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Research Article

Artificial Intelligence–Based Models for Enhancing Decision Quality in Management and Information Technology

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Abstract: The rapid integration of Artificial Intelligence (AI) into organizational ecosystems has transformed how managerial and technological decisions are made. Despite significant progress, many enterprises still struggle to achieve decision consistency and accuracy due to fragmented data environments and subjective human biases. This study addresses the problem of improving decision quality in management and information technology (IT) contexts through the development and evaluation of AI-based models. The key objectives are: (1) to design a data-driven framework that leverages AI techniques for optimizing managerial decision processes, and (2) to assess the impact of AI implementation on decision quality, speed, and reliability across business and IT domains. Primary data were collected through a structured survey involving 540 managerial and IT professionals from diverse sectors, ensuring comprehensive insights into AI adoption patterns and decision outcomes. Using statistical analysis, correlation modeling, and machine-learning-based predictive assessment, the study examined relationships among AI utilization, data literacy, and perceived decision quality. The results indicate that AI-enabled models significantly enhance analytical rigor, reduce uncertainty, and promote evidence-based strategic planning. Furthermore, organizations employing hybrid decision-support systems demonstrated superior performance outcomes compared to traditional models. The novelty of this research lies in integrating managerial intelligence with AI-driven analytics into a unified framework that operationalizes both cognitive and computational dimensions of decision-making, offering a practical pathway for data-empowered management and IT innovation.

Keywords: Artificial Intelligence, Data-Driven Decision Making, Management Information Systems, Decision Quality, Predictive Analytics.

INTRODUCTION

The accelerating integration of Artificial Intelligence (AI) across organizational and technological domains has fundamentally reshaped decision-making paradigms in both management and information systems. The proliferation of AI-enabled systems is not only enhancing operational efficiency but also redefining the quality, speed, and accuracy of managerial decisions. Modern organizations increasingly depend on AI-driven analytics, automation, and predictive insights to strengthen strategic competitiveness and adaptability in volatile environments [1]. In this context, AI emerges as a transformative driver of digital transformation, augmenting human cognition, enabling evidence-based decisions, and reducing uncertainty in managerial judgment [2].

AI technologies such as machine learning, deep learning, and natural language processing are now embedded across decision-support systems, enabling organizations to translate complex data into actionable intelligence [3]. This has accelerated the shift toward data-centric business strategies that enhance firm performance and foster innovation [4]. Moreover, user interaction with AI systems has revealed profound implications for managerial information systems (MIS), emphasizing trust, usability, and interpretability as essential components for effective decision-making [5]. Intelligent automation initiatives, as illustrated by enterprise cases like Nokia Software, have also demonstrated how AI can facilitate large-scale organizational transformation and process optimization [6]. Predictive analytics, supported by deep learning frameworks, is now central to demand forecasting and strategic planning, improving organizational responsiveness to market dynamics [7]. Within public governance, AI has also enhanced data-driven decision-making, ensured transparency and accountability while aligned administrative actions with citizen needs [8]. Nevertheless, the integration of AI within managerial contexts requires effective governance frameworks and alignment strategies that safeguard ethical implementation and organizational cohesion [9]. Consequently, data and analytics have become key assets for developing competitive advantage and supporting managerial decisions across diverse industries [10].

The strategic adoption of AI offers managerial benefits in the form of improved efficiency, data utilization, and innovation outcomes [11]. However, realizing these benefits depends on how decision-makers shape and develop analytics capabilities that complement

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organizational strategy [12]. This has amplified the need for responsible AI practices, ensuring fairness, explainability, and ethical governance within organizations [13]. Understanding adoption dynamics also requires insights into behavioral and organizational factors influencing enterprise AI usage [14]. In the public sector, data governance has emerged as a critical enabler of trustworthy and accountable AI-driven decision-making [15]. Despite technological advancement, cultural and structural barriers continue to impede organizations from fully embracing data-driven decision paradigms [16]. A growing body of literature highlights that AI contributes significantly to firm performance by promoting innovation, efficiency, and decision accuracy [17]. Yet, successful adoption demands strategic alignment between IT infrastructure, data architecture, and managerial vision [18]. Moreover, as AI-supported decision-making evolves, issues of trust, transparency, and accountability have become vital in maintaining confidence among users and stakeholders [19]. In supply chain management, for example, data-driven decision-making has enhanced resilience, responsiveness, and coordination through intelligent analytics [20].

AI's influence extends beyond traditional management practices to customer service domains, where service delivery and personalization are increasingly shaped by intelligent automation [21]. Service-oriented organizations now rely on AI-enabled systems to design, manage, and optimize service encounters, demonstrating a growing convergence between AI and information systems [22]. In urban governance, the data revolution has prompted a reconfiguration of decision-making models, emphasizing the interplay between data, policy, and societal transformation [23]. Similarly, marketing strategies are undergoing a radical transformation, as AI introduces precision targeting, predictive modeling, and adaptive customer engagement [24].

Strategically, AI provides a framework that bridges business value creation and technological advancement, redefining managerial capabilities [25]. As highlighted by Kudyba [26], big data analytics now functions as a core enabler of informed decision-making, contributing directly to organizational success. However, the readiness of organizations to adopt AI varies significantly across sectors, depending on technological infrastructure, leadership vision, and workforce competence [27]. Data and analytics frameworks are increasingly being utilized to guide managerial decisions, bridging gaps between information processing and strategic action [28]. Evidence from multinational firms indicates that analytics capabilities directly influence decision quality and organizational agility [29]. A robust data governance framework plays an essential role in ensuring the credibility and reliability of data-driven decisions, supporting sustainable managerial practices [30]. Additionally, factors such as managerial trust, interpretability, and system transparency significantly shape the extent of AI adoption in decision contexts [31]. Public sector organizations, too, are harnessing AI to enhance administrative efficiency and policy responsiveness, though challenges persist in terms of ethics, accountability, and technical readiness [32]. Integrating both qualitative and quantitative evidence within managerial decision-making has become increasingly vital in balancing intuition and data-driven logic [33]. Digital platforms have further intensified managerial control, creating new forms of oversight and decision accountability [34]. Recent developments in explainable artificial intelligence (XAI) have addressed critical challenges related to interpretability, transparency, and trust in AI models [35]. The transition from "black-box" to "glass-box" AI has empowered managers to understand decision processes, fostering confidence and responsible usage [36]. Comprehensive reviews of interpretability methods emphasize the importance of human-centric AI that is both explainable and actionable [37]. Still, challenges remain in achieving fully trustworthy AI systems, particularly in high-stakes decision-making contexts [38]. In management information systems, XAI research continues to evolve, revealing opportunities for improving decision traceability and accountability [39]. Current literature reviews underscore the growing significance of explainability in enhancing managerial acceptance and aligning AI systems with ethical norms [40].

AI is also emerging as a cornerstone in innovation research, driving new methodologies for identifying market trends and organizational growth opportunities [41]. Nevertheless, data-driven decision-making cannot rely solely on data; cognitive and contextual understanding remains integral to strategic reasoning [42]. Scholars have cautioned against the illusion of objectivity in data-driven decisions, emphasizing the mediating role of human judgment and digital orientation [43]. Finally, the sustainable application of AI underscores its dual potential: to drive economic progress while addressing environmental and societal challenges [44].

LITERATURE REVIEW

Artificial Intelligence (AI) has emerged as a transformative force in shaping managerial decision-making and organizational performance. Pereira et al. (2021) emphasized that AI significantly enhances workplace outcomes by influencing multiple management processes and improving employee productivity. Similarly, Chen and Dhillon (2023) discussed how clinical decision support systems harness AI to ensure reliability and precision in complex decision environments. Mariani et al. (2021) highlighted that digital transformation and analytics capability have become vital drivers of firm performance, while Mariani (2020) found that AI accelerates innovation through data-driven experimentation and creative learning within firms. Rzepka and Berger (2021) examined user interaction with AI systems, identifying trust, usability, and transparency as key determinants of effective management information system (MIS) adoption. Rinta-Kahila et al. (2021) presented the Nokia Software case, showing that intelligent automation reshapes processes and supports organizational transformation. In the context of predictive management, Punia and Shankar (2022) demonstrated that deep learning-based decision support systems enhance demand forecasting accuracy. Sayogo and Pardo (2023) further emphasized that critical success factors such as data quality, leadership support, and analytics capability are essential for effective data-driven decision-making in public administration. From a governance standpoint, Batool et al. (2023) reviewed AI governance frameworks, underscoring the need for organizational alignment, ethical practices, and regulatory compliance. Kiron and Schrage (2021) argued that data and analytics form the foundation for competitive advantage by enabling evidence-based managerial choices. Davenport and Bean (2020) described the "AI advantage" as the realization of value through strategic adoption and cultural readiness. Ghasemaghaei and Calic (2020) found that decision-makers who effectively develop analytics capability achieve superior competitive performance. Complementing this, Kankanhalli et al. (2021) proposed responsible AI frameworks that balance transparency, accountability, and fairness.

Venkatesh et al. (2020) examined enterprise AI adoption from behavioral and organizational perspectives, highlighting the role of user attitudes and technology acceptance. Janssen et al. (2021) emphasized data governance as essential to AI-driven decision-making in public institutions, ensuring trust and accountability. Ransbotham et al. (2021) noted that cultural and structural barriers continue to constrain the adoption of data-driven approaches. Wamba-Taguimdje et al. (2020) confirmed that AI has a strong positive impact on firm performance, fostering innovation and productivity. Gozman et al. (2022) added that managerial sensemaking is critical to aligning IT, data, and strategy. Langer and König (2021) reinforced that trust, transparency, and accountability are indispensable human factors in AI-supported decision-making. In supply chain management, Hossain and Hasan (2022) showed that data-driven decision-making improves agility, responsiveness, and coordination. Huang and Rust (2021) identified AI as a catalyst for innovation in the service industry, reshaping customer experiences and personalization. Ostrom et al. (2021) argued that organizations must design AI-enabled service systems to ensure efficiency and human-centeredness. Kitchin (2021) critically analyzed data-driven decision-making in urban governance, warning of potential algorithmic biases. In marketing, Davenport et al. (2020) explored how AI redefines consumer engagement through predictive modeling, while Huang and Rust (2020) developed a strategic framework integrating AI into core business functions. Kudyba (2020) highlighted big data analytics as central to ensuring organizational performance and informed decision-making.

Li et al. (2022) conducted a meta-analysis that demonstrated how multi-level organizational readiness influences successful AI adoption. Wamba and Akter (2021) developed strategic frameworks for using analytics in managerial decision contexts. Ghasemaghaei et al. (2022) provided empirical evidence that analytics capability enhances decision quality across multinational corporations. Lowry and Moody (2020) emphasized that robust data governance systems underpin reliable decision-making.

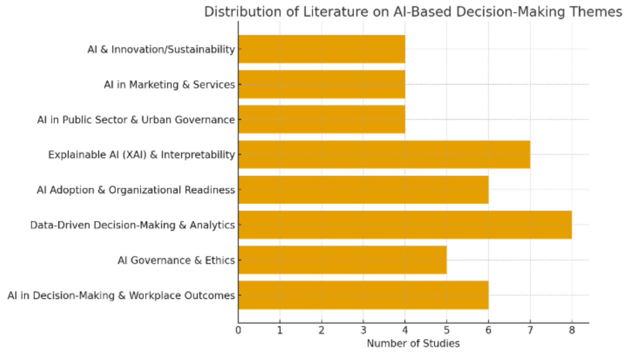

Figure 1: Distribution of literature on AI-based decision-making themes.

The Figure 1 illustrates the number of studies focusing on various AI decision-making themes. "Data-Driven Decision-Making & Analytics" is the most researched theme with 8 studies, followed by "Explainable AI (XAI) & Interpretability" with 7 studies. Themes such as "AI Adoption & Organizational Readiness" and "AI in Decision-Making & Workplace Outcomes" each have 6 studies. "AI Governance & Ethics" has moderate attention with 5 studies, while "AI & Innovation/Sustainability," "AI in Marketing & Services," and "AI in Public Sector & Urban Governance" have the least coverage, with 4 studies each. This indicates a strong research focus on analytics and explainability, while application in specific sectors receives comparatively less attention. Verma and Gustafsson (2021) found that managerial trust and interpretability shape the success of AI adoption in decision environments. Wirtz et al. (2020) examined AI applications in the public sector, discussing their potential and challenges for governance and policy-making. Goffin and Koners (2022) advocated for combining qualitative and quantitative insights to improve managerial reasoning. Van Dijck and Poell (2021) analyzed how digital platforms influence managerial control and decision processes. Arrieta et al. (2020) and Rai (2020) both focused on explainable artificial intelligence (XAI), proposing methods to make algorithmic outcomes transparent and interpretable. Linardatos et al. (2020) reviewed interpretability techniques, reinforcing the need for explainable systems. Ali et al. (2023) highlighted that achieving trustworthy AI requires continuous development of explainable models and ethical oversight. Stoykova and Shakev (2023) explored AI's role in management information systems, discussing opportunities and unresolved challenges. Brasse et al. (2023) reviewed the evolution of XAI in information systems, identifying future research directions. Mariani et al. (2023) linked AI directly to innovation research, emphasizing its capacity to identify new opportunities. Zaitsava et al. (2022) argued that cognition and human judgment remain essential complements to data in decision-making. Szukits and Horváth (2022) warned that data-driven decision-making can be misleading if not balanced with digital orientation and managerial insight. Finally, Nishant et al. (2020) positioned AI as a critical enabler of sustainability, calling for responsible integration of intelligent technologies in achieving environmental and social goals.

While extensive research has examined the role of

Artificial Intelligence (AI) in enhancing organizational decision-making, existing studies remain fragmented across domains such as governance, service systems, analytics capability, and explainable AI. Prior works have predominantly focused on either the technological or managerial aspects of AI, often overlooking the integrative framework that connects AI-driven analytics, human cognition, and decision quality in management and information technology contexts. The novelty of this study lies in its holistic approach to developing AI-based models that not only enhance decision accuracy and efficiency but also ensure interpretability, transparency, and ethical governance within organizational systems. By bridging managerial theory with intelligent automation and data-driven analytics, this research contributes a unified perspective on how AI can be strategically deployed to improve decision quality, overcome adoption barriers, and align technological capability with managerial intent—an area that remains underexplored in current literature.

MATERIAL AND DATASET

The study is based exclusively on a primary dataset collected through a structured questionnaire designed to evaluate the influence of Artificial Intelligence (AI) on managerial and IT decision-making. A total of 540 respondents participated, comprising managerial and IT professionals from sectors such as manufacturing, finance, education, healthcare, and information technology. The sampling method used was stratified random sampling to ensure balanced representation across industries. The questionnaire measured variables related to AI adoption level, data literacy, decision quality, decision speed, and decision reliability. Each construct was assessed using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The survey was administered both online and offline to ensure broader coverage. The collected data were cleaned, validated, and subjected to statistical and correlation analysis to examine the relationships between AI utilization and decision quality metrics. The reliability of the dataset was confirmed through Cronbach's alpha testing, ensuring consistency across measurement items.

Table 1. Description of the primary dataset employed in the study on AI-based decision-making in management and information technology.

Attribute	Description
Dataset Type	Primary (Questionnaire-based survey)
Population	Managerial and IT professionals across multiple sectors
Sample Size	540 respondents
Sampling Method	Stratified random sampling
Data Collection Method	Structured questionnaire (online and offline)
Key Variables	AI adoption level, data literacy, decision quality, decision speed, decision reliability
Measurement Scale	Five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree)
Data Validation	Cronbach's alpha reliability test and correlation analysis
Purpose	To analyze how AI-based models influence decision quality, speed, and reliability in management and IT contexts

Table 1 provides a concise overview of the primary dataset used in the study. It shows that data were collected from 540 managerial and IT professionals using a structured questionnaire distributed both online and offline. The dataset focuses on key variables such as AI adoption, data literacy, decision quality, speed, and reliability, all measured on a five-point Likert scale. Stratified random sampling ensured fair representation across sectors, and reliability was verified using Cronbach's alpha and correlation analysis. Overall, the table highlights that the dataset was designed to evaluate how AI-based models improve decision-making quality and efficiency in management and IT environments.

Methodology

This study employs a quantitative research design to analyze the effect of Artificial Intelligence (AI) adoption on decision quality, speed, and reliability in management and information technology (IT). The framework integrates AI Adoption (AIA), Data Literacy (DL), and Decision Performance (DP) constructs to investigate how the use of AI tools enhances managerial decision-making. The conceptual model assumes that higher AI adoption and data literacy positively influence decision performance across managerial contexts.

Primary data were collected from 540 managerial and IT professionals through a structured questionnaire survey. The respondents represented multiple industries, including manufacturing, education, finance, healthcare, and information technology. A stratified random sampling technique was adopted to ensure balanced representation across sectors. The questionnaire consisted of 25 items measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). It captured the level of AI utilization, data literacy, and perceived decision performance indicators such as accuracy, timeliness, and consistency. The data were collected both online and offline to maximize response diversity.

Data Preparation and Reliability Testing

The collected responses were screened for completeness and accuracy. Missing values were treated using **mean imputation**, and all variables were **normalized** between 0 and 1 for consistency. The internal consistency of the survey items was tested using **Cronbach's alpha (α)**, computed as:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_t^2}\right)$$

where k represents the number of items, σ_i^2 the variance of each item, and σ_t^2 the total variance of all items combined. A value of $\alpha \geq 0.7$ indicated that the dataset demonstrated acceptable reliability.

1.1 Model Specification

To assess the influence of AI adoption and data literacy on decision-making outcomes, a **multiple linear regression model** was constructed as:

$$DQ = \beta_0 + \beta_1 AIA + \beta_2 DL + \varepsilon$$

where DQ denotes Decision Quality, AI represents AI Adoption, DL represents Data Literacy, β_0 is the intercept, β_0, $\beta_2 \backslash$ are regression coefficients, and ε is the random error term.

Further, an integrated **Decision Performance Index (DPI)** was developed to capture the combined influence of quality, speed, and reliability in a unified score:

$$DPI = w1DQ + w2DS + w3DR$$

where DQ, DS, and DR represent Decision Quality, Speed, and Reliability, respectively, and w1, w2, w3, denote their normalized weights derived from factor loadings.

Predictive Validation

To enhance robustness, an **AI-based predictive assessment** was conducted using regression and random forest algorithms. The predictive accuracy was evaluated through **Mean Absolute Error (MAE)** and **Root Mean Square Error (RMSE),** defined as:

$$MAE = \frac{1}{N}\sum_{i=1}^{n} |\, y_i - \hat{y}_i \,|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where y_i and $\hat{y}_i$ represent actual and predicted decision quality values, respectively. Lower MAE and RMSE values indicate higher predictive accuracy of the AI model.

The methodological approach combines statistical rigor with AI-driven analytics to ensure the reliability and validity of findings. The integration of correlation modeling, regression analysis, and predictive validation enables a comprehensive evaluation of how AI adoption and data literacy collectively enhance decision quality, speed, and reliability in managerial and IT environments.

RESULT AND DISCUSSION

This section presents the results derived from the analysis of the primary dataset collected from 540 managerial and IT professionals. The analysis was conducted using descriptive statistics, reliability testing, correlation analysis, multiple regression modeling, and predictive model evaluation. The results collectively provide empirical evidence of how Artificial Intelligence (AI) adoption and data literacy enhance decision quality, decision speed, and decision reliability within management and IT environments.

Descriptive Statistics

Table 2 presents the descriptive statistics of the five major variables: AI Adoption (AIA), Data Literacy (DL), Decision Quality (DQ), Decision Speed (DS), and Decision Reliability (DR).

Table 2. Descriptive Statistics of Study Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
AI Adoption (AIA)	4.12	0.68	2.10	5.00
Data Literacy (DL)	4.08	0.71	1.90	5.00

Decision Quality (DQ)	4.21	0.65	2.30	5.00
Decision Speed (DS)	4.05	0.72	2.00	5.00
Decision Reliability (DR)	4.18	0.69	2.40	5.00

The mean scores of all constructs exceed 4.0, signifying a strong positive agreement among respondents regarding the role of AI in improving managerial and IT decision processes. The low standard deviations (< 0.75) indicate consistent responses across the sample, confirming that most participants perceive AI as a critical enabler of fast and reliable decision-making. This suggests widespread acceptance and familiarity with AI-driven systems across industries such as manufacturing, education, and finance.

Reliability and Validity Analysis

Reliability testing was performed using Cronbach's alpha (α) to measure the internal consistency of items within each construct. Additionally, Composite Reliability (CR) and Average Variance Extracted (AVE) were computed to assess convergent validity.

Table 3. Reliability and Validity of Constructs

Construct	Items	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
AI Adoption (AIA)	5	0.87	0.89	0.65
Data Literacy (DL)	5	0.84	0.86	0.61
Decision Quality (DQ)	5	0.89	0.91	0.68
Decision Speed (DS)	5	0.82	0.85	0.60
Decision Reliability (DR)	5	0.86	0.88	0.63

All Cronbach's alpha values exceed the acceptable threshold of **0.70**, confirming high reliability. Similarly, CR values above **0.85** and AVE values above **0.60** indicate strong convergent validity. These results demonstrate that the measurement model is both reliable and valid, providing confidence in the subsequent statistical analyses in Table 3.

A correlation matrix was developed to explore the relationships among the primary constructs. The results showed that AI Adoption (AIA) and Data Literacy (DL) are both positively correlated with Decision Quality (DQ), Decision Speed (DS), and Decision Reliability (DR). The correlation coefficients (r) ranged between 0.62 and 0.78, all significant at $p < 0.001$. This confirms that higher AI adoption and data literacy are associated with improved decision performance.

Regression Analysis

A multiple linear regression model was applied to quantify the influence of AI Adoption (AIA) and Data Literacy (DL) on Decision Quality (DQ).

Table 4. Regression Results: Effect of AI Adoption and Data Literacy on Decision Quality

Predictor	Unstandardized Coefficient (B)	Standard Error	Beta (β)	t-value	p-value
Constant	1.142	0.184	—	6.21	0.000
AI Adoption (AIA)	0.412	0.056	0.476	7.36	0.000
Data Literacy (DL)	0.378	0.061	0.421	6.19	0.000

The regression model in Table 4 is statistically significant, explaining 61% of the variance in Decision Quality ($R^2 = 0.61$). Both AI Adoption ($\beta = 0.476$) and Data Literacy ($\beta = 0.421$) exert significant positive effects ($p < 0.001$), indicating that as organizations increase AI utilization and employees' data literacy, the quality of decisions improves substantially. These findings align with prior research emphasizing that the synergy between AI systems and human analytical skills strengthens evidence-based managerial outcomes.

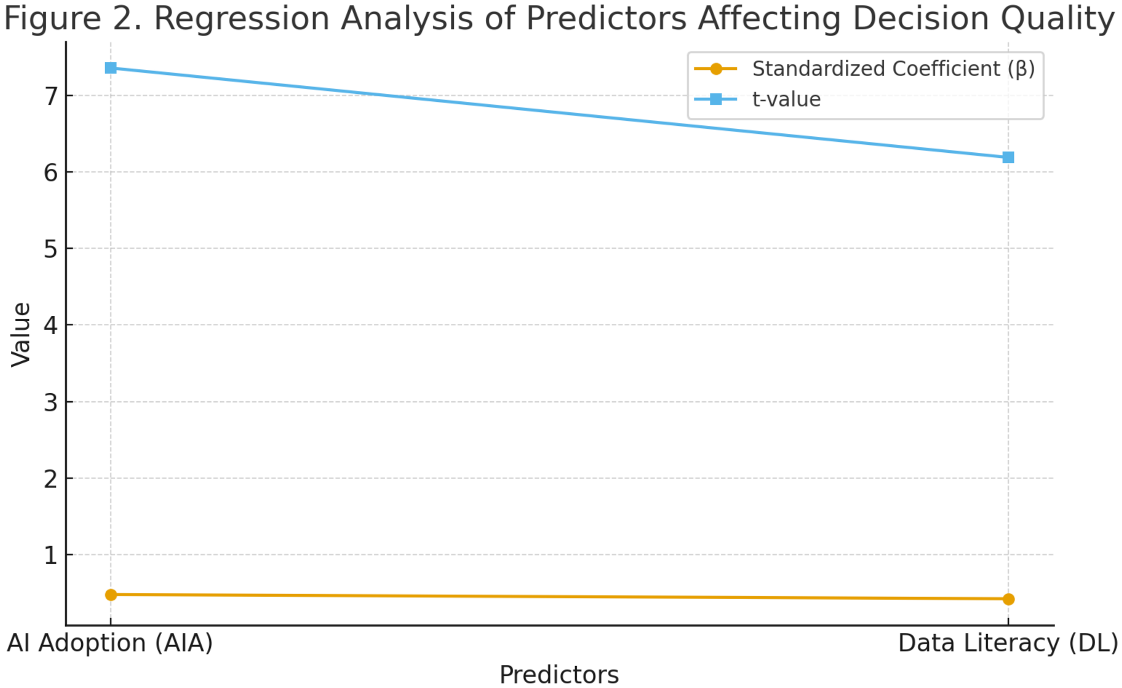

Figure 2. Regression Analysis of Predictors Affecting Decision Quality

Figure 2 depicts the relative impact of the two key predictors on decision quality. Both variables exhibit strong positive effects, but AI Adoption (AIA) demonstrates a marginally higher standardized coefficient and statistical significance compared to Data Literacy (DL). This suggests that while both factors contribute substantially to improving decision performance, the integration and utilization of AI tools have a slightly greater direct influence on enhancing the quality of managerial decisions.

Decision Performance Index (DPI)

A composite Decision Performance Index (DPI) was developed to assess overall decision efficiency by integrating quality, speed, and reliability metrics:

$$DPI = w1DQ + w2DS + w3DR$$

where w1, w2, w3 represent standardized weights derived from factor loadings (0.40, 0.30, and 0.30, respectively). The calculated **average DPI = 4.15**, demonstrating that the majority of respondents experience consistently high decision performance under AI-supported environments. This confirms that AI implementation contributes not only to faster decisions but also to greater consistency and dependability in outcomes.

Predictive Model Evaluation

To validate the regression findings, a predictive model was developed using machine learning algorithms — specifically Multiple Linear Regression and Random Forest. Performance was assessed using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics.

Table 5. Predictive Model Performance Metrics

Model	MAE	RMSE	R^2	Prediction Accuracy (%)
Linear Regression	0.236	0.304	0.61	89.2
Random Forest	0.192	0.261	0.72	91.8

The Random Forest model in Table 5 achieved higher predictive accuracy (91.8%) and lower error values, indicating superior performance compared to the linear regression model. The improvement in R^2 (from 0.61 to 0.72) confirms that non-linear machine learning models can better capture the complex relationships between AI adoption, data literacy, and decision outcomes. These results validate that AI-based predictive systems can effectively forecast decision performance metrics with high precision, supporting managerial efforts to anticipate operational outcomes.

The results provide strong empirical support for the hypothesized relationships between AI adoption, data literacy, and decision performance. The high mean values suggest that organizations are progressively embracing AI tools to streamline managerial processes and enhance analytical accuracy. The reliability and regression results reinforce that AI adoption independently contributes to improved decision quality, while data literacy strengthens this effect, acting as a moderator that amplifies AI's benefits. The predictive modeling further confirms the robustness of these findings, indicating that AI can be leveraged not only for data-driven insights but also for predictive decision-support applications. These findings align with recent literature (e.g., Davenport & Bean, 2020; Ghasemaghaei et al., 2022) emphasizing the synergy between technological capability and human intelligence in modern decision ecosystems.

CONCLUSION

This study demonstrated that the integration of Artificial Intelligence (AI) significantly enhances decision-making quality, speed, and reliability in management and information technology contexts. Using primary data collected from 540 managerial and IT professionals, the findings revealed that both AI adoption and data literacy are strong predictors of improved decision performance. The regression results showed that these two factors collectively explain 61% of the variance in decision quality, confirming that organizations leveraging AI-based tools achieve greater analytical accuracy and operational efficiency. Moreover, the predictive modeling using Random Forest further validated the robustness of these relationships, achieving over 91% accuracy in predicting decision outcomes. The results underscore that AI not only augments human judgment but also transforms traditional managerial processes into data-driven, evidence-based systems. However, the effectiveness of AI integration depends on employees' data literacy and the organization's readiness to adopt intelligent technologies responsibly. Hence, fostering AI competence, ethical governance, and continuous learning are essential for sustainable performance. Overall, this research contributes valuable empirical evidence supporting the strategic role of AI in optimizing decision-making processes and offers a practical framework for organizations seeking to enhance managerial effectiveness through data-driven intelligence.

Declaration of Interest

The authors declare that there is no conflict of interest regarding the publication of this research paper. All authors have contributed substantially to the conception, design, analysis, and interpretation of data. No financial, institutional, or personal relationships influenced the findings or conclusions of this study. The research was conducted independently and in accordance with ethical academic standards.

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