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Artificial Intelligence–Driven Demand Forecasting and Inventory Performance in Omnichannel Supply Chains: The Contingent Roles of Data Quality, Demand Volatility, and Organizational Analytics Maturity

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ABSTRACT

This study examined the effect of artificial intelligence–driven demand forecasting on inventory performance in omnichannel supply chains and tested the moderating roles of data quality, demand volatility, and organizational analytics maturity. A quantitative cross-sectional study was conducted among 312 managers, supervisors, analysts, and specialists employed in omnichannel organizations in Tehran, Iran. Data were collected using a structured questionnaire measuring artificial intelligence–driven demand forecasting, inventory performance, data quality, demand volatility, and organizational analytics maturity. The measurement model and structural relationships were analyzed using partial least squares structural equation modeling with 5,000 bootstrap resamples. Reliability, convergent validity, discriminant validity, multicollinearity, explanatory power, predictive relevance, effect sizes, and interaction effects were assessed. Artificial intelligence–driven demand forecasting had a significant positive effect on inventory performance ($\beta = 0.421$, $p < 0.001$). Data quality ($\beta = 0.263$, $p < 0.001$) and organizational analytics maturity ($\beta = 0.196$, $p < 0.001$) positively predicted inventory performance, whereas demand volatility had a significant negative effect ($\beta = -0.148$, $p < 0.001$). Data quality strengthened the forecasting–performance relationship ($\beta = 0.163$, $p < 0.001$), while demand volatility weakened it ($\beta = -0.121$, $p = 0.001$). Organizational analytics maturity also amplified the positive effect of artificial intelligence forecasting ($\beta = 0.142$, $p = 0.001$). The final model explained 61.2% of the variance in inventory performance and demonstrated acceptable predictive relevance and fit. Artificial intelligence–driven demand forecasting improves inventory performance in omnichannel supply chains, but its benefits are greatest when organizations possess high-quality integrated data and mature analytics capabilities and are reduced under highly volatile demand conditions.

Keywords: artificial intelligence; demand forecasting; inventory performance; omnichannel supply chain; data quality; demand volatility; analytics maturity.

Introduction

The rapid convergence of digital commerce, mobile platforms, physical retailing, and distributed fulfillment has fundamentally altered the architecture of contemporary supply chains. Organizations increasingly serve customers through interconnected stores, websites, mobile applications, social-commerce platforms, marketplaces, and direct-delivery channels, creating an omnichannel environment in which purchasing, delivery, return, and service activities must be coordinated as parts of a unified customer experience. Unlike conventional multichannel systems, in which

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individual channels may operate relatively independently, omnichannel supply chains require real-time coordination of demand information, inventory positions, order-routing decisions, and fulfillment resources across organizational and geographical boundaries. The expansion of e-commerce has intensified the need to redesign logistics systems around integrated order processing, flexible fulfillment, and coordinated product flows, while new retail models have blurred the traditional distinction between online and offline operations (1, 2). Research on omnichannel retailing has consequently emphasized seamless channel integration, customer experience, distribution flexibility, and the need for new operational models capable of supporting increasingly complex patterns of consumption and fulfillment (3, 4). The transformation of food retailing through platform-based business groups further illustrates how digital ecosystems can reshape the organization of retail networks, relationships among supply chain actors, and the allocation of operational capabilities across channels (5). Moreover, the evolution of omnichannel fulfillment performance in grocery retailing demonstrates that operational effectiveness develops through cumulative changes in processes, technologies, organizational routines, and channel configurations rather than through the isolated adoption of a single digital tool (6).

Within this environment, inventory performance has become one of the most consequential indicators of supply chain effectiveness. Omnichannel firms must maintain sufficient inventory availability to meet customer expectations while avoiding excessive safety stock, duplication of inventory across locations, unnecessary carrying costs, markdowns, obsolescence, and inefficient interfacility transfers. These objectives are difficult to reconcile because inventory may be simultaneously used to serve store customers, online orders, click-and-collect transactions, home deliveries, and cross-channel returns. Product proliferation further complicates this problem by increasing the number of stock-keeping units that must be positioned across supply chain stages, thereby amplifying forecasting errors and allocation complexity (7). Inventory management research has therefore increasingly addressed the coordination of perishable goods, channel supply, cooperation among supply chain members, and the management of trade-offs between responsiveness and efficiency (8). In multi-echelon omnichannel distribution systems, inventory decisions cannot be separated from order allocation because the location from which an order is fulfilled affects product availability, transportation cost, delivery time, and future replenishment requirements (9). Transshipment models similarly demonstrate the operational importance of transferring inventory among channel locations to correct imbalances and reduce shortages, although such interventions may also introduce additional cost and complexity (10). Physical Internet–enabled city logistics solutions extend this coordination challenge by emphasizing interconnected logistics resources, shared infrastructure, and multilevel distribution arrangements suited to new retail environments (11). Inventory performance must also account for reverse flows, particularly in sectors such as fashion, where product returns and disruption recovery can create substantial omnichannel reverse-logistics risks (12). Accordingly, inventory is not merely a buffer against uncertainty; it is a strategically allocated resource whose performance reflects the quality of forecasting, information integration, risk management, and operational coordination.

Demand forecasting is central to this relationship because virtually every major inventory decision depends on an expectation regarding future demand. Procurement quantities, replenishment timing, safety-stock levels, production schedules, capacity allocation, workforce planning, distribution requirements, and channel-specific inventory placement are all affected by forecast quality. Retail forecasting research has long acknowledged the gap between formal forecasting methods and organizational practice, emphasizing that forecasting effectiveness depends not only on statistical accuracy but also on implementation, judgment, decision processes, and the ability to translate predictions into operational action (13). In contemporary retail environments, demand prediction has become particularly important because market conditions, customer preferences, promotional campaigns, competitor actions, and channel-switching behavior generate large volumes of rapidly changing information (14). Information technology capability can improve supply chain agility when it enables organizations to collect, process, and use demand information effectively, with demand forecasting serving as an important mechanism through which digital capability contributes to responsiveness (15). Big data analytics can further support retail marketing and supply chain optimization by revealing purchasing patterns, customer segments, product associations, and emerging demand signals that may not be detected by traditional forecasting systems (16). The integration of supply chain analytics with marketing information is especially relevant in omnichannel contexts because customer interactions, campaigns, search behavior, and transaction histories can provide complementary insights into future purchasing behavior (17). Likewise, the integration of management information systems across operational and customer relationship functions can strengthen the economic value of information by reducing fragmentation between customer-facing activities and internal decision processes (18).

Artificial intelligence has expanded the potential scope, speed, and adaptability of demand forecasting. Artificial intelligence–driven systems can process nonlinear relationships, large-scale transaction records, external market indicators, promotional information, product attributes, customer behavior, temporal patterns, and real-time channel data. Machine-learning models can update predictions as new information becomes available, identify hidden interactions among demand drivers, and generate forecasts at finer levels of product, location, channel, and time. In manufacturing, artificial intelligence has been positioned as an important component of high-quality industrial development because it can support intelligent decision-making, process optimization, predictive analysis, and flexible production (19). Digital transformation in logistics and transportation similarly points to a future in which forecasting, automation, connectivity, and advanced analytics become integral to the planning and control of manufacturing-related supply chains (20). Industry 4.0 integration models further indicate that data-driven technologies achieve greater operational value when they are combined with coherent managerial systems and process-improvement approaches, including lean management (21). Preparing supply chains for future technological infrastructure therefore requires mapping relationships among actors, information systems, physical resources, and digital capabilities rather than treating technology adoption as an isolated technical intervention (22). Information sharing and blockchain-based coordination may additionally improve supply chain performance by increasing information visibility, traceability, and trust among supply chain partners, thereby strengthening the informational foundation on which forecasting systems operate (23).

Despite these technological possibilities, the implementation of artificial intelligence does not automatically guarantee improved inventory performance. Forecasting algorithms generate probabilistic estimates rather than certain outcomes, and their operational benefits depend on how accurately model outputs reflect actual demand conditions and how effectively organizations convert those outputs into inventory decisions. A technically sophisticated forecast may fail to produce performance improvements when replenishment rules are inflexible, channel inventories are not visible, departments do not share information, managers distrust analytical recommendations, or decision rights are poorly defined. Logistics integration capability is therefore essential in omnichannel retailing because coordination among logistics functions and broader supply chain integration allows organizations to translate information into consistent fulfillment and performance outcomes (24). Similarly, the development of omnichannel fulfillment performance is likely to require alignment among forecasting, inventory placement, process design, resource allocation, and organizational learning (6). These observations suggest that the relationship between artificial intelligence forecasting and inventory performance should be examined through a contingency perspective. Rather than assuming a universally strong technological effect, such a perspective recognizes that artificial intelligence produces different outcomes depending on the informational, environmental, and organizational conditions under which it is implemented.

Data quality represents one of the most important conditions shaping the value of artificial intelligence–driven forecasting. Forecasting models depend on historical and real-time data for training, validation, updating, and prediction. When sales, inventory, customer, pricing, promotion, and fulfillment data are accurate, complete, timely, consistent, accessible, and integrated, artificial intelligence systems can develop more reliable representations of demand behavior. In contrast, missing transactions, delayed updates, inconsistent product codes, duplicated customer records, inaccurate inventory balances, and disconnected channel databases can distort model estimation and weaken operational recommendations. This issue is particularly important in omnichannel systems because data are generated by multiple platforms and organizational units that may use incompatible definitions, formats, and update frequencies. Big data analytics can support retail optimization only when data resources are sufficiently reliable and usable for decision-making (16), while combining supply chain analytics with marketing information requires consistency across customer, operational, and market datasets (17). Management information systems integration can reduce informational fragmentation and improve the coordination of operational and customer-related decisions (18). Information-sharing arrangements may similarly enhance supply chain performance when shared data are trustworthy, timely, and interpretable by participating organizations (23). Therefore, data quality may not only exert a direct influence on inventory performance but also strengthen the performance effect of artificial intelligence forecasting by improving the informational inputs used to generate and implement predictions.

Demand volatility constitutes a second major contingency. Omnichannel demand is frequently affected by short product life cycles, dynamic pricing, social media trends, seasonal variation, promotional campaigns, competitor initiatives, economic uncertainty, channel migration, and sudden external disruptions. Under relatively stable conditions, artificial intelligence models can identify recurrent patterns and use historical relationships to improve forecast accuracy. Under highly volatile conditions, however, past demand may provide a weaker basis for predicting future behavior, especially when disruptions create structural breaks or unprecedented purchasing patterns. The COVID-19 crisis demonstrated how rapidly supply chain assumptions could become obsolete as consumer demand, product availability, transportation capacity, and operating restrictions changed simultaneously (25). Research on resilient retail supply chains likewise emphasizes that disruption mitigation requires flexibility, visibility, collaboration, and adaptive strategies rather than reliance on routine planning processes alone (26). Reverse-logistics research also indicates that disruption recovery in omnichannel systems is associated with interconnected risks that can affect inventory flows, returns, capacity, and service performance (12). Enterprise risk management may influence firm operations through its effects on inventory policies and the capacity to recognize and respond to uncertainty (27). These considerations indicate that demand volatility may have a dual role: it can increase the strategic need for advanced forecasting while simultaneously reducing the strength of the relationship between forecasting capability and inventory performance when changes are too abrupt or irregular for models to learn effectively.

The broader predictive analytics literature also illustrates that model performance is inseparable from the structure and stability of the environment being modeled. Data-driven methods have been applied to technically complex domains such as pricing on-chain derivatives, analyzing the relationship between option trading and underlying returns, and modeling environmental attainment under changing atmospheric conditions (28-30). Although these applications differ substantively from supply chain forecasting, they demonstrate a general analytical principle: predictive models depend on suitable data, defensible assumptions, appropriate calibration, and sensitivity to changing regimes. In omnichannel supply chains, the same principle implies that artificial intelligence forecasting should not be assessed solely according to its technical architecture. Its inventory consequences must be evaluated in relation to the quality of the data environment, the volatility of demand patterns, and the capacity of the organization to understand and use analytical outputs.

Organizational analytics maturity represents the third contingency examined in this study. Analytics maturity refers to the extent to which an organization has developed the technological infrastructure, analytical expertise, governance arrangements, managerial commitment, cross-functional coordination, and decision routines needed to use data systematically. A low-maturity organization may acquire artificial intelligence software without possessing the skills to validate models, interpret uncertainty, redesign planning processes, or integrate predictions into procurement and replenishment. In contrast, a mature organization is more likely to maintain data standards, employ qualified analysts, monitor forecast performance, coordinate analytical activities across departments, and establish clear mechanisms for converting forecasts into operational actions. Industry 4.0 and lean integration research highlights the importance of aligning advanced technologies with managerial practices and organizational processes (21). Digital transformation in logistics similarly requires organizational change, skills development, and process redesign in addition to technology implementation (20). Technology infrastructure mapping also underscores the need to consider organizational readiness and interdependencies when preparing supply chains for future digital systems (22). Furthermore, artificial intelligence–enabled industrial development depends on an organization’s capacity to institutionalize intelligent decision-making rather than merely purchase digital tools (19). Analytics maturity may therefore strengthen the effect of artificial intelligence forecasting by ensuring that predictions are trusted, communicated, evaluated, and incorporated into coordinated inventory decisions.

Existing research has generated important insights into retail forecasting, supply chain agility, information integration, omnichannel logistics, inventory allocation, digital transformation, and disruption resilience. However, these streams have often developed separately. Forecasting studies have concentrated on predictive methods and implementation challenges, inventory research has emphasized allocation and optimization, and omnichannel studies have examined channel integration, logistics capability, customer experience, and fulfillment structures (4, 9, 13). Other studies have addressed information technology capability, demand forecasting, logistics integration, transshipment, and digital infrastructure without jointly testing the conditions that determine when artificial intelligence forecasting produces superior inventory outcomes (10, 15, 24). As a result, insufficient attention has been given to an integrated model in which artificial intelligence–driven demand forecasting predicts inventory performance while data quality, demand volatility, and organizational analytics maturity simultaneously shape the strength of that relationship. Addressing this gap is important because organizations may otherwise overinvest in forecasting technologies without recognizing the complementary data and organizational capabilities needed to realize performance gains or the environmental uncertainty that may constrain those gains.

The proposed framework contributes to the literature by treating artificial intelligence forecasting as an organizational capability embedded within a wider supply chain system. It recognizes that forecast generation, inventory optimization, information integration, and operational execution are mutually dependent. It also responds to calls for more comprehensive research on the future of omnichannel retailing and distribution management by connecting technological capability with operational performance and contextual conditions (4). By examining the direct effects of artificial intelligence forecasting, data quality, demand volatility, and analytics maturity, as well as their interactive relationships, the framework provides a more realistic account of how predictive technologies create value. Such an approach is especially relevant for omnichannel firms seeking to reduce stockouts and excess inventory while preserving responsiveness, service quality, and cost efficiency across multiple fulfillment pathways.

Accordingly, the aim of this study was to examine the effect of artificial intelligence–driven demand forecasting on inventory performance in omnichannel supply chains and to determine the contingent roles of data quality, demand volatility, and organizational analytics maturity in this relationship.

Methods and Materials

This study employed an applied, quantitative, cross-sectional research design to examine the effect of artificial intelligence–driven demand forecasting on inventory performance in omnichannel supply chains and to determine whether data quality, demand volatility, and organizational analytics maturity condition this relationship. The statistical population consisted of managers, supervisors, analysts, and senior specialists employed in retail, distribution, logistics, manufacturing, and e-commerce organizations operating omnichannel supply chains in Tehran, Iran, during 2026. Eligible participants were required to have at least two years of professional experience in supply chain management, inventory planning, demand forecasting, business analytics, operations management, logistics, procurement, retail operations, or e-commerce fulfillment. In addition, participants were required to have sufficient familiarity with their organization's forecasting and inventory management practices and to be directly involved in, or knowledgeable about, the use of artificial intelligence, machine learning, predictive analytics, or data-driven decision-support systems. Employees whose responsibilities were unrelated to forecasting, inventory, logistics, analytics, or omnichannel operations were excluded from the study. Because a comprehensive sampling frame of all qualified professionals was unavailable, participants were recruited through a multistage purposive and convenience sampling procedure. Initially, retail chains, online marketplaces, distribution companies, logistics service providers, consumer goods manufacturers, and hybrid online–offline businesses located in Tehran were identified. Organizational representatives were then contacted, and eligible employees were invited to participate through professional networks, organizational communication channels, and direct distribution of the questionnaire. A total of 368 questionnaires were distributed, of which 329 were returned. After excluding 17 questionnaires because of substantial missing data, uniform response patterns, or failure to meet the eligibility criteria, 312 complete and usable questionnaires were retained for the final analysis. The final sample therefore consisted of exactly 312 participants. Before completing the questionnaire, all respondents received a written explanation of the study objectives, voluntary nature of participation, confidentiality of organizational and personal information, and their right to discontinue participation without any adverse consequences. No personally identifying information was collected, and informed consent was obtained electronically or in writing from all participants.

Data were collected using a structured self-report questionnaire consisting of demographic and professional information and six multi-item measurement scales assessing artificial intelligence–driven demand forecasting, inventory performance, data quality, demand volatility, organizational analytics maturity, and relevant organizational control variables. The questionnaire was developed through a systematic review of the literature on artificial intelligence applications in supply chain management, information systems, demand forecasting, inventory management, organizational analytics capabilities, and omnichannel operations. Items were adapted to the context of organizations operating integrated physical and digital sales channels. All substantive items were measured on a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree, except for the demand volatility items, which assessed the frequency and intensity of changes in customer demand using response categories ranging from 1, very low, to 5, very high. Higher scores represented stronger artificial intelligence–driven forecasting capability, better inventory performance, higher data quality, greater demand volatility, and more advanced organizational analytics maturity. The initial questionnaire was reviewed by a panel of seven experts in supply chain management, operations research, business analytics, information systems, and organizational research to assess the clarity, relevance, comprehensiveness, and contextual appropriateness of the items. Based on their recommendations, ambiguous expressions were revised, conceptually overlapping items were removed, and terminology was adjusted to reflect the operational characteristics of omnichannel supply chains in Iran. A pilot study was subsequently conducted with 35 professionals who met the study eligibility criteria but were not included in the final sample. The pilot findings indicated that the questionnaire items were understandable and that the preliminary internal consistency coefficients of all constructs were above the acceptable threshold of 0.70.

Artificial intelligence–driven demand forecasting was assessed using a researcher-adapted scale designed to measure the extent to which an organization uses artificial intelligence and advanced analytics to predict customer demand across interconnected sales and fulfillment channels. The scale contained eight items addressing the use of machine-learning algorithms, automated demand-pattern recognition, integration of real-time sales information, incorporation of customer and market data, continuous updating of forecasts, identification of nonlinear demand patterns, generation of channel-specific forecasts, and use of predictive recommendations in inventory decisions. Representative content included the organization's ability to use artificial intelligence to update demand forecasts when new information becomes available and to integrate demand signals from physical stores, websites, mobile applications, marketplaces, and distribution centers. The items were formulated to measure organizational capability rather than the use of a single software package or forecasting technique. A higher total score indicated a more extensive and sophisticated application of artificial intelligence in demand forecasting. The construct was modeled as a reflective latent variable because the items were considered observable manifestations of the organization's underlying artificial intelligence–enabled forecasting capability.

Inventory performance was measured with a seven-item scale evaluating the effectiveness and efficiency of inventory management across omnichannel operations. The items covered inventory availability, reduction of stockouts, reduction of excess inventory, improvement in inventory turnover, accuracy of replenishment decisions, reduction of inventory holding costs, and the organization's ability to position inventory across stores, warehouses, distribution centers, and fulfillment locations. Respondents were asked to evaluate inventory outcomes relative to the operational expectations and recent performance of their organizations. Because omnichannel inventory performance extends beyond minimizing inventory quantities, the scale incorporated both efficiency indicators and customer-service outcomes. Accordingly, high scores reflected the organization's capacity to maintain product availability while controlling surplus inventory, carrying costs, and inefficient stock allocation. The measurement approach also recognized that inventory performance in omnichannel environments depends on the visibility and coordinated use of inventory across multiple sales and delivery channels.

Data quality was assessed using a six-item scale covering the accuracy, completeness, timeliness, consistency, accessibility, and integration of data used in forecasting and inventory decisions. The items evaluated whether sales, inventory, customer, promotion, product, pricing, and fulfillment data were reliable and sufficiently updated for analytical use. Particular attention was given to the consistency of data across physical stores, online platforms, warehouses, and third-party distribution channels because fragmented information is a major obstacle to effective omnichannel forecasting. Respondents rated the extent to which organizational data were free from errors, available at the required time, comparable across information systems, and integrated into a usable analytical format. Higher scores indicated that the organization possessed more reliable and decision-relevant data resources. Data quality was examined as a moderator because the predictive value of artificial intelligence systems is expected to depend on the quality of the information used for model training, updating, and operational decision-making.

Demand volatility was measured with five items assessing the unpredictability, frequency, and magnitude of changes in customer demand. The scale addressed rapid changes in sales volume, difficulty in anticipating customer preferences, irregular fluctuations across channels, sensitivity of demand to promotions and external events, and variation in product demand over relatively short periods. Respondents evaluated demand conditions experienced by their organizations during recent operational periods rather than reporting a single numerical measure of sales variability. A higher score represented greater instability and lower predictability of demand. Demand volatility was included as a contingent variable because rapidly changing demand conditions may increase the need for adaptive artificial intelligence forecasting while simultaneously reducing forecast accuracy when historical patterns become less informative. The measurement items therefore captured both temporal fluctuations and differences in demand patterns across online and offline channels.

Organizational analytics maturity was assessed through an eight-item scale measuring the degree to which analytics had been institutionalized within organizational structures, processes, human resources, and decision-making routines. The scale included items related to managerial support for analytics, availability of employees with analytical expertise, integration of analytics into strategic and operational decisions, adequacy of technological infrastructure, cross-functional sharing of analytical information, standardization of data-driven processes, continuous evaluation of analytical models, and the organization’s ability to convert analytical outputs into operational actions. The scale was designed to distinguish organizations that merely possess analytical technologies from those that have developed the managerial, technical, and cultural capabilities required to use them effectively. Higher scores indicated greater analytics maturity. Organizational analytics maturity was treated as a moderator because the operational benefits of artificial intelligence forecasting may depend on whether managers and employees are capable of interpreting, trusting, communicating, and implementing the system’s outputs.

The questionnaire also collected information on participants’ age, gender, educational level, organizational position, professional experience, and functional area. Organizational characteristics included industry sector, number of employees, length of omnichannel operating experience, approximate number of active sales channels, and level of digitalization. Organizational size, industry type, and omnichannel experience were included as control variables because they could influence both the adoption of artificial intelligence and inventory performance. To reduce common method bias, the questionnaire assured respondents that there were no correct or incorrect answers, emphasized the confidentiality of responses, used clear and neutral wording, and separated predictor, moderator, and outcome variables into distinct sections. Item order was partially randomized, and negatively worded items were avoided to reduce confusion and artificial response patterns.

Data analysis was performed using IBM SPSS Statistics version 29 and SmartPLS version 4. Before testing the research hypotheses, the dataset was examined for missing values, unengaged responses, outliers, and violations of basic statistical assumptions. Questionnaires with substantial missing information or invariant response patterns were removed before the final analysis. For the retained cases, the small number of randomly distributed missing values was handled using the expectation-maximization method. Univariate outliers were examined through standardized scores, and multivariate outliers were evaluated using Mahalanobis distance. Descriptive statistics, including frequency, percentage, mean, standard deviation, minimum, maximum, skewness, and kurtosis, were calculated to describe participant characteristics and the distributions of the principal study variables. Pearson correlation coefficients were also calculated to provide an initial assessment of the direction and magnitude of associations among the constructs. Potential multicollinearity was assessed using tolerance values and variance inflation factors, with variance inflation factor values below 5 considered indicative of acceptable collinearity.

Partial least squares structural equation modeling was used to evaluate the measurement and structural models because the study included several latent variables, multiple interaction effects, and a prediction-oriented conceptual framework. The measurement model was assessed by examining indicator loadings, Cronbach's alpha, composite reliability, rho_A, average variance extracted, and discriminant validity. Indicator loadings of 0.70 or higher were considered desirable, although items with loadings between 0.40 and 0.70 were retained when their removal did not meaningfully improve construct reliability or convergent validity and when they contributed to the conceptual coverage of the construct. Cronbach's alpha, composite reliability, and rho_A values of at least 0.70 were considered acceptable. Convergent validity was established when the average variance extracted for each construct exceeded 0.50. Discriminant validity was evaluated through the heterotrait–monotrait ratio of correlations, with values below 0.85 interpreted as evidence that the constructs were empirically distinct. Cross-loadings and the Fornell–Larcker criterion were also inspected as supplementary indicators of discriminant validity.

After confirming the adequacy of the measurement model, the structural model was evaluated using standardized path coefficients, t statistics, confidence intervals, coefficients of determination, effect sizes, predictive relevance, and model fit indicators. The significance of direct and moderating effects was tested using a nonparametric bootstrapping procedure with 5,000 resamples and bias-corrected 95% confidence intervals. The direct effect of artificial intelligence–driven demand forecasting on inventory performance was tested first. Interaction terms were then created to evaluate the moderating effects of data quality, demand volatility, and organizational analytics maturity on the relationship between artificial intelligence–driven demand forecasting and inventory performance. All predictor and moderator variables were standardized before constructing the interaction terms to facilitate interpretation and reduce nonessential multicollinearity. A significant interaction coefficient indicated that the strength or direction of the relationship between artificial intelligence–driven forecasting and inventory performance varied according to the level of the moderator. Significant interactions were interpreted through simple-slope analyses at low, average, and high levels of the moderator, defined as one standard deviation below the mean, the mean, and one standard deviation above the mean, respectively.

The explanatory power of the model was assessed using the R^2 and adjusted R^2 values for inventory performance. Effect sizes were examined using f^2 statistics, with values of approximately 0.02, 0.15, and 0.35

interpreted as small, medium, and large effects, respectively. Predictive relevance was evaluated through the blindfolding procedure and Q^2 values, with values greater than zero indicating that the model possessed predictive relevance for the endogenous construct. The standardized root mean square residual was examined as an approximate indicator of overall model fit, with values below 0.08 considered acceptable. The predictive performance of the model was further evaluated using the PLSpredict procedure, which compared the prediction errors of the structural model with those generated by a linear benchmark model. Harman's single-factor test and full-collinearity variance inflation factors were used as diagnostic procedures to examine the possibility of common method variance. Statistical significance was determined at the 0.05 level, and all hypothesis tests were two-tailed.

Findings and Results

The final analysis was conducted using data obtained from 312 managers, supervisors, analysts, and senior specialists employed in organizations operating omnichannel supply chains in Tehran. The participants' mean age was 39.84 years, with a standard deviation of 8.17 years and a range of 25 to 59 years. Of the participants, 184 individuals were men, representing 59.0% of the sample, and 128 were women, representing 41.0%. Regarding age distribution, 96 participants, or 30.8%, were between 25 and 34 years of age, 128 participants, or 41.0%, were between 35 and 44 years, 67 participants, or 21.5%, were between 45 and 54 years, and 21 participants, or 6.7%, were 55 years of age or older. In terms of educational attainment, 132 participants, equivalent to 42.3%, held a bachelor's degree, 151 participants, equivalent to 48.4%, held a master's degree, and 29 participants, equivalent to 9.3%, held a doctoral degree. The predominance of participants with postgraduate qualifications indicated that most respondents possessed sufficient academic and professional knowledge to evaluate advanced forecasting, analytics, and inventory management practices within their organizations.

With respect to organizational position, 58 participants, or 18.6%, were senior managers, 91 participants, or 29.2%, were middle-level managers, 76 participants, or 24.4%, were supervisors or team leaders, and 87 participants, or 27.9%, were analysts or senior specialists. Participants had an average of 10.73 years of professional experience, with a standard deviation of 5.48 years. Seventy respondents, representing 22.4% of the sample, had between two and five years of professional experience, 102 respondents, representing 32.7%, had between six and ten years of experience, 83 respondents, representing 26.6%, had between 11 and 15 years of experience, and 57 respondents, representing 18.3%, had more than 15 years of professional experience. Regarding functional responsibilities, 101 participants, or 32.4%, worked primarily in supply chain planning, procurement, or inventory management, 76 participants, or 24.4%, worked in demand planning, business intelligence, or data analytics, 63 participants, or 20.2%, worked in logistics, warehousing, or order fulfillment, and 72 participants, or 23.1%, worked in e-commerce, retail operations, or omnichannel management.

In terms of organizational sector, 88 participants, representing 28.2% of the sample, were employed in retail chains, 64 participants, representing 20.5%, worked in e-commerce or online marketplace organizations, 61 participants, representing 19.6%, were employed in distribution and logistics organizations, 56 participants, representing 17.9%, worked in consumer goods manufacturing companies, and 43 participants, representing 13.8%, were employed in hybrid service, technology, or multisector organizations with integrated physical and digital channels. Eighty-one respondents, or 26.0%, worked in organizations with 50 to 249 employees, 109 respondents, or 34.9%, worked in organizations with 250 to 999 employees, and 122 respondents, or 39.1%, worked in organizations with 1,000 or more employees. Overall, the demographic and professional composition of the sample demonstrated adequate variation in organizational position, sector, experience, and functional expertise, while also indicating that the respondents were sufficiently familiar with forecasting, inventory, analytics, and omnichannel supply chain processes to provide informed assessments of the study constructs.

Before hypothesis testing, the data were screened for missing values, univariate and multivariate outliers, distributional irregularities, and multicollinearity. Missing responses accounted for less than 0.5% of the total data points and were distributed randomly across the dataset. These values were estimated using the expectation-maximization procedure. Standardized scores did not reveal any severe univariate outliers, and the examination of Mahalanobis distance showed that no retained case exceeded the critical threshold for multivariate outliers. The absolute skewness values ranged from 0.09 to 0.34, while the absolute kurtosis values ranged from 0.12 to 0.31, indicating that the variables did not demonstrate severe distributional irregularities. Variance inflation factor values for the predictor and moderator variables ranged from 1.31 to 2.74, remaining below the threshold of 5 and indicating that multicollinearity did not threaten the stability of the estimated structural coefficients.

Table 1. Descriptive Statistics and Correlations Among the Principal Study Variables

Variable	Mean	Standard deviation	Skewness	Kurtosis	1	2	3	4	5
1. Artificial intelligence–driven demand forecasting	3.68	0.64	−0.34	−0.12	1.00				
2. Inventory performance	3.74	0.61	−0.28	−0.24	0.58**	1.00			
3. Data quality	3.59	0.66	−0.21	−0.18	0.54**	0.56**	1.00		
4. Demand volatility	3.47	0.71	0.16	−0.31	0.11	−0.17**	−0.09	1.00	
5. Organizational analytics maturity	3.55	0.68	−0.19	−0.15	0.57**	0.52**	0.49**	−0.12*	1.00

As shown in Table 1, the mean scores of the principal study variables were above the theoretical midpoint of 3.00, suggesting that the participating organizations generally reported moderate to relatively high levels of artificial intelligence–driven forecasting, inventory performance, data quality, demand volatility, and organizational analytics maturity. Inventory performance had the highest mean score at 3.74, followed by artificial intelligence–driven demand forecasting at 3.68, data quality at 3.59, organizational analytics maturity at 3.55, and demand volatility at 3.47. Artificial intelligence–driven demand forecasting was positively and significantly correlated with inventory performance, $r = 0.58$, $p < 0.01$, indicating that organizations reporting more extensive use of artificial intelligence in forecasting also tended to report better stock availability, fewer stockouts, lower excess inventory, more accurate replenishment decisions, and improved inventory turnover. Artificial intelligence–driven demand forecasting was also positively associated with data quality, $r = 0.54$, $p < 0.01$, and organizational analytics maturity, $r = 0.57$, $p < 0.01$. These associations indicated that artificial intelligence forecasting was more extensively developed in organizations possessing reliable, integrated, and timely data and in organizations with stronger analytical infrastructure, expertise, and managerial support.

Data quality demonstrated a substantial positive association with inventory performance, $r = 0.56$, $p < 0.01$, suggesting that accurate, complete, timely, consistent, and integrated data supported more effective inventory decisions. Organizational analytics maturity was also positively correlated with inventory performance, $r = 0.52$, $p < 0.01$, indicating that organizations capable of embedding analytical information into operational and strategic decision processes tended to achieve superior inventory outcomes. In contrast, demand volatility was negatively correlated with inventory performance, $r = −0.17$, $p < 0.01$, demonstrating that rapid, irregular, and difficult-to-predict changes in customer demand were associated with weaker inventory availability and efficiency. The correlation between artificial intelligence–driven demand forecasting and demand volatility was positive but not statistically significant, r = 0.11, p > 0.05, suggesting that the degree of demand instability alone did not necessarily determine the level of artificial intelligence adoption. None of the correlations exceeded 0.80, providing additional evidence that the study variables represented empirically distinguishable constructs and that excessive overlap among the predictors was unlikely.

Table 2. Measurement Model Reliability and Convergent and Discriminant Validity Results

Construct	Number of items	Standardized loading range	Cronbach's alpha	rho_A	Composite reliability	Average variance extracted	Maximum HTMT value
Artificial intelligence–driven demand forecasting	8	0.72–0.88	0.91	0.92	0.93	0.62	0.76
Inventory performance	7	0.74–0.87	0.89	0.90	0.92	0.61	0.78
Data quality	6	0.75–0.89	0.90	0.91	0.93	0.68	0.74
Demand volatility	5	0.70–0.84	0.82	0.83	0.87	0.57	0.43
Organizational analytics maturity	8	0.73–0.88	0.92	0.92	0.94	0.64	0.76

Table 2 presents the assessment of the reflective measurement model. All standardized indicator loadings were 0.70 or higher, with values ranging from 0.70 to 0.89, indicating that each observed item had an acceptable relationship with its intended latent construct. Consequently, no measurement item was removed from the final model. The loadings for artificial intelligence–driven demand forecasting ranged from 0.72 to 0.88, demonstrating that the items concerning machine-learning use, real-time forecast updating, cross-channel data integration, demand-pattern recognition, and predictive decision support adequately represented the underlying forecasting capability. The inventory performance item loadings ranged from 0.74 to 0.87, confirming that inventory availability, stockout reduction, excess stock reduction, turnover, replenishment accuracy, holding costs, and inventory positioning reflected a coherent organizational performance construct.

All Cronbach's alpha coefficients exceeded the minimum criterion of 0.70 and ranged from 0.82 for demand volatility to 0.92 for organizational analytics maturity. The rho_A coefficients ranged from 0.83 to 0.92, while the composite reliability coefficients ranged from 0.87 to 0.94. These results demonstrated satisfactory to excellent internal consistency across all constructs. The average variance extracted values ranged from 0.57 to 0.68 and exceeded the recommended threshold of 0.50, indicating that each latent variable explained more than half of the variance in its corresponding indicators. Data quality had the highest average variance extracted value at 0.68, followed by organizational analytics maturity at 0.64, artificial intelligence–driven demand forecasting at 0.62, inventory performance at 0.61, and demand volatility at 0.57.

Discriminant validity was supported by the heterotrait–monotrait ratio results. All pairwise HTMT values were below 0.85, ranging from 0.18 to 0.78. The highest value, 0.78, occurred between artificial intelligence–driven demand forecasting and inventory performance, but it remained below the conservative threshold of 0.85. The square root of the average variance extracted for each construct was also greater than its correlations with the other constructs, supporting the Fornell–Larcker criterion. Examination of indicator cross-loadings further showed that every item loaded more strongly on its intended construct than on any alternative construct. Taken together, the loading, reliability, convergent validity, and discriminant validity findings confirmed that the measurement model was psychometrically adequate and that the structural relationships could be tested without substantial measurement contamination.

Common method variance was also examined because the predictor, moderator, and outcome variables were measured using responses obtained from the same participants. An unrotated exploratory factor analysis showed that the first factor accounted for 31.8% of the total variance, which was substantially below the 50% threshold commonly used to indicate a serious single-factor problem. In addition, the full-collinearity variance inflation factor values ranged from 1.46 to 2.89 and remained below the conservative threshold of 3.3. These findings suggested that common method variance was unlikely to provide a sufficient explanation for the observed associations among the study variables.

Table 3. Structural Model Results for the Direct Effects on Inventory Performance

Predictor	Standardized coefficient	Standard error	t value	p value	95% confidence interval	f^2 effect size	Result
Artificial intelligence–driven demand forecasting	0.421	0.048	8.77	<0.001	0.327 to 0.514	0.244	Significant positive effect
Data quality	0.263	0.046	5.72	<0.001	0.171 to 0.351	0.103	Significant positive effect
Demand volatility	−0.148	0.039	3.79	<0.001	−0.224 to −0.072	0.041	Significant negative effect
Organizational analytics maturity	0.196	0.045	4.36	<0.001	0.109 to 0.283	0.061	Significant positive effect
Organizational size	0.052	0.039	1.32	0.188	−0.025 to 0.128	0.006	Nonsignificant
Omnichannel operating experience	0.087	0.040	2.20	0.028	0.010 to 0.165	0.015	Significant positive control effect
Retail sector	0.031	0.038	0.82	0.412	−0.044 to 0.105	—	Nonsignificant
E-commerce sector	0.046	0.037	1.26	0.208	−0.026 to 0.119	—	Nonsignificant
Distribution and logistics sector	−0.026	0.042	0.62	0.538	−0.107 to 0.056	—	Nonsignificant
Hybrid or multisector organization	0.038	0.039	0.97	0.331	−0.039 to 0.114	—	Nonsignificant

The structural model results presented in Table 3 showed that artificial intelligence–driven demand forecasting had a positive and statistically significant effect on inventory performance, $\beta = 0.421$, SE = 0.048, $t = 8.77$, $p < 0.001$. The bias-corrected 95% confidence interval ranged from 0.327 to 0.514 and did not include zero, confirming the stability of the estimated relationship. The coefficient indicated that, after controlling for data quality, demand volatility, organizational analytics maturity, organizational size, omnichannel experience, and industry sector, a one-standard-deviation increase in artificial intelligence–driven demand forecasting was associated with a 0.421-standard-deviation improvement in inventory performance. The f^2 value of 0.244 indicated a moderate and practically meaningful contribution of artificial intelligence forecasting to the explanation of inventory outcomes. This was the strongest direct effect in the model, demonstrating that the integration of machine learning, real-time demand signals, cross-channel information, and automated forecast updating contributed substantially to inventory availability, replenishment accuracy, stockout reduction, inventory turnover, and control of excess stock.

Data quality also exerted a positive and significant direct effect on inventory performance, $\beta = 0.263$, SE = 0.046, $t = 5.72$, $p < 0.001$, with a 95% confidence interval from 0.171 to 0.351. This result indicated that organizations with more accurate, complete, timely, accessible, and integrated data achieved better inventory outcomes independently of their level of artificial intelligence forecasting. Its f^2 value of 0.103 represented a small-to-moderate effect. Organizational analytics maturity had an additional positive effect on inventory performance, $\beta = 0.196$, SE = 0.045, t = 4.36, p < 0.001. This finding indicated that analytical infrastructure, managerial support, employee expertise, cross-functional coordination, and the institutionalization of data-based decision processes improved organizations' ability to convert forecasts into effective inventory actions.

Demand volatility had a statistically significant negative direct effect on inventory performance, $\beta = -0.148$, SE = 0.039, t = 3.79, $p < 0.001$. Its confidence interval ranged from −0.224 to −0.072, demonstrating that higher unpredictability and greater fluctuations in customer demand reduced the ability of organizations to maintain an efficient balance between product availability and inventory cost. Although the f^2 value of 0.041 indicated a relatively small direct effect, the result remained operationally relevant because even moderate deterioration in inventory performance may lead to stockouts, excess safety stock, emergency replenishment, and cross-channel fulfillment disruptions.

Among the organizational control variables, omnichannel operating experience had a small but statistically significant positive effect on inventory performance, $\beta = 0.087$, $p = 0.028$. This result indicated that organizations with longer experience in integrating physical and digital channels tended to achieve better inventory outcomes. Organizational size did not have a statistically significant effect, $\beta = 0.052$, $p = 0.188$, suggesting that larger organizations did not automatically achieve superior inventory performance once their forecasting, data, and analytical capabilities were considered. The industry dummy variables were also nonsignificant. Therefore, the central relationships were not attributable to the concentration of respondents in a particular organizational sector.

The model including the direct effects and control variables explained 54.7% of the variance in inventory performance. After the interaction effects were introduced, the explained variance increased to 61.2%, with an adjusted R^2 value of 0.600. The increase of 6.5 percentage points demonstrated that the contingent effects of data quality, demand volatility, and organizational analytics maturity provided meaningful additional explanatory power beyond the main effects. The Stone–Geisser Q^2 value for inventory performance was 0.421, which was greater than zero and indicated substantial predictive relevance. The standardized root mean square residual was 0.061, remaining below the threshold of 0.08 and supporting acceptable approximate model fit. In the PLSpredict analysis, the structural model produced lower root mean square prediction errors than the linear benchmark model for six of the seven inventory performance indicators. This pattern provided evidence that the model possessed moderate to strong out-of-sample predictive capability.

Table 4. Moderating Effects and Conditional Relationships Between Artificial Intelligence–Driven Demand Forecasting and Inventory Performance

Effect or conditional relationship	Standardized coefficient	Standard error	t value	p value	95% confidence interval	f^2 effect size
Interaction effects						
AI-driven forecasting × Data quality	0.163	0.040	4.08	<0.001	0.085 to 0.241	0.047
AI-driven forecasting × Demand volatility	−0.121	0.038	3.18	0.001	−0.195 to −0.047	0.028
AI-driven forecasting × Organizational analytics maturity	0.142	0.041	3.46	0.001	0.063 to 0.221	0.036
Conditional effect at levels of data quality						
Low data quality, one SD below the mean	0.258	0.055	4.69	<0.001	0.150 to 0.366	—
Mean data quality	0.421	0.048	8.77	<0.001	0.327 to 0.514	—
High data quality, one SD above the mean	0.584	0.057	10.25	<0.001	0.472 to 0.696	—
Conditional effect at levels of demand volatility						

Low demand volatility, one SD below the mean	0.542	0.057	9.51	<0.001	0.431 to 0.653	—
Mean demand volatility	0.421	0.048	8.77	<0.001	0.327 to 0.514	—
High demand volatility, one SD above the mean	0.300	0.054	5.56	<0.001	0.194 to 0.406	—
Conditional effect at levels of organizational analytics maturity						
Low analytics maturity, one SD below the mean	0.279	0.057	4.89	<0.001	0.167 to 0.391	—
Mean analytics maturity	0.421	0.048	8.77	<0.001	0.327 to 0.514	—
High analytics maturity, one SD above the mean	0.563	0.059	9.54	<0.001	0.448 to 0.678	—

As presented in Table 4, data quality significantly strengthened the positive relationship between artificial intelligence–driven demand forecasting and inventory performance, $\beta = 0.163$, SE = 0.040, $t = 4.08$, $p < 0.001$. The confidence interval from 0.085 to 0.241 excluded zero, confirming the significance of the interaction. At a low level of data quality, the conditional effect of artificial intelligence forecasting on inventory performance was positive and statistically significant but comparatively modest, $\beta = 0.258$, $p < 0.001$. At the mean level of data quality, the effect increased to $\beta = 0.421$, $p < 0.001$, and at a high level of data quality, the effect increased further to $\beta = 0.584$, $p < 0.001$. Therefore, the inventory benefits associated with artificial intelligence forecasting were substantially greater when forecasting algorithms had access to accurate, complete, timely, consistent, and integrated data. Although artificial intelligence forecasting remained beneficial under conditions of relatively weak data quality, its contribution to inventory performance was more than twice as strong in organizations reporting high data quality compared with those reporting low data quality.

Demand volatility significantly weakened the relationship between artificial intelligence–driven demand forecasting and inventory performance, $\beta = -0.121$, SE = 0.038, $t = 3.18$, $p = 0.001$. The confidence interval ranged from −0.195 to −0.047 and excluded zero. Under low demand volatility, the positive effect of artificial intelligence forecasting on inventory performance was relatively strong, $\beta = 0.542$, $p < 0.001$. At the mean level of demand volatility, the effect was $\beta = 0.421$, $p < 0.001$, whereas under high demand volatility, it decreased to $\beta = 0.300$, $p < 0.001$. Thus, artificial intelligence forecasting continued to improve inventory performance even under highly volatile demand conditions, but its effectiveness was reduced when customer demand changed rapidly, irregularly, and unpredictably. This finding suggested that abrupt structural changes, promotion-driven fluctuations, short-term shifts in channel preferences, and unusual market events limited the extent to which algorithmic forecasts could be translated into stable inventory improvements.

Organizational analytics maturity also significantly strengthened the positive effect of artificial intelligence–driven demand forecasting on inventory performance, $\beta = 0.142$, SE = 0.041, $t = 3.46$, $p = 0.001$. At a low level of analytics maturity, the conditional effect of artificial intelligence forecasting was $\beta = 0.279$, $p < 0.001$. The effect increased to $\beta = 0.421$ at the mean level and to $\beta = 0.563$ at a high level of organizational analytics maturity. These findings indicated that organizations possessing well-developed analytical infrastructure, qualified personnel, managerial commitment, standardized analytical processes, and cross-functional decision routines obtained greater inventory benefits from artificial intelligence forecasting. Technology adoption alone was therefore insufficient to maximize performance; organizations also required the managerial and organizational capacity to interpret model outputs, evaluate their operational implications, coordinate responses across departments, and translate predictions into purchasing, allocation, replenishment, and fulfillment decisions.

The interaction effect involving data quality had an f^2 value of 0.047, the interaction involving organizational analytics maturity had an f^2 value of 0.036, and the interaction involving demand volatility had an f^2 value of 0.028. Although these interaction effect sizes were relatively small, they produced a meaningful combined increase in the explained variance of inventory performance. In moderation research, interaction effects commonly account for less variance than main effects because they represent the incremental contribution of a product term after the main predictors have already been considered. The statistical significance, consistent confidence intervals, simple-slope patterns, and improvement in explained variance therefore provided adequate evidence that the effectiveness of artificial intelligence–driven forecasting was contingent on organizational and environmental conditions.

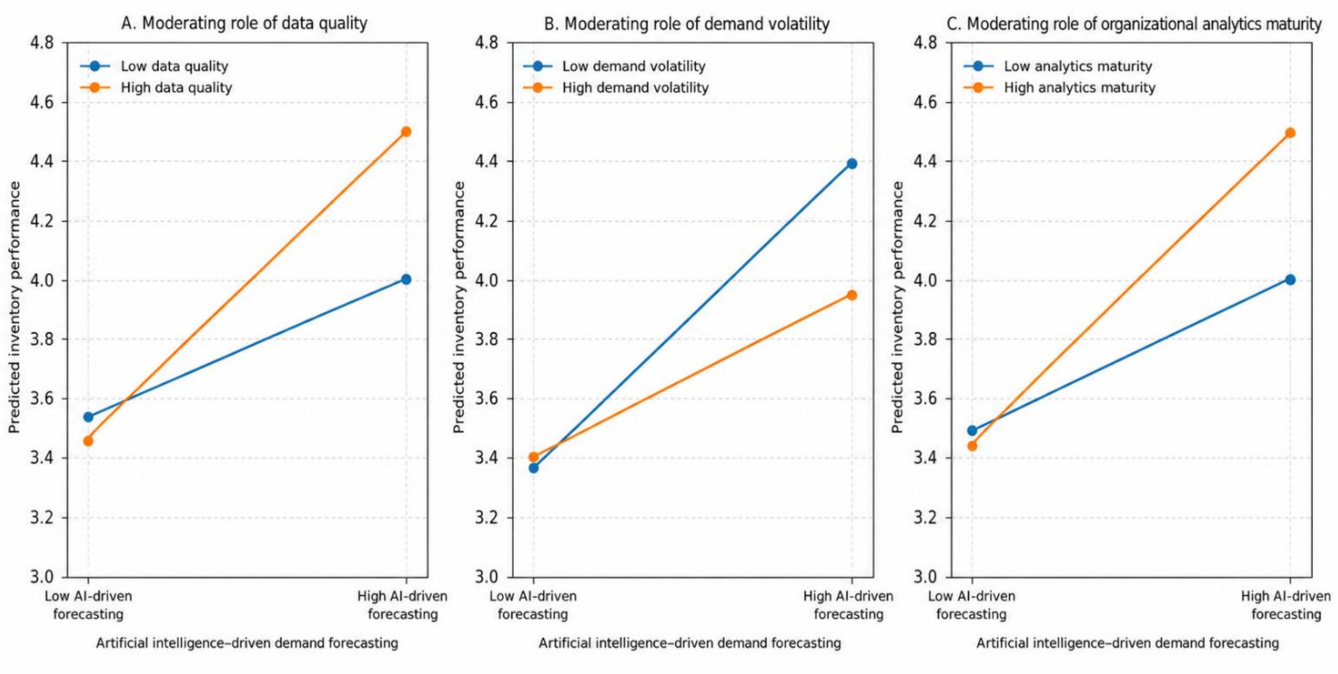

Figure 1. Conditional Effects of Artificial Intelligence–Driven Demand Forecasting on Inventory Performance at Low and High Levels of Data Quality, Demand Volatility, and Organizational Analytics Maturity

Figure 1 illustrates the three statistically significant moderating relationships. In the data quality panel, the predicted inventory performance line for organizations with high data quality rises more steeply than the line for organizations with low data quality. The difference between the two lines becomes progressively larger as artificial intelligence–driven forecasting increases, demonstrating that data quality amplifies the performance contribution of artificial intelligence forecasting. Organizations with low levels of artificial intelligence forecasting show relatively limited differences in inventory performance across levels of data quality, whereas organizations combining advanced forecasting with high-quality data achieve the highest predicted inventory performance.

In the demand volatility panel, both lines show a positive association between artificial intelligence forecasting and inventory performance, but the line representing low demand volatility is substantially steeper. The predicted inventory advantage associated with artificial intelligence forecasting is therefore greater in relatively stable demand environments. Under high demand volatility, the slope remains positive, indicating that artificial intelligence forecasting continues to provide operational value, but the improvement is weaker because rapidly changing demand patterns reduce the reliability and persistence of historically derived predictive relationships. The greatest predicted inventory performance occurs when advanced artificial intelligence forecasting is combined with low demand volatility, while organizations characterized by limited forecasting capability and high demand volatility display the lowest predicted performance.

In the organizational analytics maturity panel, the slope for organizations with high analytics maturity is considerably steeper than the slope for organizations with low analytics maturity. This pattern shows that analytics maturity enables organizations to extract greater operational value from artificial intelligence forecasting. At low levels of artificial intelligence use, the difference between organizations with high and low analytics maturity is comparatively modest. However, as artificial intelligence forecasting capability increases, the predicted difference in inventory performance expands. The combination of advanced artificial intelligence forecasting and high analytics maturity produces the highest inventory performance, whereas advanced technology accompanied by weak organizational analytics maturity generates a more limited improvement. The graphical patterns were therefore fully consistent with the interaction coefficients and conditional-effect results reported in Table 4.

Overall, the findings demonstrated that artificial intelligence–driven demand forecasting was a substantial predictor of inventory performance in omnichannel supply chains. The positive direct relationship remained statistically significant after accounting for organizational characteristics, data quality, demand volatility, and organizational analytics maturity. Data quality and analytics maturity independently improved inventory performance and amplified the contribution of artificial intelligence forecasting. Demand volatility directly reduced inventory performance and weakened, but did not eliminate, the positive effect of artificial intelligence forecasting. The final model explained 61.2% of the variance in inventory performance and demonstrated satisfactory explanatory power, predictive relevance, measurement quality, and approximate model fit. These results supported a contingent perspective in which artificial intelligence forecasting generates its greatest inventory benefits when it is supported by high-quality cross-channel data, embedded within a mature organizational analytics environment, and applied under demand conditions that remain sufficiently interpretable for predictive models.

Discussion and Conclusion

The present study examined the effect of artificial intelligence–driven demand forecasting on inventory performance in omnichannel supply chains and assessed whether data quality, demand volatility, and organizational analytics maturity conditioned this relationship. The findings showed that artificial intelligence–driven demand forecasting had a strong, positive, and statistically significant effect on inventory performance. Organizations that more extensively used machine learning, automated pattern recognition, real-time updating, cross-channel information integration, and predictive recommendations reported higher inventory availability, fewer stockouts, lower excess inventory, more accurate replenishment decisions, improved turnover, and better allocation of inventory across stores, warehouses, distribution centers, and fulfillment locations. This result supports the view that artificial intelligence forecasting functions as an operational capability rather than merely as an information-processing tool. In omnichannel systems, where demand signals originate from multiple interconnected channels and where a single unit of inventory may be used to satisfy store purchases, online orders, click-and-collect transactions, or home delivery, the ability to continuously update forecasts and detect complex demand patterns can substantially improve inventory decisions. The result is consistent with the argument that demand forecasting connects information technology capability to supply chain agility by enabling organizations to identify changes in demand and adjust operational plans more rapidly (15). It also aligns with research emphasizing that artificial intelligence can support high-quality industrial development through intelligent prediction, process optimization, and data-based operational control (19). In addition, the finding supports the broader retail forecasting literature, which identifies forecast quality and the effective use of forecasting outputs as central determinants of inventory and operational performance (13).

The positive relationship between artificial intelligence–driven forecasting and inventory performance can be explained by the particular complexity of omnichannel fulfillment. Conventional forecasting systems often rely on aggregated historical sales and relatively stable channel structures, whereas omnichannel supply chains require more granular predictions across products, locations, channels, customer segments, and short planning horizons. Artificial intelligence systems can integrate transactional, promotional, pricing, customer, and fulfillment data and identify nonlinear interactions that may be difficult to capture through traditional models. This capability is especially valuable when organizations must determine not only how much inventory to hold but also where inventory should be positioned and from which location orders should be fulfilled. The result therefore complements studies showing that inventory optimization and order allocation must be coordinated in omnichannel multi-echelon networks (9). It is also consistent with the transshipment perspective, which demonstrates that inventory imbalances across locations can be corrected more effectively when organizations possess timely information and coordinated allocation mechanisms (10). Furthermore, the finding corresponds with research on product proliferation, which shows that increasing assortment complexity intensifies supply chain coordination and inventory management challenges (7). Artificial intelligence forecasting may reduce these challenges by producing more differentiated demand estimates and enabling organizations to avoid applying uniform replenishment rules across products and channels with distinct demand profiles.

Data quality had a significant positive direct effect on inventory performance, indicating that organizations with more accurate, complete, timely, consistent, accessible, and integrated data achieved better inventory outcomes even after the level of artificial intelligence forecasting was considered. This finding confirms that inventory decisions depend not only on the sophistication of forecasting algorithms but also on the reliability of the data infrastructure supporting operational planning. In omnichannel environments, inconsistencies between point-of-sale records, online orders, warehouse balances, return transactions, pricing systems, and promotional databases can generate inaccurate demand estimates and misleading replenishment signals. When inventory records are delayed or channel data are fragmented, organizations may simultaneously experience stockouts in one location and surplus inventory in another. The result is consistent with studies emphasizing that big data analytics contributes to retail marketing and supply chain optimization when organizations can transform large and diverse datasets into reliable operational information (16). It also supports the proposition that integrating supply chain analytics with marketing information enhances customer and demand insights by connecting operational data with market-facing signals (17). Similarly, the economic value of management information systems integration derives from improved coordination between operations and customer relationship activities, which can reduce information fragmentation and support more coherent decisions (18).

More importantly, data quality significantly strengthened the positive effect of artificial intelligence–driven demand forecasting on inventory performance. The effect of artificial intelligence forecasting was positive at low, average, and high levels of data quality, but it was substantially stronger when data quality was high. This result demonstrates that artificial intelligence cannot compensate fully for unreliable or fragmented information. Machine-learning systems learn from the data supplied to them; consequently, errors, missing observations, inconsistent product identifiers, delayed inventory updates, and incomplete channel histories can become embedded in model outputs.

High-quality data, in contrast, allow algorithms to identify demand patterns more accurately, update forecasts more quickly, and generate recommendations that are more suitable for operational execution. This finding aligns with evidence that information sharing and blockchain-supported visibility can improve supply chain performance when they increase the reliability, traceability, and accessibility of shared information (23). It also extends research on logistics integration by showing that the benefits of predictive technology are amplified when information can move consistently across supply chain functions and partners (24). The result therefore suggests a complementary relationship: data quality improves inventory performance directly and simultaneously increases the value obtained from artificial intelligence forecasting.

Demand volatility had a significant negative direct effect on inventory performance. Organizations operating under rapidly changing, irregular, and difficult-to-predict demand conditions reported weaker inventory outcomes, including greater difficulty maintaining availability, controlling surplus stock, and making efficient replenishment decisions. This result is theoretically expected because inventory policies are often calibrated using assumptions about demand distributions, lead times, service levels, and forecast errors. When demand changes abruptly, historical relationships may become less informative, safety-stock requirements may increase, and replenishment cycles may no longer correspond to actual market behavior. The finding is consistent with evidence from the COVID-19 period, when sudden changes in customer behavior, product demand, operating restrictions, and supply availability disrupted conventional inventory planning systems (25). It also supports research emphasizing the need for resilient retail supply chain strategies under pandemic-related and other systemic disruptions (26). Enterprise risk management research similarly indicates that uncertainty and operational risk can affect inventory management and broader firm operations (27). In omnichannel systems, the consequences of volatility may be especially pronounced because fluctuations can occur not only in aggregate demand but also in channel preferences, delivery choices, return rates, and the geographical distribution of orders.

The moderation analysis further showed that demand volatility weakened the positive relationship between artificial intelligence–driven demand forecasting and inventory performance. Artificial intelligence forecasting remained beneficial even at high levels of volatility, but its positive effect was considerably stronger when demand conditions were relatively stable. This result indicates that advanced forecasting systems are valuable under uncertainty but are not immune to structural breaks, rare events, abrupt changes in customer behavior, or demand patterns that have little precedent in historical data. Artificial intelligence models can detect complex relationships and adapt as new information becomes available, yet their predictive performance may deteriorate when the underlying data-generating process changes faster than the model can be retrained or when external disruptions produce conditions not represented in prior observations. The finding is compatible with studies of omnichannel reverse logistics, which show that disruption recovery involves interconnected risks affecting returns, inventory flows, capacity, and service performance (12). It also accords with research highlighting that digital transformation in logistics must be accompanied by flexible planning and adaptive decision structures rather than exclusive reliance on automated predictions (20). Thus, the weakening effect of volatility should not be interpreted as evidence against artificial intelligence forecasting. Instead, it indicates that highly volatile environments require shorter forecast-update cycles, scenario-based planning, human judgment, rapid exception management, and flexible replenishment policies in addition to predictive models.

Organizational analytics maturity had a significant positive direct effect on inventory performance. Organizations with stronger analytical infrastructure, greater managerial support, qualified personnel, standardized analytical processes, cross-functional information sharing, and established routines for converting analytical outputs into decisions reported superior inventory outcomes. This finding demonstrates that inventory performance is influenced by the organizational capacity to interpret and act on information, not simply by the availability of technology. A forecasting system may generate accurate predictions, but performance improvements will remain limited if procurement, logistics, merchandising, marketing, and store operations do not coordinate their responses. The result is consistent with Industry 4.0 and lean integration research, which emphasizes that digital technologies produce greater value when they are aligned with process discipline, managerial systems, and continuous improvement practices (21). It also supports the view that future supply chain technology infrastructure should be designed through comprehensive mapping of organizational, informational, and physical interdependencies (22). In addition, the result corresponds with research on omnichannel transformation, which shows that performance development is embedded in broader changes in organizational structures, platform relationships, and operational capabilities (5, 6).

Organizational analytics maturity also strengthened the positive effect of artificial intelligence–driven forecasting on inventory performance. The conditional effect of forecasting was substantially greater in organizations with high analytics maturity than in those with low maturity. This finding suggests that technology adoption alone is insufficient for maximizing operational value. Mature organizations are more likely to monitor model accuracy, investigate forecast deviations, integrate predictions with replenishment systems, assign clear decision responsibilities, and combine algorithmic recommendations with managerial knowledge. They are also more capable of coordinating decisions across functional boundaries and ensuring that forecasting outputs influence purchasing, allocation, inventory positioning, and fulfillment. The finding aligns with research on logistics integration capability, which indicates that integrated supply chain processes mediate and enhance performance in omnichannel retailing (24). It is also compatible with studies of digital transformation in manufacturing and logistics, where successful implementation depends on organizational readiness, skill development, and process redesign (19, 20). The interaction effect therefore reveals that analytics maturity acts as a value-realization mechanism: it allows organizations to translate technical forecasting capability into coordinated inventory action.

The model explained a substantial proportion of the variance in inventory performance, and the addition of the three interaction terms meaningfully increased its explanatory power. The results therefore support a contingency-based interpretation of artificial intelligence value creation. Artificial intelligence–driven demand forecasting was the strongest direct predictor, but its effectiveness depended on the quality of organizational data, the stability of demand conditions, and the maturity of analytical capabilities. These findings integrate several previously separate streams of research. Studies of e-commerce logistics have emphasized the redesign of fulfillment systems and the need for coordinated logistics frameworks (1); studies of omnichannel retailing have highlighted seamless customer experience and channel integration (3, 4); and inventory research has examined product allocation, channel supply, and multi-echelon optimization (8, 9). The present findings connect these perspectives by showing that forecasting capability contributes to inventory performance most strongly when the surrounding information and organizational systems support its effective application. They also reinforce the broader principle, evident across complex predictive domains, that analytical models depend on the quality, structure, and stability of the environments in which they are used (28-30).

This study had several limitations that should be considered when interpreting its findings. First, the cross-sectional design did not permit definitive causal conclusions, because artificial intelligence forecasting, data quality, analytics maturity, and inventory performance were measured at one point in time. Second, the study relied primarily on perceptual self-report data provided by managers, supervisors, and specialists, which may have been affected by social desirability, recall error, or overly favorable assessments of organizational capabilities. Third, the sample was limited to organizations operating in Tehran, and the findings may not fully represent firms in other regions, countries, institutional environments, or levels of technological development. Fourth, the use of purposive and convenience sampling may have increased the participation of organizations that were already more interested in analytics and digital transformation. Fifth, demand volatility and inventory performance were measured using multi-item perceptual scales rather than objective transaction-level indicators such as forecast error, fill rate, stockout frequency, inventory turnover, or holding cost. Finally, the study examined analytics maturity as an overall organizational capability and did not separately evaluate technical infrastructure, analytical talent, governance, culture, and managerial decision routines.

Future studies should use longitudinal and panel designs to examine how artificial intelligence forecasting capabilities and inventory performance evolve over time and whether changes in data quality or analytics maturity precede improvements in operational outcomes. Researchers should combine survey data with objective organizational records, including forecast accuracy, mean absolute percentage error, service level, lost sales, inventory turnover, order cycle time, markdown rates, and fulfillment costs. Multi-country and cross-regional studies could determine whether the observed relationships differ according to digital infrastructure, market development, regulation, industry structure, or supply chain complexity. Future models may distinguish among specific artificial intelligence techniques, including gradient boosting, neural networks, reinforcement learning, probabilistic forecasting, and hybrid human–machine forecasting. Additional moderators such as supply disruption, product perishability, assortment complexity, channel integration, lead-time uncertainty, managerial trust in artificial intelligence, and human override behavior should also be examined. Qualitative case studies could provide deeper insight into how firms redesign planning routines, manage resistance, interpret model uncertainty, and coordinate decisions across marketing, operations, logistics, and information technology functions.

Managers should treat artificial intelligence forecasting as part of an integrated operational transformation rather than as an isolated software acquisition. Before expanding artificial intelligence use, organizations should establish common product identifiers, reliable inventory records, consistent channel definitions, automated data validation, and clear ownership of data quality. Forecasting outputs should be connected directly to replenishment, allocation, and exception-management processes while preserving human review for unusual events and structural market changes. Firms operating under high demand volatility should shorten forecast-update intervals, use scenario planning, monitor model drift, maintain flexible safety-stock rules, and create rapid-response teams for exceptional demand conditions. Organizations should also invest in analytical training for managers and operational employees, establish cross-functional forecasting governance, define responsibilities for acting on recommendations, and routinely compare predicted and realized inventory outcomes. The greatest performance gains are likely to occur when advanced forecasting technology is supported by high-quality integrated data, mature analytical routines, and flexible decision processes capable of responding to changing omnichannel demand.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adheried in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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