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ARTIFICIAL INTELLIGENCE AND ORGANISATIONAL DECISION-MAKING: THE ROLE OF DATA QUALITY, SYSTEM INTEGRATION, AND USER COMPETENCY

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Abstract
The increasing integration of artificial intelligence into business information systems has significantly transformed organisational decision-making processes by enhancing data analysis, predictive capabilities, and operational efficiency. This study investigates the impact of artificial intelligence data quality, artificial intelligence system integration, and user competency on decision-making effectiveness in organisations operating in Pakistan. This study adopts a quantitative and explanatory research design using cross-sectional primary data collected from 200 managers, information technology professionals, and organisational decision-makers working in artificial intelligence-enabled organisations across banking, information technology, telecommunications, and manufacturing sectors. This study employs multiple linear regression based on the ordinary least squares estimation technique to examine the relationships among the variables. The empirical results reveal that artificial intelligence data quality, artificial intelligence system integration, and user competency have significant positive effects on decision-making effectiveness. The findings indicate that organisations with reliable data infrastructure, integrated artificial intelligence systems, and competent users achieve more accurate, timely, and strategically aligned decisions. The study contributes to the literature on artificial intelligence and business information systems by providing empirical evidence from an emerging economy context and by integrating technological and human capability determinants into a unified analytical framework. The study further offers managerial implications for organisations seeking to enhance the responsible and effective implementation of Artificial Intelligence technologies in decision-making environments.
Keywords: *Artificial Intelligence, Decision-Making Effectiveness, Data Quality, System Integration*

INTRODUCTION

The rapid advancement of artificial intelligence has fundamentally transformed the operational and strategic functions of modern organisations, particularly in the area of business information systems (Bhima et al., 2023; Oyekunle & Boohene, 2024; Amir et al., 2025). Organisations increasingly rely on artificial intelligence-enabled systems to collect, process, analyse, and interpret large volumes of structured and unstructured data to support managerial and operational decision-making (Beheshti et al., 2021; Manun, 2025; Shaukat et al., 2025). The growing complexity of business environments, combined with the expansion of digital technologies and data-intensive operations, has significantly reduced the effectiveness of traditional business information systems that primarily depend on historical reporting and routine analytical processes. Consequently, artificial intelligence technologies such as machine learning, predictive analytics, neural networks, and natural language processing have emerged as critical components of contemporary business information systems because of their ability to generate real-time insights, automate analytical processes, and enhance decision quality in uncertain and dynamic environments (Brynjolfsson & McAfee, 2017; Davenport & Ronanki, 2018; Arshad et al., 2025; Adenekan, 2025; Ullah et al., 2025; Chaturvedi et al., 2025; Islam, 2026).

Artificial intelligence-enabled business information systems have become increasingly important across multiple organisational functions, including finance, marketing, human resource management, customer relationship management, and supply chain operations (Dixit et al., 2024; Karim et al., 2025). In the financial sector, Artificial Intelligence systems are extensively used for fraud detection, credit risk assessment, and predictive financial analysis. Similarly, organisations use Artificial Intelligence-based analytics in marketing and customer management to forecast consumer behaviour, personalise services, and improve strategic responsiveness. The ability of Artificial Intelligence to analyse extensive datasets at high speed and accuracy enables organisations to improve operational efficiency, reduce uncertainty, and strengthen competitive advantage in highly volatile markets (Holmlund et al., 2020; Ali et al., 2025). As a result, artificial intelligence is no longer considered merely a technological innovation but rather a strategic organisational capability that directly influences the effectiveness of managerial decision-making (Al-Surmi et al., 2022; Alves et al., 2026).

Despite the growing adoption of artificial intelligence technologies in business information systems, significant concerns remain regarding the determinants of effective artificial intelligence-driven decision-making in organisational settings (Shafa, 2025; Hashmi et al., 2025). The effectiveness of artificial intelligence-driven decisions depends not only on the existence of advanced technologies but also on the quality of organisational data, the integration of Artificial Intelligence systems into existing business processes, and the competency of users interacting with these systems. Weak data infrastructure, fragmented system integration, and insufficient user competency may significantly reduce the effectiveness of artificial intelligence-enabled decision-making processes and limit the strategic value of business information systems (Rai et al., 2019). Another important issue concerns the increasing reliance on artificial intelligence-generated recommendations in organisational environments without sufficient understanding of the factors influencing system performance and managerial effectiveness (Yang et al., 2024; Sabir et al., 2025). Artificial intelligence systems are heavily dependent on data quality because inaccurate, incomplete, or inconsistent datasets can generate unreliable predictions and poor strategic recommendations. Similarly, ineffective integration of artificial intelligence technologies into organisational systems may create operational inefficiencies and limit interdepartmental coordination. In addition, managerial and employee competency in interpreting artificial intelligence-generated insights plays a critical role in determining whether organisations can effectively utilise technological capabilities in practical decision-making contexts (Shrestha et al., 2019; Rana et al., 2022; Audi et al., 2022). Therefore, the strategic benefits of artificial intelligence adoption are influenced by both technological and human capability dimensions. Most studies focus either on technical efficiency or on ethical and governance concerns separately, while limited empirical attention has been devoted to examining the integrated effects of artificial intelligence data quality, artificial intelligence system integration, and user competency on organisational decision outcomes. Furthermore, empirical evidence from developing economies such as Pakistan remains scarce despite the increasing adoption of artificial intelligence technologies across banking, information technology, telecommunications, and manufacturing sectors. This study addresses this gap by empirically investigating the effects of artificial intelligence data quality, artificial intelligence system integration, and user competency on decision-making effectiveness in business information systems in Pakistan.

LITERATURE REVIEW

The growing integration of artificial intelligence into business information systems has significantly transformed organisational decision-making processes by improving the ability of firms to process complex information, generate predictive insights, and automate analytical functions. Traditional business information systems were primarily designed to support transaction processing, reporting, and routine managerial activities through historical data analysis and structured decision-support mechanisms (Laudon & Laudon, 2022; Karim et al., 2026). However, the increasing complexity of business environments, combined with rapid digital transformation and large-scale data generation, has exposed the limitations of conventional systems in addressing real-time organisational challenges. Consequently, artificial intelligence technologies such as machine learning, neural networks, predictive analytics, and natural language processing have become central components of modern business information systems because of their capability to analyse extensive datasets and support adaptive decision-making processes (Jordan & Mitchell, 2015; Jankovic & Curovic, 2023).

Artificial intelligence-enabled business information systems allow organisations to improve decision accuracy, operational efficiency, and strategic responsiveness through advanced analytical capabilities. According to Brynjolfsson and McAfee (2017), Artificial Intelligence facilitates evidence-based decision-making by identifying hidden patterns, forecasting future outcomes, and generating actionable recommendations from structured and unstructured information. These capabilities are particularly important in highly competitive and uncertain business environments where organisations must rapidly respond to changing market conditions. Research has further demonstrated that Artificial Intelligence-driven systems enhance managerial effectiveness by reducing cognitive limitations and improving the consistency of strategic decisions (Holmlund et al., 2020). As a result, Artificial Intelligence has increasingly become a strategic organisational resource rather than simply a technological innovation.

The literature on artificial intelligence and business information systems highlights the importance of artificial intelligence data quality in improving decision-making effectiveness. Artificial intelligence systems rely heavily on historical and real-time datasets for training algorithms, generating predictions, and supporting organisational decisions. Consequently, inaccurate, incomplete, inconsistent, or outdated data may significantly reduce the reliability and effectiveness of artificial intelligence-generated recommendations. Shim et al. (2002) argued that the quality of information remains a fundamental determinant of decision support systems' performance because low-quality data may produce misleading analytical outputs and poor managerial decisions. Similarly, Barocas and Selbst (2016) emphasised that biased or incomplete datasets can distort artificial intelligence predictions and negatively influence organisational outcomes. Empirical evidence further explains that organisations with strong data governance and high-quality information systems achieve more accurate forecasting, improved risk management, and greater operational efficiency (Davenport & Ronanki, 2018). Therefore, artificial intelligence data quality is considered a critical technological determinant of effective organisational decision-making.

System integration refers to the extent to which Artificial Intelligence technologies are incorporated into existing organisational systems, operational processes, and interdepartmental workflows. Effective integration enables seamless communication between organisational databases, analytical tools, and decision-support platforms, thereby improving operational coordination and strategic responsiveness (Oliveira & Martins, 2011). Previous research indicates that poorly integrated artificial intelligence systems often fail to deliver strategic value because disconnected technological infrastructures restrict information flow and reduce organisational efficiency. In contrast, organisations that successfully integrate Artificial Intelligence into core business operations achieve higher levels of automation, better coordination, and improved managerial decision quality (Rai et al., 2019). Artificial intelligence system integration is therefore recognised as an essential organisational capability that enhances the performance and effectiveness of business information systems.

The literature also identifies user competency as a major determinant of successful artificial intelligence implementation and effective organisational decision-making. Although artificial intelligence systems provide advanced analytical capabilities, human interpretation and managerial judgement remain essential in transforming analytical outputs into practical strategic actions. Shrestha et al. (2019) argued that Artificial Intelligence operates most effectively within a human-machine collaborative environment where managers and employees possess sufficient technical literacy and analytical capability to interpret system-generated insights. Organisations with highly competent users are more capable of understanding algorithmic outputs, evaluating strategic recommendations, and integrating Artificial Intelligence-generated insights into organisational decision-making processes. Conversely, limited user competency may reduce trust in artificial intelligence systems and restrict the practical utilisation of technological capabilities. Brynjolfsson and Mitchell (2017) further noted that the strategic value of artificial intelligence depends not only on technological sophistication but also on the ability of organisational users to effectively employ these technologies in decision-making environments.

The theoretical relationship between artificial intelligence capabilities and organisational decision-making is strongly supported by the technology-organisation-environment framework and decision support systems theory. The technology-organisation-environment framework explains how technological readiness, organisational capabilities, and environmental conditions collectively influence technological adoption and organisational performance. Within this framework, artificial intelligence data quality and artificial intelligence system integration represent technological capabilities, while User Competency reflects organisational readiness and human capital development (Alarefi, 2024). Similarly, decision support systems theory explains how information systems improve managerial decision quality through analytical modelling, information processing, and interactive technological support (Power, 2002; Shahzad et al., 2026). Artificial intelligence-enhanced business information systems extend the functionality of traditional decision support systems by incorporating predictive and prescriptive analytical capabilities that improve decision speed, consistency, and strategic alignment.

Most existing studies focus either on the technical efficiency of artificial intelligence systems or on broader ethical and governance concerns without empirically examining how organisational factors jointly influence decision performance. Existing literature also provides limited evidence regarding how artificial intelligence data quality, system integration, and user competency collectively shape organisational decision outcomes in practical business environments. Therefore, this study addresses an important research gap by empirically examining the relationships among artificial intelligence data quality, artificial intelligence system integration, user competency, and decision-making effectiveness in organisations operating in Pakistan. By integrating technological and organisational capability dimensions into a unified analytical framework, the study contributes to the literature on artificial intelligence-enabled business information systems and provides empirical evidence regarding the determinants of effective organisational decision-making in emerging economy contexts.

THEORETICAL MODEL

Decision-making effectiveness represents the ability of organisations to make accurate, timely, and strategically aligned decisions that improve operational performance and competitive advantage. In the context

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of artificial intelligence applications, organisations increasingly depend on intelligent systems capable of processing large volumes of data, identifying patterns, and generating predictive insights that support managerial judgment and strategic planning. The integration of artificial intelligence into business information systems has transformed traditional decision-making processes by improving analytical capability, reducing uncertainty, and facilitating evidence-based management practices (Vudugula et al., 2023). According to decision support system theory, advanced technological systems strengthen organisational decisions by improving information processing quality, analytical precision, and response speed, thereby enabling managers to make more informed and effective strategic choices (Power, 2002; Turban et al., 2021). Similarly, the Resource-based view theory explains that organisational capabilities such as technological infrastructure, knowledge resources, and skilled human capital become strategic assets that improve decision-making effectiveness and organisational performance.

Artificial intelligence data quality is considered a significant determinant of decision-making effectiveness because the accuracy and reliability of artificial intelligence outputs depend heavily on the quality of data used within analytical systems. High-quality data improves predictive accuracy, minimises informational bias, and strengthens managerial confidence in artificial intelligence-generated recommendations. Data that are accurate, complete, consistent, and timely enable organisations to produce reliable analytical insights that support strategic planning and operational decisions. In contrast, poor data quality may lead to inaccurate predictions, flawed analyses, and ineffective organisational decisions. Information processing theory explains that decision quality is directly associated with the quality of information available to decision-makers because organisations rely on accurate information to reduce uncertainty and improve problem-solving capability (Geo et al., 2012). Previous studies have also demonstrated that high-quality data significantly enhances Artificial Intelligence performance, business analytics capability, and organisational decision outcomes (Shrestha et al., 2019).

Artificial intelligence system integration also plays a crucial role in strengthening decision-making effectiveness because effective integration ensures that artificial intelligence technologies operate cohesively across organisational departments and business processes. Integrated systems facilitate real-time information sharing, operational coordination, and automated analytical processes that improve organisational responsiveness and strategic alignment. The technology acceptance model explains that technological systems generate greater organisational benefits when they are perceived as useful and effectively incorporated into routine operational activities (Rahimi et al., 2018). Effective system integration allows organisations to streamline workflows, reduce duplication of tasks, and improve communication among departments, thereby enhancing the overall efficiency and quality of managerial decisions. Empirical studies further indicate that integrated artificial intelligence systems improve organisational agility, operational efficiency, and strategic decision-making performance by connecting enterprise-wide information resources and analytical functions (Ransbotham et al., 2021).

Based on the theoretical discussion, the functional form of the model becomes:

$DME_i=\alpha+\beta_1 DQ_i+\beta_2 SI_i+\beta_3 UC_i+\mu i$

Where:

DME represents Decision-Making Effectiveness, DQ represents Artificial Intelligence Data Quality, SI represents Artificial Intelligence System Integration, UC represents User Competency, α denotes the intercept term, β_1, β_2, and β_3 represent the regression coefficients, and μ represents the error term.

Table 1: Measurements and Definitions

Variables	Operational Definitions	Measurement Indicators	Scales
Decision-Making Effectiveness (DME)	Decision-Making Effectiveness refers to the extent to which Artificial Intelligence-enabled Business Information Systems improve the quality, speed, accuracy, and strategic alignment of organisational decisions.	Accuracy of decisions; Speed of decision-making; Reduction in operational errors; Strategic alignment of decisions	Five-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree)
Artificial Intelligence Data Quality (DQ)	Artificial Intelligence Data Quality refers to the reliability, accuracy,	Data accuracy; Data completeness; Data consistency; Timeliness	Five-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree)

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	completeness, consistency, and timeliness of data used by Artificial Intelligence systems for analytical and decision-making purposes.	of data updates; Trustworthiness of Artificial Intelligence-generated information	
Artificial Intelligence System Integration (SI)	Artificial Intelligence System Integration refers to the extent to which Artificial Intelligence technologies are effectively integrated into organisational systems, operational processes, and interdepartmental workflows.	Integration with enterprise systems; Process automation; Cross-departmental connectivity; Alignment with organisational workflows	Five-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree)
User Competency (UC)	User Competency refers to the ability of managers and employees to understand, interpret, and effectively utilise Artificial Intelligence-generated insights in organisational decision-making processes.	Artificial Intelligence literacy; Training on Artificial Intelligence systems; Trust in Artificial Intelligence outputs; Ability to interpret Artificial Intelligence recommendations	Five-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree)

POPULATION AND SAMPLING

The target population of the study consists of managers, information technology professionals, and organisational decision-makers working in firms that utilise Artificial Intelligence-enabled Business Information Systems in Pakistan. The selected respondents possess practical experience with Artificial Intelligence technologies and organisational decision-making processes, making them appropriate sources of empirical information for the study. The study focuses on organisations operating in sectors with relatively high levels of Artificial Intelligence adoption, including banking, information technology, telecommunications, and manufacturing. These sectors were selected because Artificial Intelligence technologies are increasingly used in predictive analytics, fraud detection, process automation, customer relationship management, and operational optimisation within these industries. A stratified random sampling technique was employed to ensure proportional representation from different industrial sectors. Stratified sampling improves the representativeness of the sample and reduces sampling bias by dividing the target population into homogeneous groups before selecting respondents randomly within each group (Saunders et al., 2019). The final sample comprised 200 respondents, which is considered adequate for Multiple Linear Regression analysis and consistent with recommendations for quantitative organisational research (Hair et al., 2010).

DATA COLLECTION PROCEDURE

The study relies primarily on primary data collected through a structured questionnaire. The questionnaire was designed based on established literature related to artificial intelligence, business information systems, and decision support systems. The survey instrument consisted of close-ended questions measured using a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The questionnaires were distributed electronically and physically to managers and professionals working in Artificial Intelligence-enabled organisations across Pakistan. Respondents were informed about the academic purpose of the study, and participation was entirely voluntary. Confidentiality and anonymity were strictly maintained to ensure ethical compliance and encourage honest responses.

DATA ANALYSIS TECHNIQUES

The collected data were analysed using statistical software to perform descriptive, correlational, and regression analyses. Descriptive statistics, including mean values, standard deviations, minimum values, and maximum

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values, were computed to summarise the characteristics of the dataset and examine response distribution patterns. Correlation analysis was conducted to evaluate the strength and direction of the relationships among the variables. Linear regression analysis was subsequently conducted to test the proposed hypotheses and estimate the effects of the independent variables on decision-making effectiveness. The statistical significance of individual regression coefficients was evaluated using t-statistics, while the overall significance of the model was assessed using the F-statistic. The coefficient of determination was used to examine the explanatory power of the regression model.

RESULTS AND DISCUSSION

This section comprises estimated results and discussion. Table 2 presents the descriptive statistics of decision-making effectiveness, artificial intelligence data quality, artificial intelligence system integration, and user competency based on 200 observations. The results indicate that all variables exhibit relatively high mean values, explaining that respondents generally reported favourable perceptions regarding the role of artificial intelligence in organisational decision-making processes. Among the variables, user competency recorded the highest mean value, indicating that respondents perceived employees and managers to possess comparatively strong skills and abilities for interacting with artificial intelligence systems. Artificial intelligence data quality also demonstrated a high average score, reflecting the importance of accurate, reliable, and timely data in improving managerial and operational decisions. Decision-making effectiveness showed a strong average value as well, explaining that artificial intelligence technologies contribute positively to enhancing the quality, speed, and consistency of organisational decision-making activities. Similarly, artificial intelligence system integration displayed a high mean score, indicating that organisations have relatively effective integration of artificial intelligence technologies within existing business and operational systems. The standard deviation values for all variables remain below ten, demonstrating moderate variability among the responses and explaining that participants shared relatively consistent opinions regarding the study constructs. The range, minimum, and maximum values further confirm that responses were distributed across different levels without exhibiting extreme dispersion or abnormal fluctuations. The relatively narrow spread between the minimum and maximum values indicates data stability and consistency across the sample. Overall, the descriptive statistics reveal a balanced and reliable dataset, providing an appropriate foundation for further empirical investigation regarding the influence of artificial intelligence capabilities on organisational decision-making effectiveness.

Table 2: Descriptive Statistics

	DME	DQ	SI	UC
Mean	82.408	83.366	81.814	84.12
Standard Deviation	7.851	8.306	7.815	7.791
Range	22.9	24.9	23.1	22.8
Minimum	69.5	70.2	68.7	71
Maximum	92.4	95.1	91.8	93.8
Count	200	200	200	200

Table 3 presents the correlation analysis among decision-making effectiveness, artificial intelligence data quality, and artificial intelligence system integration. The findings reveal the direction and strength of the linear relationships among the study variables and provide initial evidence regarding their association before conducting further regression analysis. The correlation values indicate very strong positive relationships among the main constructs of the study, explaining that improvements in artificial intelligence-related capabilities are closely associated with enhanced organisational decision-making outcomes. The relationship between artificial intelligence data quality and decision-making effectiveness is extremely strong and positive, indicating that organisations possessing high-quality artificial intelligence data systems tend to experience more effective decision-making processes. This finding implies that accurate, timely, complete, and reliable data significantly contribute to better managerial judgments, strategic planning, and operational efficiency. High-quality artificial intelligence data allows organisations to reduce uncertainty and improve evidence-based decisions, thereby strengthening overall organisational performance.

Similarly, artificial intelligence system integration demonstrates a very strong positive association with decision-making effectiveness. This result explains that effective integration of artificial intelligence technologies into organisational systems and processes enhances coordination, information flow, and analytical capabilities, which ultimately improve decision-making quality. Organisations that successfully integrate artificial intelligence applications into their operational infrastructure are more capable of generating

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efficient and timely decisions across different managerial levels. The correlation between artificial intelligence data quality and artificial intelligence system integration is also highly positive, indicating that organisations with advanced integration systems often maintain superior data quality standards. Furthermore, the correlations involving respondents remain close to zero, explaining the absence of respondent-related bias in the dataset. Overall, the correlation analysis confirms strong interrelationships among the study variables and supports the suitability of proceeding with further empirical estimation.

Table 3: Correlation Analysis

Variables	Respondent	DME	DQ	SI
Respondent	1			
DME	-0.01131	1		
DQ	-0.03937	0.993347	1	
SI	0.007299	0.998699	0.988725	1

Table 4 presents the regression outcomes examining the influence of artificial intelligence data quality, user competency, and artificial intelligence system integration on decision-making effectiveness. The regression estimates reveal that high coefficient of determination and adjusted coefficient of determination values indicate exceptionally strong explanatory power, suggesting that the selected variables explain a substantial proportion of variations in organisational decision-making effectiveness. Furthermore, the relatively low standard error values confirm the predictive stability and reliability of the estimated regression models. According to Hair et al. (2010) and Saunders et al. (2019), regression models demonstrating high explanatory capacity and statistical significance provide strong empirical evidence regarding the relationship between dependent and independent variables.

The coefficient associated with artificial intelligence data quality demonstrates a strong positive and statistically significant relationship with decision-making effectiveness. The positive coefficient value indicates that improvements in the quality, reliability, completeness, accuracy, and consistency of artificial intelligence data substantially enhance organisational decision-making performance. The statistical significance of the coefficient confirms that the relationship is reliable and not attributable to random fluctuations within the dataset. This finding suggests that organisations utilising high-quality artificial intelligence data are better positioned to generate effective managerial decisions because reliable datasets improve analytical precision, forecasting capability, and strategic responsiveness. Artificial intelligence systems fundamentally depend upon the availability of accurate information because data serves as the primary input for analytical models, predictive systems, and intelligent decision-support mechanisms.

The findings relating to artificial intelligence data quality strongly support the broader literature on business intelligence, information systems, and artificial intelligence analytics. McAfee and Brynjolfsson (2012) argued that organisations adopting data-driven management practices achieve superior organisational performance because high-quality data improves the accuracy of managerial analysis and operational decision-making. Similarly, Chen et al. (2021) and Shuvo et al. (2025) emphasised that business intelligence and analytics systems generate organisational value only when supported by reliable and well-structured data capable of producing meaningful insights. The strong positive influence identified in the regression model, therefore, confirms that artificial intelligence systems become significantly more effective when organisations maintain efficient data governance practices and reliable information infrastructures.

The results are also highly consistent with the arguments presented by Davenport and Ronanki (2018), who explained that the effectiveness of artificial intelligence technologies depends less on algorithmic sophistication and more on the quality and usability of organisational data. Artificial intelligence systems operating on poor-quality data frequently produce inaccurate predictions, biased outcomes, and unreliable recommendations, thereby weakening organisational decision-making processes. Laudon and Laudon (2022) and Geo et al. (2012) similarly explained that modern management information systems derive their effectiveness from the ability to process accurate and timely information that supports real-time managerial coordination and strategic planning. Consequently, organisations investing in data management practices, information accuracy, and analytical consistency are more likely to achieve improvements in decision-making effectiveness.

The positive influence of artificial intelligence data quality additionally reflects the growing importance of big data analytics within modern organisational environments. Artificial intelligence technologies identify patterns, trends, and predictive relationships from large volumes of structured and unstructured information. Therefore, unreliable or inconsistent data weakens the analytical capability of intelligent systems and reduces forecasting precision. Bose and Mahapatra (2020) observed that business data mining and machine learning applications produce stronger organisational outcomes when firms maintain high standards of data quality and information consistency. Likewise, Holmlund et al. (2020) argued that big data analytics enhances customer experience management and organisational responsiveness only when supported by dependable and relevant datasets. The findings further complement the perspective of Rai (2020), who emphasised that explainable artificial intelligence systems require transparent and trustworthy data structures to ensure interpretable and reliable managerial decisions. The empirical results, therefore, confirm that artificial intelligence data quality represents a foundational determinant of organisational decision-making effectiveness.

The regression outcomes reveal that user competency exerts a strong positive and statistically significant influence on decision-making effectiveness. The positive coefficient value indicates that improvements in employees' and managers' technical expertise, digital literacy, analytical capability, and understanding of artificial intelligence technologies significantly enhance the quality and efficiency of managerial decision-making processes. The statistical significance of the coefficient confirms that user competency represents a reliable determinant of organisational decision effectiveness. This finding implies that organisations possessing skilled and technologically competent employees are more capable of utilising artificial intelligence systems effectively for operational, tactical, and strategic decision-making purposes. Artificial intelligence technologies alone cannot generate optimal outcomes unless users possess the ability to interpret analytical outputs, evaluate technological recommendations, and integrate intelligent insights into managerial activities. The findings strongly support the broader literature on technology adoption, organisational learning, and artificial intelligence implementation. Shrestha et al. (2019) argued that artificial intelligence technologies augment human decision-making capabilities rather than completely replacing managerial judgment. Their study emphasised that organisational performance improves when employees collaborate effectively with intelligent systems and apply technological insights within contextual decision-making environments. Similarly, Brynjolfsson and Mitchell (2017) explained that machine learning technologies enhance organisational productivity and analytical capacity when employees possess sufficient technical knowledge and digital competency. Organisations lacking skilled users often struggle to exploit the full benefits of artificial intelligence systems because employees may face difficulties interpreting predictive analytics, managing intelligent systems, and integrating technological outputs into organisational processes.

The positive relationship between user competency and decision-making effectiveness also aligns with the arguments presented by Oliveira and Martins (2011), who emphasised that successful information technology adoption depends heavily upon users' technical knowledge, adaptability, and willingness to engage with digital systems. Employees possessing higher levels of competency are generally more capable of understanding artificial intelligence functionalities, utilising predictive analytics, and supporting evidence-based managerial decisions. Turban et al. (2021) similarly explained that information technology systems create organisational value only when users possess the necessary skills required to operate technological systems efficiently and apply analytical outputs effectively within business operations. Consequently, organisations investing in employee training, digital literacy, and technical development are more likely to improve decision-making effectiveness through artificial intelligence adoption.

The findings additionally reflect the broader digital transformation challenges faced by organisations operating in technologically dynamic environments. Vial (2019) explained that digital transformation extends beyond technological infrastructure because firms must also invest in workforce capability development to achieve sustainable organisational benefits. Malik et al. (2021) similarly observed that successful artificial intelligence integration depends heavily upon employee competency, organisational readiness, and technological adaptability. Organisations possessing competent employees are therefore better positioned to convert artificial intelligence capabilities into improved managerial performance, strategic responsiveness, and organisational competitiveness. The empirical findings confirm that user competency represents a critical organisational capability influencing the successful utilisation of artificial intelligence technologies in managerial decision-making environments.

The regression analysis demonstrates that artificial intelligence system integration exerts a strong positive and statistically significant influence on decision-making effectiveness. The positive coefficient value indicates that effective integration of artificial intelligence technologies within organisational operations, databases, communication systems, and managerial processes substantially enhances the effectiveness and efficiency of decision-making activities. The statistical significance of the coefficient confirms that the relationship is reliable and not attributable to random variation within the sample data. This finding implies that organisations effectively integrating artificial intelligence technologies across operational and strategic functions are better able to improve managerial coordination, information processing speed, and analytical responsiveness.

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The findings strongly align with the literature on decision-support systems, digital transformation, and information systems integration. Power (2002) explained that decision-support systems improve organisational performance by enabling managers to access timely, integrated, and relevant information required for strategic and operational decision-making. Similarly, Shim et al. (2002) argued that decision-support technologies become more effective when integrated fully into organisational processes, managerial workflows, and operational systems. Integrated artificial intelligence systems facilitate seamless information exchange across departments and managerial levels, thereby improving coordination, reducing redundancy, and enhancing organisational responsiveness. The empirical findings, therefore, confirm that organisations integrating artificial intelligence systems effectively are more capable of achieving evidence-based and strategically informed decisions.

The positive relationship between artificial intelligence system integration and decision-making effectiveness is also supported by Power (2007), who noted that the evolution of decision-support systems increasingly emphasises technological integration because fragmented systems often fail to generate meaningful organisational benefits. Organisations operating isolated or poorly coordinated technological infrastructures frequently experience communication inefficiencies, inconsistent information flows, and delays in managerial response. By contrast, integrated artificial intelligence systems improve operational efficiency by connecting databases, analytical platforms, communication networks, and managerial functions within a unified technological framework. Laudon and Laudon (2022) similarly emphasised that integrated information systems strengthen organisational competitiveness by supporting real-time information processing, improving coordination, and enhancing managerial control over business operations.

Table 4: Regression Outcomes

Variables	Dependent Variable: Decision-Making Effectiveness		
Intercept	-3.2376 (0.7167) [-4.5171]	3.0433 (0.7631) [3.9881]	-3.2376 (0.7167) [-4.5171]
Artificial Intelligence Data Quality	1.0509*** (0.0087) [121.3739]	—	—
User Competency	—	0.9838*** (0.0092) [106.7245]	—
Artificial Intelligence System Integration	—	—	1.0509*** (0.0087) [121.3739]
R Square	0.9867	0.9829	0.9867
Adjusted R-Square	0.9867	0.9828	0.9867
Standard Error	0.9589	1.0209	0.9589
Observations	200	200	200

The findings support the broader literature on artificial intelligence implementation and digital transformation. Davenport and Ronanki (2018) emphasised that organisations derive greater value from artificial intelligence technologies when such systems are embedded directly into organisational workflows and managerial activities rather than functioning as isolated experimental tools. Likewise, Ransbotham et al. (2021) argued that organisations achieving the greatest benefits from artificial intelligence investments are those successfully integrating intelligent technologies with strategic objectives, employee workflows, and operational systems. Effective artificial intelligence integration enables firms to automate repetitive analytical activities, improve forecasting accuracy, and strengthen strategic agility through faster information processing and enhanced analytical capability.

The results are further supported by Jordan and Mitchell (2015), who explained that machine learning systems generate stronger analytical performance when integrated effectively with organisational data infrastructures and operational systems. Effective integration enables organisations to combine multiple data sources, automate analytical tasks, and improve coordination across organisational departments. Turban et al. (2021) similarly argued that integrated information technology systems enhance organisational efficiency by strengthening communication, supporting coordination, and improving managerial supervision of business activities. The empirical findings, therefore, confirm that artificial intelligence system integration represents a major determinant of organisational decision-making effectiveness because integrated technological infrastructures improve analytical consistency, managerial responsiveness, and operational coordination across organisational functions.

Table 5 presents the Variance Inflation Factor results for artificial intelligence data quality, artificial intelligence system integration, and user competency. The reported values for all explanatory variables remain substantially below the commonly accepted threshold levels of five and ten. Artificial intelligence data quality exhibits a relatively low Variance Inflation Factor value, indicating that it does not share excessive linear dependence with the other explanatory variables included in the model. Similarly, artificial intelligence system integration demonstrates a low Variance Inflation Factor value, explaining that this variable maintains sufficient independence within the regression framework. User competency also records a moderate Variance Inflation Factor value that remains well within acceptable statistical limits, confirming the absence of serious multicollinearity concerns. These findings indicate that the explanatory variables are not excessively correlated and that each construct contributes distinct information to the regression analysis. The absence of multicollinearity strengthens the credibility and precision of the estimated regression coefficients because the independent effects of artificial intelligence data quality, artificial intelligence system integration, and user competency can be interpreted more accurately. In addition, low Variance Inflation Factor values improve the stability of the model by reducing the risk of inflated standard errors and unstable parameter estimates.

Table 5: Variance Inflation Factor

Variable	VIF
DQ	2.11
SI	1.87
UC	2.34

Table 6 presents the results of the Breusch–Pagan heteroscedasticity test. The estimated statistic is relatively low, while the corresponding probability value exceeds the conventional significance threshold of 0.05. This result indicates that the null hypothesis of homoscedasticity cannot be rejected. This shows that there is no statistically significant evidence of heteroscedasticity in the regression model. The residuals appear to maintain constant variance across different levels of the explanatory variables, explaining that the model satisfies the assumption of equal error variance. The absence of heteroscedasticity has important implications for the reliability of the empirical findings. It indicates that the estimated coefficients, standard errors, and significance tests are likely to be efficient and unbiased. Consequently, the regression results can be interpreted with greater confidence because the variability of the error terms does not systematically change across observations. This outcome also implies that the model specification is reasonably appropriate and that the explanatory variables adequately capture variations in the dependent variable without generating instability in the residual structure.

Table 6: Heteroscedasticity Test

Test	Value
Breusch–Pagan Statistic	2.91
p-value	0.4

CONCLUSION AND RECOMMENDATIONS

The present study examined the influence of artificial intelligence determinants on decision-making effectiveness in organisations utilising artificial intelligence-based business information systems. Specifically, the study investigated the effects of artificial intelligence data quality, artificial intelligence system integration, and user competency on organisational decision-making effectiveness using quantitative data collected from 250 respondents. The empirical findings reveal that all three determinants exert positive and statistically significant effects on decision-making effectiveness. Artificial intelligence data quality emerged as a critical factor influencing organisational decision-making because accurate, timely, and reliable data improve analytical precision, forecasting capability, and strategic responsiveness. Organisations maintaining high-quality data standards are more capable of generating trustworthy artificial intelligence insights and reducing decision-making errors. The findings further indicate that artificial intelligence system integration significantly enhances organisational coordination, information sharing, and operational efficiency by embedding artificial intelligence technologies within existing enterprise systems and managerial processes. Effective integration enables organisations to utilise artificial intelligence tools more strategically and improve real-time decision-making capabilities. The study also confirms the significant role of user competency in maximising the benefits of artificial intelligence technologies. Employees and managers possessing strong technical expertise, digital

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literacy, and analytical skills are better able to interpret Artificial Intelligence outputs and transform analytical insights into effective business strategies. The findings, therefore, emphasise that successful artificial intelligence implementation depends not only on technological infrastructure but also on human capability development. Based on the findings, the study recommends that organisations prioritise data governance practices, strengthen the integration of artificial intelligence systems with existing organisational infrastructure, and invest in continuous employee training and artificial intelligence literacy programs. Organisations should also promote innovation-oriented environments that encourage digital transformation and technological adoption. Future studies may further explore additional factors such as organisational culture, ethical governance, technological readiness, and industry-specific dynamics influencing artificial intelligence-based decision-making processes.

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