Management Strategies and Engineering Sciences 2027; 9(1):1-18



Designing an Intelligent Decision-Support Model to Enhance Strategic Decision-Making in Organizations Using Business Intelligence and Machine Learning: A Case Study of the Iranian Retail Industry

Esmaeil Khoobi[1], Mohammadreza Sanaei[1*], Reza Ehtesham Rasi[2]

[1] Department of IT Management, QA.C., Islamic Azad University, Qazvin, Iran
[2] Department of Industrial Management, Qa.C., Islamic Azad University, Qazvin, Iran

*** Corresponding author email address**: MR.Sanaei@iau.ac.ir

Received: 2026-06-09 **Revised:** 2026-10-24 **Accepted:** 2026-11-01 **Initial Publish:** 2026-11-01 **Final Publish:** 2027-01-01

Abstract

This study aimed to design and validate an intelligent decision-support model for enhancing strategic decision-making through the integrated use of business intelligence and machine learning in the Iranian retail industry. This applied, quantitative, cross-sectional study was conducted among 327 senior and middle managers, strategic planning specialists, business intelligence experts, information technology managers, data analysts, and other decision-related professionals working in retail organizations in Tehran, Iran. Data were collected using a researcher-developed questionnaire assessing data quality, information integration, business intelligence infrastructure, analytical capability, organizational readiness, machine-learning capability, predictive insight quality, decision speed, decision accuracy, strategic decision quality, and decision-support effectiveness, together with selected organizational and retail performance indicators. The measurement and structural models were analyzed using SPSS 29 and SmartPLS 4. Machine-learning models, including random forest, extreme gradient boosting, support vector machine, and multilayer perceptron neural network, were developed and evaluated in Python using training, validation, and test subsets. Information integration ($\beta = .41$, $p < .001$) and data quality ($\beta = .29$, $p < .001$) significantly predicted business intelligence infrastructure. Business intelligence infrastructure significantly predicted analytical capability ($\beta = .46$, $p < .001$), while analytical capability ($\beta = .43$, $p < .001$) and organizational readiness ($\beta = .31$, $p < .001$) predicted machine-learning capability. Machine-learning capability strongly predicted predictive insight quality ($\beta = .48$, $p < .001$), which subsequently predicted decision speed ($\beta = .44$, $p < .001$), decision accuracy ($\beta = .51$, $p < .001$), and strategic decision quality ($\beta = .36$, $p < .001$). Decision accuracy was a stronger predictor of strategic decision quality ($\beta = .39$, $p < .001$) than decision speed ($\beta = .17$, $p < .001$). The model explained 74.3% of the variance in strategic decision quality and 76.1% of the variance in decision-support effectiveness. Extreme gradient boosting achieved the best predictive performance with test $R^2 = .87$ and AUC = .94. The findings demonstrate that the integration of reliable business intelligence infrastructure with organizational readiness, analytical capability, and machine learning can substantially improve the quality, speed, accuracy, and overall effectiveness of strategic decision-making in retail organizations.

Keywords: *Business Intelligence; Machine Learning; Strategic Decision-Making; Intelligent Decision-Support System; Predictive Analytics; Organizational Intelligence; Retail Industry.*

How to cite this article:

Khoobi, E., Sanaei, M., & Ehtesham Rasi, R. (2027). Designing an Intelligent Decision-Support Model to Enhance Strategic Decision-Making in Organizations Using Business Intelligence and Machine Learning: A Case Study of the Iranian Retail Industry. Management Strategies and Engineering Sciences, 9(1), 1-18.

1. Introduction

Strategic decision-making has become increasingly complex in contemporary organizations as competitive environments grow more volatile, digitally interconnected, data-intensive, and uncertain. Organizations are no longer required merely to process larger volumes of information; they must transform heterogeneous, rapidly changing data into timely strategic insight capable of guiding decisions concerning market positioning, customer behavior, resource

© 2027 The author(s). Published By: The Research Department of Economics and Management of Tomorrow's Innovators. This is an open access article under the terms of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC 4.0) License.

allocation, supply chain coordination, pricing, innovation, investment, risk, and organizational adaptation. This shift has elevated the strategic importance of organizational intelligence, which can be understood as the capacity of an organization to acquire, interpret, integrate, and use information in ways that improve collective judgment and coordinated action. Within this context, intelligence should not be regarded as a purely technological property but as a multidimensional organizational capability emerging from the interaction of data, cognition, managerial routines, information systems, human expertise, and institutional structures [1]. The growing knowledge economy has further reinforced the role of cognitively informed leadership and knowledge-intensive management, particularly as organizations attempt to combine analytical evidence with human interpretation, intuition, experience, and strategic awareness [2]. Behavioral strategy research has likewise demonstrated that strategic choices are influenced not only by formal analysis but also by cognitive heuristics, managerial perceptions, bounded rationality, emotions, and organizational context [3]. Evidence concerning emotions in boardroom decision-making similarly indicates that strategic judgment cannot be reduced to purely rational computation because emotional and behavioral mechanisms shape risk perception, prioritization, conflict, and choice among strategic alternatives [4]. These developments have intensified interest in intelligent decision-support architectures that can combine the strengths of computational analysis with the contextual reasoning of managers, rather than attempting to substitute one for the other.

The digital transformation of organizations has provided the technological infrastructure necessary for this transition. Business intelligence has evolved from a predominantly reporting-oriented function into a strategic capability that integrates operational databases, enterprise systems, customer information, financial records, market signals, and external intelligence into analytical environments that support decision-making. Competitive intelligence has long been recognized as an important component of strategic management because it enables organizations to monitor competitors, interpret environmental developments, and convert external information into strategic responses [5]. Intelligence management also contributes to entrepreneurship and modernization by enabling firms to connect knowledge, behavior, and managerial intelligence with opportunity recognition and industrial development [6]. The quality of such intelligence, however, depends heavily on the underlying information architecture. Effective data-driven governance requires data models that ensure consistency, traceability, integration, and reliable access across organizational processes [7]. In addition, information processing must be interactive rather than merely archival; research in enterprise risk management has shown that structured information exchange, feedback, and continuous interpretation can strengthen organizational responses to complex and uncertain conditions [8]. When information volumes exceed human processing capacity, however, more data do not automatically produce better decisions. Agent-based research on collective decision-making has shown that information-sharing strategies must be carefully designed because information overload can impair coordination, slow processing, and weaken group-level outcomes [9]. Consequently, the strategic challenge is not simply to accumulate data but to establish systems that select, organize, prioritize, interpret, and contextualize information in ways that support managerial action.

Artificial intelligence and machine learning have substantially expanded the capabilities of such systems by allowing organizations to identify patterns that are difficult to detect using conventional reporting or descriptive analytics. Artificial intelligence is increasingly connected with business strategy and digital transformation because it enables predictive modeling, automation, adaptive resource allocation, and algorithmically supported decision processes [10]. More recent work suggests that the AI revolution is changing the architecture of business decision-making itself by shifting organizations from retrospective analysis toward anticipatory and predictive decision processes [11]. Intelligent automation further extends this transition by integrating analytical reasoning with process execution, enabling organizations to use predictive outputs not only to understand events but also to redesign workflows and managerial responses [12]. Cognitive automation illustrates a related development in which computational systems increasingly perform tasks that require perception, categorization, inference, judgment, and adaptation, thereby reshaping the boundary between human and machine decision roles [13]. In industrial settings, emerging frameworks for AI-driven decentralized control demonstrate how intelligent systems can coordinate distributed operational decisions while remaining connected to broader strategic objectives [14]. Similar advances in autonomous transportation and embodied intelligence show that intelligent systems increasingly combine sensing, environmental interpretation, adaptive control, and

autonomous action in complex real-time settings [15]. Architectural research on embodied intelligent spaces likewise emphasizes integration mechanisms through which sensing, computation, environmental interaction, and decision logic can be combined within a unified technical framework [16]. Although these developments emerge from different technological domains, they collectively illustrate a broader transition toward systems capable of transforming continuous streams of organizational and environmental data into context-sensitive predictions and recommended actions.

Nevertheless, the increasing computational power of artificial intelligence does not eliminate the importance of human judgment. Rather, current scholarship increasingly emphasizes hybrid intelligence and complementary human-machine decision-making. The concept of dual-brain fusion, for example, highlights bidirectional interaction between human cognition and brain-inspired systems, suggesting that intelligent technologies are most powerful when they augment rather than simply imitate human reasoning [17]. Similar principles are visible in Industry 5.0, where design management increasingly depends on the coordinated interaction of artificial intelligence, human expertise, and machine capabilities [18]. In high-stakes settings such as critical care, artificial intelligence has been conceptualized as a support mechanism that should remain integrated with pathophysiological reasoning and clinical judgment rather than becoming an isolated decision authority [19]. AI-augmented nursing similarly emphasizes that intelligent technologies must be embedded in professional judgment, psychological awareness, and human-centered care [20]. These perspectives are directly relevant to organizational strategy because strategic problems are rarely fully structured. Managers must often interpret ambiguous signals, weigh conflicting objectives, consider organizational politics, anticipate stakeholder responses, and make decisions under incomplete information. Accordingly, the value of intelligent decision-support systems lies not only in predictive accuracy but also in their ability to generate explanations, prioritize alternatives, expose uncertainty, and enhance managerial interpretation.

The need for explainability is particularly important because algorithmic decision support can reproduce or even amplify existing cognitive and organizational biases. Intelligence analysis in digital environments remains vulnerable to anchoring, confirmation bias, overconfidence, selective attention, framing effects, and automation bias, especially when decision-makers interact with highly complex analytical outputs [21]. Research on executive decision-making suggests that big data analytics, artificial intelligence, and explainable systems can contribute to bias mitigation when they are designed to challenge intuitive assumptions, reveal alternative interpretations, and make the evidential basis of recommendations transparent [22]. Cognitive diversity can further improve analytical quality by exposing decision processes to multiple perspectives and reducing the risk of homogeneous interpretation within intelligence communities and strategic teams [23]. Research in cybersecurity similarly demonstrates that cognitive science is increasingly relevant to understanding how human attention, perception, and judgment interact with complex technical systems [24]. The growing field of neuro-management and neuro-strategy also reflects increasing interest in the cognitive foundations of leadership, organizational behavior, and strategic choice [25]. Psychological perspectives on human resource management likewise show that strategic organizational outcomes remain strongly dependent on motivation, perception, behavior, and individual differences, even in increasingly data-driven environments [26]. These findings collectively indicate that effective intelligent decision support should not be designed as a black-box prediction mechanism. It should instead create an interpretable interface between machine-generated evidence and human strategic reasoning.

The integration of business intelligence and machine learning is therefore especially promising because these technologies address complementary stages of the organizational decision process. Business intelligence systems are particularly effective at aggregating historical and current data, monitoring key performance indicators, generating dashboards, supporting descriptive analysis, and creating a shared informational basis for decision-making. Machine-learning techniques extend these capabilities by identifying nonlinear patterns, estimating future outcomes, classifying strategic conditions, detecting anomalies, and ranking alternative actions. Together, they can produce a layered decision architecture in which reliable data are collected and integrated, descriptive intelligence is generated, predictive algorithms estimate likely developments, and managers evaluate alternative strategic responses. Research on intelligent automation has shown that such integration can contribute to more adaptive and sustainable forms of organizational transformation [27]. Systematic work on organizational intelligence for sustainability further indicates that digital transformation, artificial intelligence, and capability-based mechanisms

should be understood as interconnected microfoundations of organizational intelligence rather than as isolated technological investments [28]. This capability perspective is especially important because the strategic value of technology depends not only on technical infrastructure but also on managerial competence, organizational readiness, absorptive capacity, information culture, and the ability to translate analytical outputs into action.

Implementation remains a critical challenge. Research in emerging-economy public manufacturing organizations has shown that artificial intelligence adoption may be constrained by inadequate infrastructure, technical complexity, skills shortages, resistance to change, data limitations, and organizational governance problems [29]. These barriers are likely to be equally important in private-sector organizations attempting to integrate advanced analytics with existing information systems. Cultural intelligence also affects strategy activation because managerial attitudes, organizational climate, and cultural conditions shape how strategies are interpreted and implemented [30]. Top management characteristics can influence strategic change and performance as well, demonstrating that executive composition and managerial cognition affect the organization's capacity to redirect strategic priorities [31]. Consequently, an intelligent strategic decision-support model must incorporate organizational readiness alongside technological variables. A technically sophisticated predictive model may have limited strategic utility if managers do not trust its recommendations, data are fragmented across departments, analytical outputs are not aligned with strategic objectives, or organizational structures prevent the use of evidence in decision processes.

The importance of organizational context becomes even more evident during conditions of disruption and crisis. Strategic support systems designed for crisis management must be capable of integrating rapidly changing information, evaluating uncertainty, supporting scenario analysis, and helping decision-makers compare alternative responses under time pressure [32]. Modern cyber-physical infrastructures likewise require the integration of system-information technologies and cognitive approaches because organizational resilience increasingly depends on both technical monitoring and intelligent human interpretation [33]. Emerging artificial intelligence applications also introduce new categories of organizational risk. Occupational safety research has emphasized that AI can generate novel risks related to automation, system opacity, human oversight, accountability, and technology-mediated work [34]. These concerns reinforce the need for decision-support models that explicitly preserve managerial responsibility, provide interpretable outputs, and support risk-aware strategic action. The possibility of artificial intelligence occupying executive roles has even been explored conceptually, but such proposals continue to raise questions regarding authority, accountability, contextual understanding, legitimacy, and the limits of algorithmic leadership [35]. For most organizations, therefore, the more viable approach is not fully autonomous strategic management but intelligent augmentation of executive decision-making.

The retail industry provides a particularly appropriate setting for examining this issue because retail organizations generate large volumes of heterogeneous and rapidly changing data. Sales transactions, customer interactions, loyalty programs, digital channels, inventory records, supplier performance, promotional campaigns, logistics systems, pricing information, and market signals together create a highly data-rich environment. At the same time, retail strategy is characterized by short decision cycles, demand volatility, narrow margins, changing consumer preferences, intense competition, and continuous pressure to coordinate operational and strategic decisions. Managers must make decisions concerning assortment, replenishment, pricing, promotion, customer segmentation, branch performance, supplier selection, inventory allocation, and market expansion, often under substantial uncertainty. These characteristics create strong potential for combining business intelligence with machine learning. Business intelligence can establish a coherent view of organizational performance, while machine learning can predict demand, identify emerging customer patterns, estimate the consequences of alternative decisions, and support prioritization of strategic actions. However, the usefulness of such systems depends on the quality and integration of organizational data, the maturity of analytical capabilities, the readiness of managers to use algorithmic outputs, and the extent to which predictive insights can be converted into improved decision speed and decision accuracy.

This issue is particularly important in the Iranian retail industry, where large chain stores, supermarkets, department stores, and multichannel retailers are increasingly exposed to digital competition, changing customer expectations, inflationary pressures, supply uncertainty, pricing volatility, and operational complexity. In such an environment, conventional experience-based management may remain

valuable, but it may not be sufficient for processing the breadth and speed of information required for contemporary strategic decisions. The strategic management literature increasingly recognizes that digital-era decision frameworks must integrate technological, analytical, cognitive, and organizational dimensions rather than relying on isolated managerial tools [36]. At the same time, organizational intelligence must be operationalized in a way that links data capabilities to actual strategic outcomes rather than treating intelligence as an abstract organizational attribute. Existing studies provide strong evidence for the importance of business intelligence, artificial intelligence, predictive analytics, cognitive diversity, behavioral strategy, human-machine collaboration, and organizational readiness, but these streams of research are often examined separately. Less attention has been given to integrated empirical models that connect data quality, information integration, business intelligence infrastructure, analytical capability, organizational readiness, machine-learning capability, predictive insight quality, decision speed, decision accuracy, strategic decision quality, and overall decision-support effectiveness within a single coherent framework.

This gap is important because the practical value of intelligent decision support depends on understanding the full chain through which organizational data become strategic action. Reliable data must first be available and integrated; business intelligence infrastructure must then transform these data into usable managerial information; analytical and organizational capabilities must enable advanced modeling; machine-learning methods must generate accurate and interpretable predictions; and these predictive insights must ultimately improve the quality, speed, and accuracy of managerial decisions. A fragmented approach that evaluates only one of these stages cannot adequately explain why some organizations obtain strategic value from artificial intelligence while others do not. Furthermore, the retail context requires predictive models that are not only accurate but also operationally relevant and understandable to managers. Explainable ensemble techniques such as gradient boosting are particularly suitable because they can capture complex nonlinear relationships while still allowing feature-importance analysis and managerial interpretation. Accordingly, an empirically validated decision-support architecture that integrates business intelligence, organizational capability, and machine learning can provide both theoretical and practical contributions by clarifying the mechanisms through which intelligent technologies enhance strategic decision-making.

Therefore, the aim of this study was to design and validate an intelligent decision-support model for enhancing strategic decision-making in organizations through the integrated use of business intelligence and machine learning, with specific application to the Iranian retail industry.

2. Methodology

This study employed an applied, quantitative, cross-sectional research design with a model-development and predictive analytics approach to design and validate an intelligent decision-support model for enhancing strategic decision-making through the integration of business intelligence and machine learning in the Iranian retail industry. The study was conducted in Tehran, Iran, because a substantial proportion of the headquarters, central administrative units, data-analysis departments, and strategic management offices of major Iranian retail organizations and chain stores are located in this city. The statistical population consisted of senior and middle managers, strategic planning managers, business intelligence specialists, information technology managers, data analysts, marketing managers, operations managers, supply chain managers, and other organizational experts who were directly involved in data-driven decision-making within large and medium-sized retail organizations operating in Tehran. To ensure that respondents had adequate knowledge of both organizational decision-making and data-based management systems, the inclusion criteria were having at least a bachelor's degree, a minimum of three years of professional or managerial experience in the retail industry, direct involvement in strategic or analytical decision-making processes, and familiarity with at least one organizational information system, business intelligence platform, enterprise resource planning system, customer relationship management system, or data analytics application. Individuals who had less than three years of relevant experience, occupied positions without involvement in organizational decision-making, or submitted questionnaires with substantial missing information were excluded from the study. A total of 327 eligible participants were included in the final analysis. Participants were recruited from selected chain retailers, large retail companies, department stores, supermarkets, and multichannel retail businesses in Tehran through a multistage purposive and stratified sampling procedure. In the first stage, retail organizations possessing computerized information systems and a sufficient volume of operational

and managerial data were identified. In the second stage, relevant organizational units, including strategic planning, information technology, business intelligence, marketing, sales, logistics, supply chain, finance, and operations, were selected. Participants were subsequently recruited proportionally from these functional areas to provide representation of the major organizational roles involved in strategic decision-making. The research framework conceptualized intelligent strategic decision support as an integrated mechanism in which business intelligence capabilities transform dispersed organizational data into structured managerial information, while machine-learning algorithms identify nonlinear relationships, predict organizational outcomes, and prioritize strategic alternatives. The principal constructs examined in the conceptual model included data quality, information integration, business intelligence infrastructure, analytical capability, organizational readiness, machine-learning capability, predictive insight quality, decision speed, decision accuracy, strategic decision quality, and perceived effectiveness of the intelligent decision-support system. Participation was voluntary, respondents were informed about the purpose and procedures of the research, anonymity and confidentiality were maintained throughout the study, and the collected information was analyzed only in aggregated form.

Data were collected using a researcher-developed questionnaire together with structured organizational and analytical data extracted from the participating retail organizations' information environments. Development of the questionnaire was based on the conceptual domains of business intelligence capability, data-driven management, machine-learning readiness, strategic decision-making, and intelligent decision-support systems. The initial item pool was developed after reviewing the theoretical literature and established measurement approaches in business intelligence, information systems, analytics capability, organizational decision-making, and technology-enabled strategic management. The preliminary instrument contained items designed to assess the availability, accessibility, integration, timeliness, consistency, and reliability of organizational data; the extent to which business intelligence systems supported reporting, visualization, dashboarding, multidimensional analysis, and managerial interpretation; the organization's analytical infrastructure and availability of technically qualified personnel; the use and organizational readiness for predictive and machine-learning techniques; the quality, speed, flexibility, and evidence orientation of strategic decisions; and managers' perceptions of the usefulness of an intelligent decision-support mechanism. Responses were recorded using a five-point Likert scale ranging from 1, representing strongly disagree, to 5, representing strongly agree. Content validity was assessed by a panel of experts with academic or professional expertise in strategic management, information systems, business intelligence, machine learning, data science, and retail management. The experts evaluated the clarity, relevance, representativeness, and conceptual adequacy of each item, and ambiguous or redundant items were revised or removed before administration of the final instrument. A pilot administration was also conducted with a small group of retail managers and data specialists who were not included in the final sample to examine comprehensibility, completion time, item consistency, and technical terminology. Construct validity was subsequently assessed through measurement-model analysis, and internal consistency was evaluated using Cronbach's alpha and composite reliability coefficients. Convergent validity was examined using standardized factor loadings and average variance extracted, while discriminant validity was evaluated by comparing interconstruct relationships and the heterotrait-monotrait ratio. In addition to questionnaire data, structured organizational indicators were used to develop the machine-learning component of the decision-support model. These indicators represented dimensions commonly used in strategic retail analysis, including sales performance, sales growth, inventory turnover, stock-out frequency, product return rate, gross margin, promotional response, customer purchase frequency, customer retention, average transaction value, demand variability, operational costs, supplier performance, and selected market and branch-level performance measures. Prior to analysis, all available organizational records were anonymized, standardized into a common analytical structure, and screened for inconsistencies. Personally identifiable customer information was not incorporated into the analytical dataset. The resulting integrated dataset therefore combined managerial assessments of organizational intelligence and strategic decision-making capabilities with quantitative retail performance indicators, allowing the proposed intelligent decision-support system to incorporate both organizational and operational dimensions rather than relying exclusively on subjective managerial judgments or historical transaction records.

Data analysis was conducted in several sequential stages combining conventional statistical procedures, structural-model assessment, and machine-learning techniques. Questionnaire data were initially screened for incomplete responses, implausible values, duplicate cases, and response patterns indicative of insufficient engagement. Descriptive statistics, including frequency, percentage, mean, standard deviation, skewness, and kurtosis, were calculated to characterize the participants and the principal study variables. Missing values in the analytical dataset were examined according to their extent and pattern, and appropriate imputation procedures were applied when necessary. Continuous machine-learning predictors were standardized or normalized when required by the selected algorithm, and categorical variables were transformed into machine-readable representations. Highly correlated or redundant predictors were examined to minimize unnecessary dimensionality and potential instability in the predictive models. The measurement and structural components of the conceptual model were then evaluated to establish the statistical relationships among business intelligence capability, machine-learning capability, predictive insight generation, and strategic decision-making effectiveness. Reliability was considered satisfactory when Cronbach's alpha and composite reliability coefficients met accepted thresholds, and convergent validity was evaluated using factor loadings and average variance extracted. The structural model was examined using path coefficients, coefficients of determination, effect sizes, predictive relevance statistics, and bootstrapped significance tests. Particular attention was given to determining whether business intelligence capability directly enhanced strategic decision quality and whether predictive insight generated through analytical and machine-learning capability provided an additional mechanism through which organizational data contributed to faster and more accurate strategic decisions. Following validation of the conceptual relationships, a machine-learning pipeline was developed to form the predictive core of the intelligent decision-support model. The analytical dataset was randomly partitioned into training, validation, and testing subsets using a 70%, 15%, and 15% allocation, respectively. Multiple supervised learning algorithms were compared rather than selecting a single algorithm a priori. Random forest, extreme gradient boosting, support vector machine, and multilayer perceptron neural network models were trained using the identified business intelligence, organizational, and retail performance predictors. Hyperparameters were optimized on the training and validation data, while cross-validation procedures were applied to reduce the risk of model overfitting and provide more stable estimates of predictive performance. For continuous strategic performance and decision-quality outcomes, model performance was compared using the coefficient of determination, root mean square error, and mean absolute error; where strategic alternatives or performance conditions were represented categorically, accuracy, precision, recall, F1 score, and the area under the receiver operating characteristic curve were additionally examined. The algorithm demonstrating the strongest combination of out-of-sample predictive accuracy, generalizability, and interpretability was selected as the predictive engine of the proposed decision-support model. Feature-importance analysis and model-explanation procedures were then employed to determine which organizational and business intelligence variables contributed most strongly to predictions, thereby ensuring that the resulting system provided interpretable managerial information rather than functioning exclusively as a black-box prediction mechanism. The final intelligent decision-support architecture integrated three analytical layers: a business intelligence layer responsible for data acquisition, cleaning, integration, visualization, and descriptive monitoring; a machine-learning layer responsible for pattern recognition, prediction, and estimation of likely strategic outcomes; and a decision-support layer that translated model outputs into ranked strategic alternatives and interpretable managerial recommendations. The final model was evaluated according to predictive performance, robustness, interpretability, and its ability to discriminate among alternative strategic scenarios relevant to retail management. Statistical analyses of the questionnaire and structural model were performed using SPSS version 29 and SmartPLS 4, while data preprocessing, machine-learning model development, cross-validation, and predictive evaluation were performed in Python using appropriate data-analysis and machine-learning libraries. All inferential statistical tests were evaluated at a significance level of $p < .05$.

3. Findings and Results

A total of 327 participants from retail organizations operating in Tehran were included in the final analysis after data screening and exclusion of incomplete questionnaires. Of the participants, 196 (59.94%) were male and 131 (40.06%) were female. The mean age of the respondents was 39.72 years (SD = 7.84), with ages ranging from 27 to 58

years. Regarding educational attainment, 92 participants (28.13%) held a bachelor's degree, 181 (55.35%) held a master's degree, and 54 (16.51%) held a doctoral degree. The mean professional experience of participants was 12.46 years (SD = 6.31), while their mean experience specifically within the retail industry was 9.38 years (SD = 5.17). In terms of organizational position, 63 respondents (19.27%) were senior managers or executives, 101 (30.89%) were middle-level managers, 48 (14.68%) worked in strategic planning or business development, 44 (13.46%) worked in information technology or business intelligence, 31 (9.48%) were data analysts or data science specialists, and 40 (12.23%) were employed in marketing, operations, supply chain, or other decision-related functions. With respect to organizational experience with analytical systems, 271 participants (82.87%) reported routine use of dashboards or business intelligence reports, 213 (65.14%) reported access to integrated enterprise or operational databases, and 146 (44.65%) indicated that their organizations had already implemented at least one predictive analytics or machine-learning application. These characteristics indicated that the sample was predominantly composed of experienced managers and specialists with substantial exposure to organizational information systems and strategic decision processes, thereby providing an appropriate empirical basis for evaluating the proposed intelligent decision-support model.

Table 1. Descriptive Statistics, Reliability, and Convergent Validity of the Study Constructs

Construct	Number of Items	Mean	SD	Skewness	Kurtosis	Cronbach's α	Composite Reliability	AVE
Data Quality	5	3.82	0.67	-0.41	0.18	0.88	0.91	0.67
Information Integration	5	3.69	0.72	-0.32	-0.11	0.87	0.90	0.64
Business Intelligence Infrastructure	6	3.74	0.65	-0.37	0.24	0.91	0.93	0.69
Analytical Capability	5	3.61	0.71	-0.26	-0.07	0.89	0.92	0.70
Organizational Readiness	5	3.55	0.74	-0.19	-0.28	0.86	0.90	0.64
Machine-Learning Capability	6	3.42	0.78	-0.13	-0.39	0.92	0.94	0.71
Predictive Insight Quality	5	3.58	0.70	-0.29	0.03	0.90	0.93	0.72
Decision Speed	4	3.71	0.68	-0.35	0.16	0.85	0.90	0.69
Decision Accuracy	4	3.76	0.66	-0.44	0.29	0.88	0.92	0.73
Strategic Decision Quality	6	3.73	0.64	-0.39	0.21	0.93	0.95	0.75
Decision-Support Effectiveness	5	3.79	0.69	-0.46	0.31	0.91	0.93	0.73

As shown in Table 1, the mean scores of the principal study constructs ranged from 3.42 to 3.82 on the five-point response scale, indicating generally favorable assessments of business intelligence capabilities, organizational analytical resources, and strategic decision-making conditions among the participating retail organizations. Data quality received the highest mean score (M = 3.82, SD = 0.67), followed by decision-support effectiveness (M = 3.79, SD = 0.69), decision accuracy (M = 3.76, SD = 0.66), business intelligence infrastructure (M = 3.74, SD = 0.65), and strategic decision quality (M = 3.73, SD = 0.64). Machine-learning capability showed the lowest mean score (M = 3.42, SD = 0.78), suggesting that although the participating organizations had relatively well-developed data and business intelligence environments, advanced predictive analytics and machine-learning implementation remained comparatively less mature. The distributions of all constructs were approximately normal, as the absolute values of skewness and kurtosis remained well within conventional thresholds for multivariate analysis. Internal consistency was satisfactory across all constructs, with Cronbach's alpha coefficients ranging from 0.85 for decision speed to 0.93 for strategic decision quality. Composite reliability values ranged from 0.90 to 0.95, further confirming the reliability of the measurement scales. Average variance extracted values ranged from 0.64 to 0.75, exceeding the recommended criterion of 0.50 for all constructs and demonstrating adequate convergent validity. These findings supported the psychometric adequacy of the measurement model and justified proceeding to the examination of interconstruct relationships and structural paths.

Table 2. Correlations Among the Principal Study Constructs

Construct	1	2	3	4	5	6	7	8	9	10	11
1. Data Quality	1.00										
2. Information Integration	0.61***	1.00									
3. BI Infrastructure	0.58***	0.64***	1.00								
4. Analytical Capability	0.51***	0.57***	0.66***	1.00							
5. Organizational Readiness	0.46***	0.52***	0.55***	0.59***	1.00						
6. ML Capability	0.44***	0.50***	0.56***	0.68***	0.63***	1.00					
7. Predictive Insight Quality	0.49***	0.55***	0.61***	0.69***	0.58***	0.74***	1.00				
8. Decision Speed	0.41***	0.47***	0.53***	0.56***	0.48***	0.57***	0.65***	1.00			
9. Decision Accuracy	0.48***	0.52***	0.60***	0.63***	0.54***	0.64***	0.73***	0.67***	1.00		
10. Strategic Decision Quality	0.52***	0.57***	0.66***	0.70***	0.61***	0.69***	0.78***	0.71***	0.80***	1.00	
11. Decision-Support Effectiveness	0.50***	0.56***	0.65***	0.68***	0.62***	0.71***	0.79***	0.69***	0.77***	0.84***	1.00

Table 2 presents the bivariate correlations among the principal constructs included in the proposed intelligent decision-support model. All correlations were positive and statistically significant at $p < .001$, providing preliminary support for the hypothesized relationships among business intelligence capabilities, machine-learning capability, predictive insight generation, and strategic decision outcomes. Strategic decision quality showed its strongest correlation with decision-support effectiveness ($r = .84$), followed by decision accuracy ($r = .80$), predictive insight quality ($r = .78$), decision speed ($r = .71$), analytical capability ($r = .70$), and machine-learning capability ($r = .69$). Predictive insight quality was strongly related to machine-learning capability ($r = .74$), analytical capability ($r = .69$), decision accuracy ($r = .73$), and decision-support effectiveness ($r = .79$), indicating that organizations with stronger analytical and machine-learning capabilities were more likely to produce actionable predictive information that could be incorporated into strategic decision processes. Business intelligence infrastructure was also positively associated with strategic decision quality ($r = .66$), decision accuracy ($r = .60$), and predictive insight quality ($r = .61$). Data quality and information integration displayed moderate-to-strong associations with the other business intelligence dimensions, supporting the assumption that reliable and integrated data constitute fundamental antecedents of effective analytics. Although several correlations were relatively high, none exceeded levels suggesting problematic redundancy among the constructs. The pattern of associations therefore supported both the theoretical coherence of the model and the empirical distinctiveness of the individual dimensions, while also indicating that predictive insight quality and decision accuracy were likely to occupy particularly important positions in explaining strategic decision effectiveness.

Table 3. Structural Model Results for Predicting Strategic Decision-Making Outcomes

Structural Path	β	SE	t	p	95% CI	Effect Size (f^2)	Result
Data Quality → BI Infrastructure	0.29	0.049	5.92	<.001	[0.19, 0.38]	0.14	Supported
Information Integration → BI Infrastructure	0.41	0.051	8.04	<.001	[0.31, 0.51]	0.27	Supported
BI Infrastructure → Analytical Capability	0.46	0.047	9.79	<.001	[0.37, 0.55]	0.31	Supported
Organizational Readiness → Analytical Capability	0.28	0.050	5.60	<.001	[0.18, 0.38]	0.13	Supported
Analytical Capability → ML Capability	0.43	0.046	9.35	<.001	[0.34, 0.52]	0.26	Supported
Organizational Readiness → ML Capability	0.31	0.048	6.46	<.001	[0.22, 0.40]	0.16	Supported
ML Capability → Predictive Insight Quality	0.48	0.043	11.16	<.001	[0.40, 0.57]	0.36	Supported
Analytical Capability → Predictive Insight Quality	0.32	0.045	7.11	<.001	[0.23, 0.41]	0.18	Supported
Predictive Insight Quality → Decision Speed	0.44	0.049	8.98	<.001	[0.34, 0.54]	0.25	Supported
Predictive Insight Quality → Decision Accuracy	0.51	0.045	11.33	<.001	[0.42, 0.60]	0.38	Supported
BI Infrastructure → Strategic Decision Quality	0.18	0.043	4.19	<.001	[0.10, 0.27]	0.07	Supported
Predictive Insight Quality → Strategic Decision Quality	0.36	0.049	7.35	<.001	[0.27, 0.46]	0.22	Supported
Decision Speed → Strategic Decision Quality	0.17	0.041	4.15	<.001	[0.09, 0.25]	0.08	Supported
Decision Accuracy → Strategic Decision Quality	0.39	0.047	8.30	<.001	[0.30, 0.48]	0.29	Supported
Strategic Decision Quality → Decision-Support Effectiveness	0.62	0.041	15.12	<.001	[0.54, 0.70]	0.54	Supported
Predictive Insight Quality → Decision-Support Effectiveness	0.24	0.043	5.58	<.001	[0.16, 0.33]	0.11	Supported

The structural model results presented in Table 3 supported all proposed direct relationships. Information integration exerted a stronger effect on business intelligence infrastructure (β = .41, p < .001) than data quality (β = .29, p < .001), although both variables made significant contributions. Business intelligence infrastructure strongly predicted analytical capability (β = .46, p < .001), while organizational readiness also contributed significantly to analytical capability (β = .28, p < .001). Analytical capability emerged as an important determinant of machine-learning capability (β = .43, p < .001), and organizational readiness exerted an additional positive effect (β = .31, p < .001), demonstrating that technological sophistication alone was insufficient without organizational preparedness to adopt advanced analytical methods. Machine-learning capability was the strongest direct predictor of predictive insight quality (β = .48, p < .001), while analytical capability had an independent positive effect (β = .32, p < .001). Predictive insight quality subsequently improved both decision speed (β = .44, p < .001) and decision accuracy (β = .51, p < .001), with the stronger effect on accuracy suggesting that predictive analytics contributed particularly to reducing uncertainty and improving the correctness of strategic judgments. Strategic decision quality was directly predicted by decision accuracy (β = .39, p < .001), predictive insight quality (β = .36, p < .001), business intelligence infrastructure (β = .18, p < .001), and decision speed (β = .17, p < .001). The model explained 61.4% of the variance in machine-learning capability, 67.8% of the variance in predictive insight quality, 42.6% of the variance in decision speed, 56.9% of the variance in decision accuracy, and 74.3% of the variance in strategic decision quality. Strategic decision quality, together with predictive insight quality, explained 76.1% of the variance in overall decision-support effectiveness. The largest individual effect size was observed for the relationship between strategic decision quality and decision-support effectiveness (f^2 = 0.54), followed by predictive insight quality and decision accuracy (f^2 = 0.38), and machine-learning capability and predictive insight quality (f^2 = 0.36). These results indicated that the proposed model possessed substantial explanatory power and that the integration of business intelligence with machine-learning capabilities influenced strategic decision effectiveness both directly and through the intermediate mechanisms of predictive insight, decision speed, and decision accuracy.

Table 4. Comparative Predictive Performance of the Machine-Learning Algorithms

Algorithm	Training R^2	Test R^2	RMSE	MAE	Accuracy	Precision	Recall	F1 Score	AUC
Random Forest	0.91	0.82	0.391	0.298	0.84	0.83	0.82	0.82	0.90
Extreme Gradient Boosting	0.94	0.87	0.342	0.261	0.88	0.88	0.87	0.87	0.94
Support Vector Machine	0.86	0.78	0.421	0.324	0.81	0.80	0.79	0.79	0.87
Multilayer Perceptron Neural Network	0.92	0.84	0.373	0.283	0.85	0.85	0.84	0.84	0.91

As reported in Table 4, all four machine-learning algorithms demonstrated acceptable predictive performance, but extreme gradient boosting produced the strongest overall results on previously unseen test data. The extreme gradient boosting model achieved a test-set R^2 of 0.87, indicating that approximately 87% of the variance in the continuous strategic decision-performance outcome was explained by the predictor set. It also produced the lowest prediction errors, with an RMSE of 0.342 and an MAE of 0.261. In the classification component of the decision-support architecture, extreme gradient boosting achieved an accuracy of 0.88, precision of 0.88, recall of 0.87, an F1 score of 0.87, and an AUC of 0.94, demonstrating strong discriminatory capacity across strategic performance categories. Random forest showed the second-best performance, achieving a test R^2 of 0.82 and an AUC of 0.90, whereas the multilayer perceptron neural network achieved a test R^2 of 0.84 and an AUC of 0.91. Although the neural network demonstrated strong predictive performance, its gain over random forest was comparatively modest and its managerial interpretability was lower. The support vector machine showed the weakest performance among the four models, although its test R^2 of 0.78 and AUC of 0.87 still indicated acceptable predictive capability. Comparison of training and test performance suggested some degree of expected reduction in accuracy outside the training data, but no algorithm demonstrated an extreme discrepancy indicative of severe overfitting. The extreme gradient boosting algorithm was therefore selected as the predictive engine of the proposed intelligent decision-support model because it provided the most favorable combination of prediction accuracy, classification performance, robustness, and compatibility with feature-importance and model-explanation procedures. The superiority of the boosting

model also suggested that the relationships between organizational intelligence variables, operational retail indicators, and strategic decision outcomes were not entirely linear and could be more effectively represented by an ensemble model capable of capturing complex interactions and nonlinear patterns.

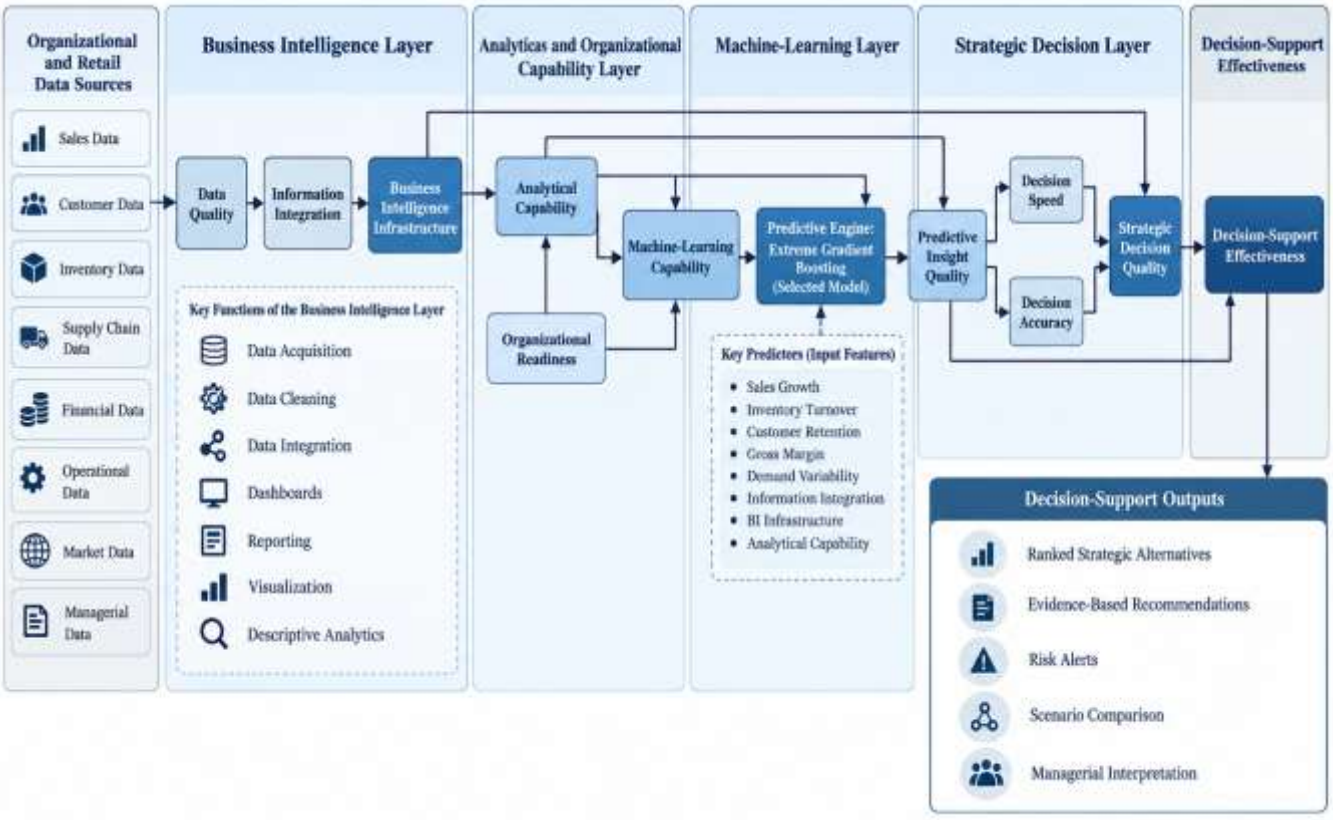


Figure 1. Final Intelligent Decision-Support Model Integrating Business Intelligence, Machine Learning, Predictive Insights, and Strategic Decision-Making

The final model illustrated in Figure 1 represents an integrated decision-support architecture in which organizational and retail data are transformed progressively from raw information into strategically actionable recommendations. The first component of the model is the business intelligence layer, in which data quality and information integration provide the foundation for the establishment of a reliable business intelligence infrastructure. This layer consolidates sales, customer, inventory, supply chain, financial, operational, and managerial information and makes these data available through standardized reporting, visualization, and analytical processes. The second component consists of organizational analytical capability and readiness, which determine the extent to which the available information infrastructure can be converted into advanced analytical and machine-learning capacity. The third component is the machine-learning layer, represented empirically by the extreme gradient boosting model selected on the basis of its superior out-of-sample performance. In this layer, historical organizational and operational indicators are processed to estimate expected strategic outcomes, detect high-impact patterns, and identify combinations of conditions associated with favorable or unfavorable decision consequences. Model-explanation analysis showed that predictive insight quality, decision accuracy, analytical capability, machine-learning capability, business intelligence infrastructure, sales growth, inventory turnover, customer retention, gross margin, demand variability, and information integration were among the most influential predictors contributing to the final decision estimates. Predictive insight quality functioned as a central bridging mechanism between technological capability and managerial decision outcomes, directly improving both decision speed and decision accuracy and also exerting an independent influence on strategic decision quality. The final decision-support layer combined predicted outcomes with managerial indicators to rank strategic alternatives according to their expected performance and decision

relevance. Rather than replacing managerial judgment, the proposed architecture was designed to augment it by presenting evidence-based estimates, highlighting influential variables, identifying potential risks, and allowing decision makers to compare alternative strategic scenarios. The empirical model therefore demonstrated that the greatest strategic value was produced not by business intelligence or machine learning in isolation, but by their sequential and coordinated integration: reliable and integrated organizational data strengthened business intelligence infrastructure; business intelligence infrastructure supported analytical capability; analytical capability and organizational readiness enabled effective machine-learning implementation; machine learning generated higher-quality predictive insight; and predictive insight improved the speed, accuracy, quality, and overall effectiveness of strategic decision-making in retail organizations.

4. Discussion and Conclusion

The present study aimed to design and validate an intelligent decision-support model for enhancing strategic decision-making through the integration of business intelligence and machine learning in the Iranian retail industry. The findings provide strong empirical support for a layered model in which data quality and information integration strengthen business intelligence infrastructure, business intelligence infrastructure enhances analytical capability, organizational readiness facilitates both analytical and machine-learning capabilities, and machine-learning capability improves predictive insight quality. Predictive insight quality, in turn, was found to increase decision speed and decision accuracy, while strategic decision quality was directly influenced by predictive insight quality, decision accuracy, decision speed, and business intelligence infrastructure. The model explained a substantial proportion of the variance in strategic decision quality and decision-support effectiveness, and the machine-learning comparison further showed that extreme gradient boosting achieved the strongest out-of-sample predictive performance among the evaluated algorithms. Taken together, these findings indicate that intelligent strategic decision-making is not produced by a single technological component but by the coordinated interaction of reliable data, integrated information infrastructure, organizational readiness, analytical capability, predictive modeling, and managerial interpretation. This pattern is consistent with the broader view that organizational intelligence emerges from combinations of technological, informational, cognitive, and managerial resources rather than from isolated information systems [1, 28]. It also supports the argument that artificial intelligence creates strategic value when embedded within organizational capabilities and business strategy rather than implemented as a stand-alone technical solution [10, 11].

One of the clearest results concerned the foundational role of data quality and information integration in strengthening business intelligence infrastructure. Information integration had a stronger structural effect on business intelligence infrastructure than data quality, although both relationships were statistically significant. This result suggests that high-quality data alone are insufficient when information remains fragmented across incompatible systems, functional silos, or disconnected operational databases. In the retail context, strategic decisions typically require simultaneous access to customer, sales, inventory, supply chain, financial, operational, and market information, and the analytical value of these data depends on whether they can be combined into a coherent decision environment. This finding is closely aligned with research emphasizing that successful data-driven governance depends on appropriate data architecture, coherent modeling structures, consistency, and integration across organizational processes [7]. It is also compatible with the argument that competitive intelligence becomes strategically meaningful when organizations are able to transform dispersed environmental and organizational information into usable strategic knowledge [5]. The positive effect of information integration further reflects the importance of interactive information processing in complex decision environments, where organizational performance depends not simply on possessing information but on ensuring that relevant information is exchanged, combined, and interpreted across organizational boundaries [8]. The result is particularly important because organizations with large volumes of disconnected information may experience information overload rather than intelligence. Research on collective decision-making has shown that poorly structured information-sharing processes can impair rather than improve decision quality when the cognitive capacity of decision-makers is exceeded [9]. Thus, the current findings support the view that intelligent decision support begins with a disciplined information architecture capable of reducing fragmentation and transforming raw data into structured organizational intelligence.

The strong relationship between business intelligence infrastructure and analytical capability was another important finding. The results showed that organizations with stronger business intelligence infrastructure were substantially more capable of performing sophisticated analytical activities, while organizational readiness also contributed independently to analytical capability. This finding suggests that analytical capacity should be understood as both a technological and organizational phenomenon. Dashboards, reporting platforms, integrated databases, and visualization tools provide the technical basis for analysis, but organizations must also possess managerial support, appropriate skills, analytical culture, and readiness to incorporate data into everyday decision processes. This interpretation is consistent with research showing that the strategic value of digital technologies depends on the development of complementary organizational capabilities rather than on technology adoption alone [28]. It also corresponds with evidence that intelligent automation requires an integrated strategic framework linking digital technologies, organizational processes, and decision objectives [12]. The role of organizational readiness is especially significant because implementation barriers such as insufficient technical skills, resistance to change, infrastructure limitations, governance weaknesses, and data-management problems can prevent artificial intelligence from being translated into organizational value [29]. The current results therefore indicate that organizations seeking to develop advanced intelligent decision-support systems should not focus exclusively on acquiring technological platforms. They must simultaneously strengthen managerial understanding, analytical competence, cross-functional cooperation, and institutional willingness to use evidence generated by digital systems.

The results further demonstrated that analytical capability and organizational readiness were significant predictors of machine-learning capability, with analytical capability exerting the larger effect. This finding supports the idea that advanced predictive modeling develops most effectively when organizations already possess an established analytical foundation. Machine learning requires more than technical algorithms; it depends on data preprocessing, variable definition, validation procedures, interpretation of outputs, and alignment between computational models and strategic questions. The result is consistent with the broader transition from descriptive business intelligence toward cognitive and predictive automation [13]. It is also in line with arguments that artificial intelligence is reshaping business decision-making by moving organizations from retrospective reporting toward anticipatory and predictive forms of analysis [11]. The current findings additionally resonate with emerging Industry 5.0 and Industry 6.0 perspectives, in which advanced intelligent systems are conceptualized as part of broader human-machine and decentralized decision architectures rather than as isolated computational tools [14, 18]. The significance of organizational readiness also reinforces the idea that sophisticated algorithms cannot generate strategic advantage if an organization lacks appropriate competencies, governance mechanisms, and decision routines for interpreting and applying model outputs.

Machine-learning capability had a particularly strong effect on predictive insight quality, and analytical capability also contributed independently to predictive insight. This result is central to the proposed model because it demonstrates the mechanism through which technological and analytical capabilities are converted into strategically meaningful information. Predictive insight quality represents more than statistical accuracy; it reflects the extent to which analytical outputs are timely, relevant, interpretable, actionable, and capable of reducing strategic uncertainty. The finding is compatible with research showing that intelligent systems increasingly integrate sensing, modeling, environmental interpretation, and adaptive decision logic in complex systems [15, 16]. Although those studies focus on embodied and autonomous systems, the underlying principle is relevant to organizational strategy: value emerges when information is transformed into context-sensitive predictions that can support adaptive action. The result also aligns with the concept of intelligent automation, in which analytical systems go beyond reporting to support the interpretation and execution of decisions [27]. In this sense, machine-learning capability functioned in the present model as a bridge between business intelligence infrastructure and high-quality strategic prediction.

Predictive insight quality significantly improved both decision speed and decision accuracy, with a stronger effect on decision accuracy. This finding suggests that machine-generated predictions may be particularly valuable for reducing uncertainty and improving the precision of managerial judgment. In complex retail environments, managers frequently face decisions concerning demand, inventory, customer retention, pricing, promotional effectiveness, supplier performance, and market conditions. Predictive systems can synthesize patterns across large

datasets and provide estimates that would be difficult to derive consistently through unaided human judgment. The stronger influence on accuracy is therefore plausible because algorithmic systems are especially useful in identifying nonlinear relationships, subtle interactions, and recurring patterns that may escape managerial attention. This interpretation is supported by research on executive decision-making showing that big data analytics, artificial intelligence, and explainable systems can help reduce cognitive bias and improve the evidential basis of managerial choices [22]. It is also consistent with research on cognitive biases in intelligence analysis, which emphasizes that digital-intelligent systems can either mitigate or amplify bias depending on how they are designed and used [21]. The present findings suggest that predictive systems are most valuable when they provide evidence that complements human judgment rather than simply accelerating decisions. This interpretation is consistent with high-stakes decision environments such as critical care and nursing, where artificial intelligence is increasingly viewed as a mechanism for augmenting professional judgment while retaining human oversight [19, 20].

The positive effect of predictive insight quality on strategic decision quality also provides evidence for the central mediating role of predictive intelligence within the model. The relationship indicates that organizations are more likely to make high-quality strategic decisions when machine-learning outputs are understandable, relevant, and aligned with managerial objectives. This finding supports hybrid intelligence perspectives emphasizing complementary interaction between human cognition and artificial systems [17]. Strategic decisions typically involve ambiguity, incomplete information, competing goals, political considerations, and uncertainty; therefore, even highly accurate predictions cannot replace managerial interpretation. The results instead support a human-in-the-loop architecture in which predictive analytics provides structured evidence while managers remain responsible for contextualization, prioritization, and final choice. This view also aligns with behavioral strategy research, which has shown that strategic decisions are influenced by cognition, heuristics, emotion, and organizational context rather than by formal rationality alone [3]. Research on emotions and boardroom decision-making similarly demonstrates that strategic choice remains partly shaped by affective and behavioral processes [4]. Accordingly, the present study indicates that predictive intelligence should be designed to augment managerial cognition, expose uncertainty, and support interpretation rather than to displace strategic judgment.

Decision accuracy emerged as a stronger predictor of strategic decision quality than decision speed. This distinction is theoretically important. Although speed is essential in volatile retail markets, a rapid decision that is poorly aligned with evidence may generate operational and strategic losses. The findings therefore suggest that the primary contribution of intelligent decision support is not simply faster decision-making but better decision-making. This result is consistent with research showing that cognitive diversity and structured analytical processes can improve intelligence quality by reducing narrow interpretations and exposing alternative explanations [23]. It also corresponds with research in cognitive science and cybersecurity emphasizing the importance of understanding how human cognitive processes interact with complex technical systems [24]. From a neuro-management perspective, the finding further supports growing attention to the cognitive foundations of leadership and strategy, particularly the interaction between analytical information and managerial reasoning [2, 25]. The result therefore reinforces the need to evaluate intelligent systems not only according to computational performance but also according to whether they improve the quality of actual organizational choices.

The direct effect of business intelligence infrastructure on strategic decision quality, even after accounting for predictive insight, decision speed, and decision accuracy, is also noteworthy. This finding indicates that traditional business intelligence continues to provide strategic value independently of advanced machine learning. Managers still require dashboards, reports, visualizations, performance indicators, historical comparisons, and structured summaries to understand current organizational conditions. Predictive analytics extends these capabilities but does not eliminate the need for descriptive and diagnostic intelligence. This interpretation is consistent with the literature on strategic management in the digital age, which emphasizes the continued importance of integrated decision frameworks rather than complete replacement of traditional managerial systems by artificial intelligence [36]. The result also aligns with work on organizational intelligence and knowledge management, where strategic performance depends on the combination of information systems, human interpretation, and organizational routines [6]. Thus, the model supports a layered view in which descriptive business intelligence and predictive machine learning operate as complementary rather than competing decision technologies.

The machine-learning comparison further strengthened the empirical contribution of the study. Extreme gradient boosting achieved the highest test-set R^2, the lowest RMSE and MAE, and the strongest classification metrics, including the highest AUC. Random forest and the multilayer perceptron also performed well, while the support vector machine showed comparatively weaker predictive accuracy. The superiority of extreme gradient boosting suggests that the relationships among organizational, operational, and strategic variables were likely characterized by nonlinearities and interactions that could be captured effectively through ensemble tree-based learning. This result is compatible with the broader shift toward intelligent and adaptive analytical systems capable of integrating complex multivariate information. It also supports the principle that predictive performance should be evaluated using out-of-sample validation rather than training accuracy alone. Importantly, the selected model was also suitable for feature-importance analysis, which is particularly valuable in managerial contexts where interpretability affects trust and adoption. This consideration is consistent with research emphasizing explainable artificial intelligence as a means of mitigating cognitive bias and improving executive understanding of model-supported decisions [22]. The need for interpretability is also reinforced by discussions of emerging AI-related risks, including opacity, accountability, and overreliance on automated systems [34]. Therefore, the empirical superiority of extreme gradient boosting is meaningful not only because of its predictive power but also because it can support a more transparent relationship between computational prediction and managerial judgment.

The final model explained a large proportion of the variance in both strategic decision quality and overall decision-support effectiveness, with strategic decision quality exerting the strongest direct effect on decision-support effectiveness. This result confirms that technological sophistication is valuable only insofar as it improves the quality of organizational decisions. The model therefore places strategic outcomes, rather than algorithmic performance, at the center of evaluation. This perspective aligns with the idea that digital transformation should be assessed according to its contribution to organizational capability, resilience, and sustainability rather than according to technology adoption alone [27, 28]. It is also consistent with human-centered approaches to intelligent systems that emphasize the need to preserve professional judgment, accountability, and contextual interpretation [18, 19]. Research on artificial intelligence in executive roles likewise highlights the conceptual limits of fully autonomous leadership and the continuing importance of human authority and accountability in strategic governance [35]. The current findings therefore support an augmentation model in which business intelligence and machine learning improve strategic decision-making without eliminating the central role of managerial responsibility.

The findings should be interpreted in light of several limitations. First, the study was cross-sectional, and although the proposed structural relationships were theoretically grounded and empirically supported, causal interpretation should be approached cautiously because the variables were measured at one point in time. Second, the study was conducted among managers and specialists working in retail organizations in Tehran, which may limit the generalizability of the findings to other cities, industries, organizational sizes, or national contexts. Third, several organizational constructs were measured using self-reported questionnaire data, which may be affected by common-method variance, social desirability, or differences in respondents' understanding of analytical and technological capabilities. Fourth, although the study incorporated operational and organizational indicators into the predictive component, access to proprietary retail data necessarily constrained the breadth and granularity of the machine-learning dataset. Fifth, the predictive algorithms were evaluated using the available dataset and selected performance metrics, and the relative performance of the models may differ in substantially larger, noisier, or more heterogeneous organizational datasets. Finally, the proposed architecture focused primarily on the informational, analytical, and organizational dimensions of strategic decision support and did not directly model other potentially important variables such as leadership style, organizational politics, ethical governance, perceived algorithmic fairness, trust in artificial intelligence, or employee resistance to automated decision systems.

Future research should evaluate the proposed model using longitudinal and multi-wave designs to examine how business intelligence maturity, machine-learning capability, and strategic decision quality evolve over time and whether changes in analytical capabilities produce subsequent changes in organizational outcomes. Replication across other industries, including banking, manufacturing, healthcare, telecommunications, logistics, and e-commerce, would also help determine the external validity of the model. Comparative studies across countries could investigate whether institutional, cultural, economic, and technological

environments moderate the effectiveness of intelligent decision-support systems. Future studies may additionally incorporate larger transactional datasets, real-time streaming data, natural language data, and external market information to improve predictive scope. Researchers could compare gradient boosting with transformer-based architectures, deep neural networks, causal machine-learning methods, reinforcement learning, and hybrid ensemble approaches. Further work should also examine explainability, trust, algorithmic fairness, managerial acceptance, ethical governance, cybersecurity, and human-AI interaction as potential mediators or moderators of model effectiveness. Experimental research could compare managerial decisions made with and without intelligent decision support to determine whether such systems actually improve strategic outcomes under controlled conditions. Finally, future studies should investigate how different levels of managerial expertise interact with machine-generated recommendations, particularly whether intelligent systems provide greater value to novice, intermediate, or highly experienced decision-makers.

From a practical perspective, retail organizations should treat intelligent decision support as an organizational transformation initiative rather than as a stand-alone software project. Managers should first strengthen data quality, standardization, interoperability, and cross-functional integration before investing heavily in advanced machine-learning applications. Business intelligence platforms should be designed to consolidate sales, customer, inventory, supply chain, financial, and market information into a unified analytical environment. Organizations should also invest in analytical skills, data literacy, and managerial training so that decision-makers can interpret predictive outputs appropriately. Machine-learning models should be evaluated using out-of-sample performance and should be accompanied by explanation mechanisms that identify the variables driving each recommendation. Decision-support interfaces should present ranked strategic alternatives, expected outcomes, uncertainty information, risk alerts, and scenario comparisons rather than simply producing opaque predictions. Senior managers should establish governance procedures defining who is responsible for validating models, approving strategic recommendations, monitoring model drift, and responding when algorithmic outputs conflict with managerial judgment. Finally, organizations should preserve human accountability in all high-impact strategic decisions and use artificial intelligence as a mechanism for improving evidence quality, reducing uncertainty, and supporting managerial reasoning rather than as an autonomous substitute for strategic leadership.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] M. M. Bodrick, H. M. Alqarni, M. I. Alsuhaim, and Y. S. Almuways, "Critical Appraisal of Definitions on Intelligence Within the Organizational Context," *Journal of Learning and Development Studies*, vol. 4, no. 2, pp. 12-20, 2024, doi: 10.32996/jlds.2024.4.2.2.

[2] C. Brătianu and R.-M. Stăneiu, "The Emergence of Neuroleadership in the Knowledge Economy," *Encyclopedia*, vol. 4, no. 3, pp. 1100-1116, 2024, doi: 10.3390/encyclopedia4030071.

[3] I. Hesselbarth, A. Alnoor, and V. Tiberius, "Behavioral Strategy: A Systematic Literature Review and Research Framework," *Management Decision*, vol. 61, no. 9, pp. 2740-2756, 2023, doi: 10.1108/md-09-2021-1274.

[4] V. Violant and E. D. d. Silva, "Emotions and Decision-Making in Boardrooms—a Systematic Review From Behavioral Strategy Perspective," *Frontiers in Psychology*, vol. 15, 2024, doi: 10.3389/fpsyg.2024.1473175.

[5] M. O. Obonyo and J. M. Kilika, "Competitive Intelligence and Corresponding Outcome in a Strategic Management Process: A Review of Literature," *Journal of Economics and Business*, vol. 3, no. 4, 2020, doi: 10.31014/aior.1992.03.04.313.

[6] F. Alfazzi, "A Knowledge Behavioral and Intelligence Management in Fostering Entrepreneurship for Modern Industries," *International Journal for Applied Information Management*, vol. 2, no. 4, pp. 95-105, 2022, doi: 10.47738/ijaim.v2i4.42.

[7] V. Biagi, "Data Model Design to Support Data-Driven IT Governance Implementation," *Technologies*, vol. 10, no. 5, p. 106, 2022, doi: 10.3390/technologies10050106.

[8] T. J. Andersen and P. C. Young, "Enhancing Public Sector Enterprise Risk Management Through Interactive Information

Processing," *Frontiers in Research Metrics and Analytics*, vol. 8, 2023, doi: 10.3389/frma.2023.1239447.

[9] D.-J. v. Veen, R. S. Kudesia, and H. R. Heinimann, "An Agent-Based Model of Collective Decision-Making: How Information Sharing Strategies Scale With Information Overload," *Ieee Transactions on Computational Social Systems*, vol. 7, no. 3, pp. 751-767, 2020, doi: 10.1109/tcss.2020.2986161.

[10] F. Kitsios and M. I. Kamariotou, "Artificial Intelligence and Business Strategy Towards Digital Transformation: A Research Agenda," *Sustainability*, vol. 13, no. 4, p. 2025, 2021, doi: 10.3390/su13042025.

[11] N. Kumar and A. Shrivastava, "The Artificial Intelligence (AI) Revolution: Evolving Business Decision-Making in the Digital Age," *Business Information Review*, vol. 42, no. 3, pp. 183-196, 2025, doi: 10.1177/02663821251364069.

[12] I. C. L. Feio and V. Santos, "A Strategic Model and Framework for Intelligent Process Automation," pp. 1-6, 2022, doi: 10.23919/cisti54924.2022.9820099.

[13] C. Engel, P. Ebel, and J. M. Leimeister, "Cognitive Automation," *Electronic Markets*, vol. 32, no. 1, pp. 339-350, 2022, doi: 10.1007/s12525-021-00519-7.

[14] A. Fernández-Miguel, S. Ortíz-Marcos, M. Jiménez, H. Alfonso Pedro Fernández del, F. E. García-Muiña, and D. Settembre-Blundo, "Toward the Theoretical Foundations of Industry 6.0: A Framework for AI-Driven Decentralized Manufacturing Control," *Future Internet*, vol. 17, no. 10, p. 455, 2025, doi: 10.3390/fi17100455.

[15] X. Zhang, T. Liu, H. Yang, Z. Hao, and L. Wang, "Principles of Autonomous Transportation System From the Perspective of Embodied Intelligence," *Iop Conference Series Materials Science and Engineering*, vol. 1343, no. 1, p. 012002, 2026, doi: 10.1088/1757-899x/1343/1/012002.

[16] X. Zhou, "Constructing Embodied Intelligent Spaces From an Architectural Perspective: Technical Frameworks, Integration Mechanisms, and Implementation Pathways," *Buildings*, vol. 16, no. 19, p. 3906, 2026, doi: 10.3390/buildings16193906.

[17] Z. Li, Q. Li, X. Li, Z. Wang, and X. Wu, "Dual-Brain Fusion: Bidirectional Empowerment Between Human Brain and Brain-Inspired Systems," *Fundamental Research*, vol. 6, no. 5, pp. 3529-3543, 2026, doi: 10.1016/j.fmre.2026.03.020.

[18] A. M. A. Nezhad, P. J. Amirkhizi, S. Pedrammehr, Z. H. Aghdam, and M. Soleimanzadeh, "Design Management in Industry 5.0: Synergy of AI, Humans, and Machines," *Administrative Sciences*, vol. 16, no. 7, p. 333, 2026, doi: 10.3390/admsci16070333.

[19] Á. Réa-Neto, "Clinical Reasoning, Pathophysiology, and Artificial Intelligence in Critical Care: A Conceptual Framework for Integrating Decision-Making," *Journal of Clinical Medicine*, vol. 15, no. 20, p. 7987, 2026, doi: 10.3390/jcm15207987.

[20] B. G. Awata, "AI-Augmented Nursing Care: Integrating Human Judgment, Mental Health, and Intelligent Technologies in Contemporary Clinical Practice," 2026, doi: 10.21203/rs.3.rs-10424558/v1.

[21] y. p. Huo, l. yu, and y. ji, "Cognitive Biases in Intelligence Analysis: Amplification Mechanisms and Intervention Strategies in the Digital-Intelligent Era," 2026, doi: 10.21203/rs.3.rs-8698493/v1.

[22] L. Theodorakopoulos, A. Theodoropoulou, and C. Halkiopoulos, "Cognitive Bias Mitigation in Executive Decision-Making: A Data-Driven Approach Integrating Big Data Analytics, AI, and Explainable Systems," *Electronics*, vol. 14, no. 19, p. 3930, 2025, doi: 10.3390/electronics14193930.

[23] D. J. Kritz, "Coming Together: Strengthening the Intelligence Community Through Cognitive Diversity," *Security and Intelligence*, vol. 7, no. 1, 2022, doi: 10.18278/gsis.7.1.3.

[24] R. Andrade, W. Fuertes, M. Cazares, I. Ortiz-Garcés, and G. Navas, "An Exploratory Study of Cognitive Sciences Applied to Cybersecurity," *Electronics*, vol. 11, no. 11, p. 1692, 2022, doi: 10.3390/electronics11111692.

[25] E. Ö. Alakaş and M. Polat, "Exploring the Nexus of Neuroscience and Management: A Bibliometric Analysis of Emerging Trends in Neuro-Management, Neuro-Leadership, and Neuro-Strategy," *Global Business and Organizational Excellence*, vol. 45, no. 3, pp. 319-340, 2025, doi: 10.1002/joe.70023.

[26] A. Asriati, "Psychological Insights Into Human Resource Management Strategy: A Qualitative Exploration and Review of Literature," *Golden Ratio of Human Resource Management*, vol. 5, no. 1, pp. 198-212, 2025, doi: 10.52970/grhrm.v5i1.503.

[27] A. Kuzior and M. Sira, "Sustainable Digital Economy Transformation Through Intelligent Automation: A Multi-Environmental Framework for Strategic Decision-Making," *Sustainability*, vol. 17, no. 17, p. 7723, 2025, doi: 10.3390/su17177723.

[28] L. Espina-Romero, D. E. R. Parra, J. G. N. Sánchez, J. I. Olmedo, E. Diaz, and Y. J. Nieto, "Bridging the Microfoundations of Organizational Intelligence for Sustainability: A Systematic Review of Digital Transformation, Artificial Intelligence, and Capability-Based Mechanisms," *Sustainability*, vol. 18, no. 12, p. 6020, 2026, doi: 10.3390/su18126020.

[29] M. Sharma, S. Luthra, and A. K. V, "Implementing Challenges of Artificial Intelligence: Evidence From Public Manufacturing Sector of an Emerging Economy," *Government Information Quarterly*, vol. 39, no. 4, p. 101624, 2022, doi: 10.1016/j.giq.2021.101624.

[30] H. A. Mustafa, K. M. Ebabekir, and G. A. Ismael, "Attitudes of Bank Managers Towards the Effect of Cultural Intelligence on Organizational Climate and the Process of Strategy Activation: With Special Reference to Commercial Banks in Erbil, Kurdistan Region," *World Journal of Business and Management*, vol. 6, no. 2, p. 15, 2020, doi: 10.5296/wjbm.v6i2.17371.

[31] Y. Zhou, Y. X. Zhou, L. Zhang, X. Zhao, and W. Chen, "Effects of Top Management Team Characteristics on Patent Strategic Change and Firm Performance," *Frontiers in Psychology*, vol. 12, 2022, doi: 10.3389/fpsyg.2021.762499.

[32] S. A. Elandaloussi and P. Zaraté, "Strategic Support Systems for Crisis Management: A Literature Review," *Foundations and Trends® in Information Systems*, vol. 8, no. 1, pp. 1-65, 2024, doi: 10.1561/2900000025.

[33] L. Sikora, N. K. Lysa, Y. Tsikalo, and O. Y. Fedevych, "System-Information and Cognitive Technologies of Man-Made Infrastructure Cyber Security," *Journal of Cyber Security and Mobility*, 2023, doi: 10.13052/jcsm2245-1439.123.7.

[34] X. Baraza and J. Torrent-Sellens, "Artificial Intelligence and Emerging Risks in Occupational Safety and Health," *Encyclopedia*, vol. 6, no. 1, p. 25, 2026, doi: 10.3390/encyclopedia6010025.

[35] A. Ünal and İ. KilinÇ, "The Feasibility of Artificial Intelligence Performing as CEO: The Vizier-Shah Theory," *Foresight*, vol. 23, no. 6, pp. 698-723, 2021, doi: 10.1108/fs-02-2021-0048.

[36] A. Choori and S. Kazemi, "Strategic Management in the Digital Age: A Review of Decision-Making Frameworks,"

Ijimob, vol. 3, no. 2, pp. 21-32, 2023, doi: 10.61838/kman.ijimob.3.2.4.