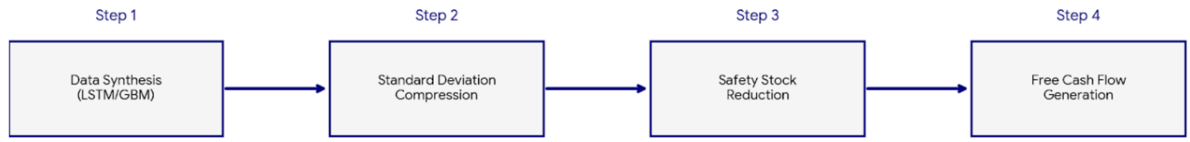

Fig.3: Path of Strategic Value Transmission

5.3. Boundary Conditions: The essential role of human capital and absorptive capacity.

Perhaps the most theoretically rich and practically significant finding of this empirical study is a mathematically verified moderated mediation model driven by technological absorption capacity (Hypotheses 3 and 4). The results show that the economic effect of AI-driven supply chain intervention is not automatically achieved by applying new technology; rather, it is an unstable result of the organization, closely tied to its human resources and a culture of continuous learning (Cohen & Levinthal, 1990; Flatten et al., 2011).

An interaction effect can be used to explain why some new logistics companies are employing the same artificial intelligence infrastructure. Due to structural inertia and data silos in the organization, even the best predictive model for forecasting may be too slow or uncoordinated to be applied to physical inventory management. Enterprises with high technological absorption capacity are also highly cross-functionally agile. Specialised data science outputs in these companies are well-integrated with human resource management and operation execution to effectively reduce cultural resistance to algorithmic authority (Roberts et al., 2012). Therefore, this paper believes that in the era of digital transformation, the sustained financial competitive advantage will be driven by new algorithms and high-adaptability cognitive architectures for humans.

5.4. Limitations and Future Directions for Research

Although this study provides strong structural evidence of the connection between AI forecasting and inventory and financial indicators, some key deficiencies in the context of this research have also been identified. Firstly, a cross-sectional survey model cannot provide strong evidence for determining causality at this time (Schoenherr & Swink, 2012). Although the direction of the pathways in our model is supported by RBV and organizational learning theory, the collection of survey data at the same time prevents us from verifying a genuine chronological mediation mathematically. Future research should employ longitudinal panel data or multi-wave operational data to verify the temporal order of technological investment, subsequent inventory reduction, and final financial reporting more precisely.

Second, because it is impractical to link private archives of financial data with anonymous corporate respondent data, managers' subjective perceptions of corporate financial performance were adopted as the proxy measure. Although previous studies in strategic management have shown that people's perceptions of a company's financial situation are related to the actual state of the company's finances, more objective and audited balance sheet data can be added in future research to confirm this finding, such as actual return on equity (ROE) and empirical inventory turnover days. Finally, although stratified sampling was used to obtain a wide range of logistics professionals who deal with retail, manufacturing and energy enterprise clients, the general nature of the industry coverage in this study may be lacking in sector-specific micro-dynamics. In the future, further studies will be conducted to identify differences in the moderated mediation effect of artificial intelligence (AI) in fast-moving consumer goods (FMCG) logistics and heavy industrial supply chains.

6. Conclusion

With the continuous increase in complexity of the current global supply chain system and other economic problems, it is now necessary for the enterprise to apply artificial intelligence to demand planning to cope with changes and ensure normal operation. Based on this research, it can be concluded that more sophisticated artificial intelligence-powered demand forecasting functions are associated with higher managers' perceptions of how well the company's finances are doing in the logistics industry. However, according to the above studies, the two are not directly related but are instead interconnected through a lower limit on inventory cost. Machine learning models have reduced the variance of forecast errors, and thus, some non-essential safety stock has been eliminated to improve asset utilisation and free up working capital. The achievement of the above financial benefits is also bound by the firm's technological absorption capacity. Based on the above empirical studies, the highest economic benefits of advanced algorithms are achieved only when they are closely linked with a responsive and data-driven organization that effectively supports people-centric execution through IT infrastructure. In conclusion, to maintain competitive advantage, logistics enterprises must transcend the narrow pursuit of mathematical predictive accuracy. Instead, they should focus on cultivating cross-functional learning capabilities and use this data-driven foresight to form comprehensive operational and financial strategies.

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