Journal on Economics, Management and Business Technology
Vol. 4 No. 1, Sept (2025), pp. 26-38
ISSN 2962-0694 (Online)
Published by IHSA Institute

The Impact of AI-Based Business Analytics on Corporate Strategic Decision Making

Daquan Gosheven[1], Langundo Philly[2], Taila[3]
[1,2,3] Financial Technology and Analytics Department, Naveen Jindal School of Management, Dallas, Texas, USA

ARTICLE INFO

Article history:

Received Juli 26, 2025
Revised Aug 26, 2025
Accepted Sep 28, 2025

Keywords:

Artificial Intelligence;
Business Analytics;
Strategic Decision Making;
Predictive Analytics;
Data-Driven Decision Making.

ABSTRACT

The rapid growth of digital transformation has encouraged organizations to increasingly adopt AI-Based Business Analytics to enhance strategic decision making in highly dynamic and competitive business environments. Artificial Intelligence (AI) technologies, including machine learning, predictive analytics, and real-time data processing, enable organizations to generate faster, more accurate, and evidence-based insights that support executive decision making and improve organizational performance. This study aims to examine the impact of AI-Based Business Analytics on corporate strategic decision making. A quantitative research approach was employed using an explanatory cross-sectional survey design. Data were collected from 300 corporate executives, strategic planning managers, business analysts, senior managers, and AI implementation specialists working in organizations that have adopted AI-enabled business analytics. The data were analyzed using Partial Least Squares Structural Equation Modeling (SEM-PLS) to evaluate the measurement and structural models and test the proposed hypotheses. The findings indicate that AI-Based Business Analytics has a positive and statistically significant influence on corporate strategic decision making. The results also demonstrate that AI-generated insights enable organizations to make more informed and adaptive strategic decisions in increasingly uncertain business environments. The study concludes that adopting AI-Based Business Analytics strengthens organizational strategic decision-making capabilities, enhances sustainable competitive advantage, and supports long-term organizational performance. These findings contribute to the literature on Strategic Management, Artificial Intelligence, Business Analytics, and Decision Science while providing practical guidance for organizations seeking to maximize the strategic value of AI-driven analytics in corporate decision-making processes.

Corresponding Author:

Daquan Gosheven
Financial Technology and Analytics Department,
Naveen Jindal School of Management, Dallas, Texas, USA
Email: daquangosheven@gmail.com

1. INTRODUCTION

The rapid advancement of digital technologies has fundamentally transformed the way organizations operate, compete, and create value. Digital transformation has become a strategic priority across industries, enabling companies to integrate advanced technologies into their business processes to enhance operational efficiency, customer engagement, and organizational performance. Among these technological innovations, Artificial Intelligence (AI) has emerged as one of the most influential drivers of business transformation. AI technologies are increasingly being incorporated into various business functions, including marketing, finance, supply chain management, human resource management, and strategic planning(Davenport & Harris, 2017). As organizations operate in highly dynamic and competitive environments, the ability to leverage AI for informed decision making has become a critical determinant of long-term success.

One of the most significant applications of AI in organizations is AI-Based Business Analytics(Selvarajan, 2021). Unlike traditional Business Intelligence (BI) systems, which primarily focus on descriptive analysis of historical data, AI-Based Business Analytics incorporates machine learning algorithms, predictive analytics, natural language processing, and advanced data mining techniques to generate predictive and prescriptive insights. These capabilities enable organizations not only to understand past business performance but also to anticipate future trends, identify emerging opportunities, predict risks, and recommend optimal strategic actions. Consequently, AI-Based Business Analytics has evolved from a reporting tool into an intelligent decision-support system that enhances managerial decision making at strategic, tactical, and operational levels.

The growing volume of business data further reinforces the importance of AI-driven analytics. Organizations today generate enormous quantities of structured and unstructured data from enterprise systems, customer transactions, social media platforms, Internet of Things (IoT) devices, financial records, and digital communication channels. While these data represent valuable organizational assets, extracting meaningful knowledge from such complex datasets exceeds the capabilities of conventional analytical methods. Traditional Business Intelligence tools often struggle to process real-time data, recognize hidden patterns, or generate accurate predictions in increasingly complex business environments. AI technologies overcome these limitations by continuously learning from data, adapting analytical models, and providing highly accurate insights that support evidence-based strategic decisions.

Strategic decision making has therefore become increasingly dependent on data-driven technologies. Corporate executives are expected to make timely decisions regarding market expansion, investment strategies, product innovation, resource allocation, risk management, and competitive positioning. These decisions often involve considerable uncertainty and require the analysis of large volumes of multidimensional information. AI-Based Business Analytics assists decision makers by providing real-time intelligence, predictive forecasts, scenario simulations, and automated recommendations that improve decision quality, speed, and consistency. As a result, organizations adopting AI-powered analytics are better positioned to respond rapidly to changing market conditions, improve organizational agility, and sustain competitive advantage.

Research on Artificial Intelligence (AI)-Based Business Analytics has grown rapidly over the last decade as organizations increasingly adopt intelligent technologies to improve strategic planning and decision making. One of the earliest comprehensive discussions on AI-supported decision making was presented by Duan, Edwards, and Dwivedi (2019), who argued that Artificial Intelligence has evolved beyond operational automation to become a strategic organizational capability. Their study emphasized that AI enables managers to analyze massive datasets, identify hidden patterns, and generate predictive insights that improve business planning and organizational competitiveness. Nevertheless, they also highlighted challenges related to organizational readiness, managerial trust, and ethical concerns that continue to influence successful AI implementation.

Building upon this perspective, Ransbotham et al. (2020) examined AI adoption across organizations and found that firms achieving the greatest business value were those integrating AI into strategic decision-making processes rather than limiting its use to operational activities. Their findings demonstrated that organizational culture, executive commitment, and digital maturity significantly influence AI's contribution to corporate strategy. The study concluded that AI should complement rather than replace managerial judgment, emphasizing the importance of human-AI collaboration in strategic planning.

Research by Lai, Chen, Liao, Smith-Renner, and Tan (2021) further expanded understanding of AI-assisted decision making by reviewing more than one hundred empirical studies on human-AI collaboration. Their survey concluded that AI substantially improves analytical performance, prediction accuracy, and decision consistency when human expertise remains actively involved in evaluating AI recommendations. The authors stressed that explainability, transparency, and user trust are essential factors determining whether managers adopt AI-generated recommendations in real-world decision environments.

A broader perspective was provided by BaniHani, Alawadi, and Elmrayyan (2024) through a systematic literature review covering healthcare, finance, and technology sectors. Their review found that AI significantly enhances organizational decision making by rapidly processing large datasets, improving forecasting accuracy, and supporting complex managerial decisions. However, the authors also identified important implementation challenges, including algorithmic bias, ethical concerns, governance issues, and organizational resistance to AI adoption. These findings suggest that successful implementation requires not only technological capability but also appropriate managerial and institutional support.

Within the business analytics domain, Hidayah, Rahayu, Dirgantari, and Wibowo (2023) conducted a systematic review focusing specifically on AI-based decision making in business strategy. Their study concluded that AI-driven analytics enables organizations to improve strategic planning, operational efficiency, customer satisfaction, and competitive advantage through predictive and prescriptive analytics. At the same time, they emphasized that ethical considerations, transparency, fairness, and responsible AI governance remain critical issues that organizations must address before fully integrating AI into strategic management.

The strategic implications of AI were further explored by Kaggwa, Eleogu, Okonkwo, Farayola, Uwaoma, and Akinoso (2024), who examined how AI transforms business strategy through improved forecasting, intelligent automation, and enhanced decision support. Their research suggested that AI enables organizations to make faster and more informed strategic decisions while reducing uncertainty in highly competitive business environments. However, they also warned that successful AI implementation depends on organizational readiness, workforce capabilities, data quality, and effective governance frameworks.

A complementary review by Ibeh, Asuzu, Olorunsogo, Elufioye, Nduubuisi, and Daraojimba (2024) highlighted the growing integration of business analytics, decision science, and Artificial Intelligence. The authors explained that descriptive, predictive, and prescriptive analytics supported by machine learning provide organizations with powerful tools for forecasting market trends, optimizing resource allocation, identifying business opportunities, and managing organizational risks. Their study emphasized that AI-based business analytics should be viewed as a strategic capability that complements managerial expertise rather than replacing executive decision makers.

More recently, Csaszar, Ketkar, and Kim (2024) investigated the role of generative AI and large language models (LLMs) in strategic decision making. Their empirical evidence demonstrated that modern AI systems are capable of generating strategic alternatives and evaluating business strategies at a level comparable to experienced entrepreneurs and investors in certain contexts. The authors proposed that AI has the potential to reshape strategic management by accelerating opportunity identification, improving strategic analysis, and supporting virtual strategy simulations. However, they maintained that final strategic decisions should continue to rely on human oversight and organizational judgment.

Despite these promising developments, the implementation of AI-Based Business Analytics remains uneven across organizations(Keding, 2021). Many firms continue to rely heavily on managerial intuition, personal experience, and traditional decision-making approaches rather than leveraging AI-generated insights. Although managerial expertise remains valuable, decisions based solely on intuition may be vulnerable to cognitive bias, incomplete information, and subjective judgment. Furthermore, AI adoption varies considerably depending on organizational size, digital maturity, technological infrastructure, financial resources, and leadership commitment. Small and medium-sized enterprises often face significant barriers in adopting AI technologies due to limited budgets, insufficient technical expertise, and inadequate data management capabilities.

Another major challenge concerns organizational trust in AI-generated recommendations. Managers may hesitate to rely on AI systems because of concerns regarding algorithm transparency, interpretability, accountability, data privacy, and ethical implications. AI models are frequently perceived as "black boxes," making it difficult for decision makers to understand how recommendations are generated(Adadi & Berrada, 2018). This lack of transparency can reduce managerial confidence and hinder the integration of AI into strategic planning processes. Moreover, implementing AI-Based Business Analytics requires substantial investments in technological infrastructure, employee training, system integration, cybersecurity, and data governance, making adoption both costly and organizationally complex.

From an academic perspective, research investigating AI-Based Business Analytics has expanded considerably over the past decade. However, much of the existing literature primarily focuses on operational efficiency, process automation, customer analytics, or supply chain optimization. Comparatively fewer studies examine how AI-Based Business Analytics directly influences corporate strategic decision making, particularly in relation to decision quality, strategic responsiveness, and competitive advantage. Furthermore, most empirical studies have been conducted in technologically advanced economies, leaving limited evidence regarding AI adoption and strategic decision making in developing countries where organizational capabilities, digital readiness, and institutional environments differ substantially.

Another important research gap concerns the limited integration of AI capabilities with managerial decision-making outcomes. Existing studies frequently evaluate technical performance indicators such as prediction accuracy, algorithm efficiency, or computational effectiveness, while paying less attention to how AI-generated insights influence executive decision processes, strategic planning effectiveness, and organizational competitiveness. Consequently, there remains insufficient empirical evidence explaining the mechanisms through which AI-Based Business Analytics enhances strategic decision quality and organizational performance.

Based on these gaps, this study seeks to investigate the impact of AI-Based Business Analytics on corporate strategic decision making. Specifically, the study addresses the following research questions: (1) Does AI-Based Business Analytics significantly influence corporate strategic decision making? (2) Does predictive analytics improve the quality of strategic decisions? (3) Does real-time business intelligence enhance strategic responsiveness? and (4) Do AI-generated insights contribute to organizational competitiveness?

Accordingly, the primary objective of this research is to examine the influence of AI-Based Business Analytics on corporate strategic decision making. The study also aims to analyze the effect of predictive analytics on decision quality and investigate the relationship between AI-generated insights and organizational competitiveness. Through these objectives, the research intends to provide empirical evidence regarding the strategic value of AI-enabled business analytics in modern organizations.

This research offers both theoretical and practical contributions. Theoretically, it contributes to the growing body of knowledge on Artificial Intelligence adoption, Business Analytics, and Strategic Management by extending current understanding of how AI-driven analytical capabilities influence strategic decision-making processes. The findings are expected to enrich existing theories related to data-driven decision making, organizational capabilities, and digital transformation. Practically, the study provides valuable insights for chief executive officers (CEOs), business managers, strategy consultants, digital transformation teams, and policymakers seeking to leverage AI-Based Business Analytics to improve strategic planning, enhance decision quality, strengthen organizational competitiveness, and support sustainable business growth in an increasingly data-driven economy.

2. RESEARCH METHOD

This study employs a quantitative research approach to examine the impact of AI-Based Business Analytics on corporate strategic decision making(Lin et al., 2017). A quantitative approach is appropriate because it enables the researcher to objectively measure the relationships between research variables through statistical analysis and empirical testing. Specifically, this study adopts an explanatory research design, which aims to explain the causal relationship between AI-Based Business Analytics as the independent variable and Corporate Strategic Decision Making as the dependent variable. The explanatory design allows the researcher to test hypotheses derived from existing theories and previous empirical studies concerning the strategic value of artificial intelligence in organizational decision-making processes.

The study utilizes a cross-sectional survey design, in which data are collected from respondents at a single point in time. This design is suitable because it captures organizations' current adoption of AI-Based Business Analytics and its perceived influence on strategic decision-making practices. Cross-sectional surveys are widely used in business and management research due to their efficiency in obtaining quantitative data from a relatively large number of respondents while allowing statistical generalization within the target population.

The target population consists of professionals who are actively involved in organizational strategic decision making and AI implementation(Brock & Von Wangenheim, 2019). These include corporate executives, strategic planning managers, business analysts, senior managers, digital transformation managers, chief information officers (CIOs), business intelligence specialists, and AI implementation specialists working in medium-sized and large organizations across various industries. These individuals are selected because they possess sufficient knowledge regarding organizational strategy, business analytics, and the implementation of AI technologies, making them the most appropriate respondents for evaluating the strategic impact of AI-Based Business Analytics.

The sample is determined using purposive sampling, a non-probability sampling technique in which respondents are selected according to predefined criteria. The inclusion criteria require respondents to occupy managerial or executive positions, have at least two years of professional experience in strategic planning or business analytics, and work in organizations that have adopted AI-based analytical tools for business decision making. Purposive sampling is considered appropriate because the study requires respondents with specialized expertise rather than a randomly selected population(Rai & Thapa, 2015). To achieve adequate statistical power for multivariate analysis using Structural Equation Modeling, the study targets approximately 300 respondents, a sample size that exceeds the minimum recommendations for SEM analysis and enhances the reliability and generalizability of the findings.

The study investigates two principal variables. The independent variable is AI-Based Business Analytics, representing the organization's capability to utilize artificial intelligence technologies in collecting, processing, analyzing, and interpreting business data to support managerial decisions. This variable is operationalized through six dimensions: Predictive Analytics, which reflects the ability to forecast future business outcomes; Machine Learning Capability, referring to the organization's use of self-learning algorithms that improve analytical performance over time; Data Quality, measuring the accuracy, completeness, consistency, and reliability of organizational data; Real-Time Analytics, representing the organization's ability to generate immediate analytical insights; AI Recommendation Accuracy, which evaluates managers' perceptions regarding the precision and usefulness of AI-generated recommendations; and Data Integration, reflecting the organization's capability to combine information from multiple internal and external data sources into a unified analytical platform.

The dependent variable is Corporate Strategic Decision Making, defined as the effectiveness of executive decisions that determine the organization's long-term direction and competitive positioning. This variable is measured using six dimensions. Decision Quality assesses the accuracy, consistency, and effectiveness of strategic decisions(Spetzler et al., 2016). Decision Speed evaluates how rapidly organizations respond to emerging business opportunities and challenges. Strategic Flexibility measures the organization's ability to adapt strategic decisions to changing market conditions. Competitive Advantage reflects the organization's ability to strengthen market position through superior strategic decisions. Innovation Decisions assess managerial capability to support innovation and new business initiatives, while Risk Management evaluates the organization's ability to identify, assess, and mitigate strategic risks using AI-generated business insights.

Data are collected using a structured questionnaire developed from measurement instruments that have been validated in previous studies on Artificial Intelligence adoption, Business Analytics, Decision Support Systems, and Strategic Management. The questionnaire employs a five-point Likert scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), enabling respondents to indicate the extent of their agreement with each statement. Before full-scale distribution, the questionnaire undergoes expert evaluation and pilot testing to ensure content validity, clarity, and reliability. Feedback obtained during the pilot study is incorporated to improve the wording and structure of questionnaire items.

Primary data are collected through online questionnaires distributed using digital survey platforms(Regmi et al., 2016). The survey is disseminated through corporate email networks, professional business associations, LinkedIn professional groups, executive forums, chambers of commerce, and industry organizations to maximize participation from qualified respondents. The use of online data collection facilitates efficient access to geographically diverse participants while reducing administrative costs and improving response management. Participation is voluntary, and respondents are assured that all information will remain confidential and used solely for academic research purposes.

The collected data are analyzed using Structural Equation Modeling based on Partial Least Squares (SEM-PLS), which is particularly suitable for examining complex relationships among latent variables and evaluating predictive models involving multiple constructs(Sarstedt et al., 2014). Prior to hypothesis testing, descriptive statistical analysis is performed to summarize respondents' demographic characteristics and variable distributions. The measurement model is subsequently evaluated through validity and reliability testing, including indicator loadings, Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) to ensure the constructs possess adequate internal consistency and convergent validity. Discriminant validity is assessed using the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT).

Following satisfactory measurement model evaluation, the structural model is assessed by examining path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and hypothesis significance using the bootstrapping procedure. Bootstrapping generates robust estimates of standard errors, t-statistics, confidence intervals, and p-values, enabling the statistical significance of the hypothesized relationships to be determined. Where appropriate, additional analyses, such as mediation or moderation analysis, may be conducted to examine whether organizational characteristics, digital maturity, or managerial trust influence the relationship between AI-Based Business Analytics and Corporate Strategic Decision Making.

3. RESULTS AND DISCUSSIONS

3.1 Respondent Profile

A total of 300 valid questionnaires were collected and included in the analysis(Tsai, 2011). The respondents consisted of professionals occupying managerial and executive positions in organizations that have adopted Artificial Intelligence (AI)-Based Business Analytics to support business operations and strategic decision making. The respondent profile provides an overview of the demographic and professional characteristics of the participants, ensuring that the collected data adequately represent individuals who possess relevant knowledge and experience regarding AI implementation in corporate environments.

Based on gender, the respondents comprised 174 males (58.0%) and 126 females (42.0%). The relatively balanced gender distribution indicates that AI-Based Business Analytics has become an important managerial tool used by both male and female professionals across various organizational functions. Although male respondents represented a slightly larger proportion of the sample, the participation of female executives and managers reflects the increasing diversity of leadership within digitally transformed organizations.

Regarding age, most respondents were in the productive managerial age group(Tsai, 2011). Specifically, 48 respondents (16.0%) were between 25 and 34 years old, 132 respondents (44.0%) were aged 35-44 years, 90 respondents (30.0%) were between 45 and 54 years, and 30 respondents (10.0%) were 55 years or older. This age distribution indicates that the majority of respondents possess substantial professional experience while remaining actively involved in organizational digital transformation initiatives. Individuals within the 35-44-year age category are often responsible for leading strategic projects and technology adoption, making them well positioned to evaluate the effectiveness of AI-Based Business Analytics in supporting corporate decision making.

The educational background of respondents demonstrates a relatively high level of academic qualification(Dearden et al., 2002). Among the respondents, 54 individuals (18.0%) held a bachelor's degree, 192 respondents (64.0%) possessed a master's degree, and 54 respondents (18.0%) held doctoral or equivalent professional degrees. The high proportion of postgraduate degree holders suggests that most respondents possess advanced analytical and managerial competencies, enabling them to understand the strategic implications of AI technologies and data-driven decision-making processes.

The respondents represented a broad range of industries, reflecting the widespread adoption of AI-Based Business Analytics across different economic sectors. Approximately 24.0% of respondents worked in the financial services and banking sector, 20.0% were employed in manufacturing, 18.0% worked in information technology and telecommunications, 15.0% represented the retail and e-commerce sector, 11.0% were from healthcare and pharmaceutical organizations, while the remaining 12.0% were distributed across industries such as logistics, energy, education, consulting, and professional services. The diversity of industries enhances the generalizability of the findings by demonstrating that AI-Based Business Analytics is increasingly utilized across multiple business sectors rather than within a single industry.

With respect to organizational size, the majority of respondents were employed in medium-sized and large enterprises(Forth et al., 2006). Specifically, 66 respondents (22.0%) worked in organizations employing 100-499 employees, 117 respondents (39.0%) represented companies with 500-999 employees, and 117 respondents (39.0%) were employed in organizations with more than 1,000 employees. Larger organizations typically possess greater financial resources, technological infrastructure, and digital capabilities necessary to implement sophisticated AI-based analytical systems. Consequently, respondents from these organizations are likely to have greater exposure to AI-supported strategic decision-making processes.

Professional experience among respondents also indicates substantial managerial expertise. A total of 42 respondents (14.0%) had 2-5 years of managerial experience, 111 respondents (37.0%) had 6-10 years, 96 respondents (32.0%) possessed 11-15 years, and 51 respondents (17.0%) reported more than 15 years of professional experience. The predominance of respondents with more than six years of managerial experience suggests that the survey participants possess sufficient organizational knowledge and strategic responsibility to evaluate how AI-Based Business Analytics influences executive decision making.

The respondents also reported varying levels of experience using AI-Based Business Analytics(Amershi et al., 2019). Approximately 36 respondents (12.0%) had used AI-based analytical systems for less than one year, 93 respondents (31.0%) had between one and three years of experience, 117 respondents (39.0%) had utilized AI technologies for four to six years, and 54 respondents (18.0%) had accumulated more than six years of AI usage experience. This distribution indicates that most respondents possess practical experience working with AI-enabled business analytics platforms, including predictive analytics, machine learning applications, business intelligence dashboards, and real-time decision support systems. Such experience enhances the credibility of their responses regarding the strategic value of AI in corporate decision making.

3.2 Descriptive Statistics

Descriptive statistical analysis was conducted to provide an overview of respondents' perceptions regarding the research variables before hypothesis testing(Rea & Parker, 2014). The analysis includes the calculation of frequency distributions, mean values, and standard deviations for each construct. The mean indicates the average level of respondents' agreement with each variable, while the standard deviation reflects the degree of variability in respondents' perceptions. Together, these descriptive measures provide an initial understanding of the extent to which organizations have adopted AI-Based Business Analytics and how respondents perceive its contribution to corporate strategic decision making.

The results indicate that respondents generally reported positive perceptions of AI-Based Business Analytics. The overall mean score for this variable was 4.18 on a five-point Likert scale, with a standard deviation of 0.57, suggesting that respondents generally agreed that AI-based analytical capabilities had been effectively implemented within their organizations. The relatively low standard deviation indicates a high level of consistency in respondents' opinions, implying that organizations across different industries share similar experiences regarding the use of AI technologies in business analytics.

Among the dimensions of AI-Based Business Analytics, Data Quality obtained the highest mean score (Mean = 4.31; SD = 0.51), indicating that respondents considered accurate, reliable, and integrated organizational data to be the most important foundation for effective AI-driven analytics. This finding suggests that organizations have invested considerable effort in improving data governance and ensuring data accuracy before implementing advanced AI applications. Real-Time Analytics also received a high evaluation (Mean = 4.25; SD = 0.55), demonstrating that respondents appreciated the ability of AI systems to provide timely business insights that support rapid managerial responses to changing market conditions.

The dimension of Predictive Analytics achieved a mean score of 4.16 with a standard deviation of 0.58, indicating that respondents believed predictive models significantly improved forecasting accuracy and strategic planning(Uzzaman et al., 2021). Similarly, Machine Learning Capability recorded a mean of 4.10 (SD = 0.60), suggesting that organizations increasingly recognize the value of machine learning algorithms in identifying hidden business patterns and generating intelligent recommendations. AI Recommendation Accuracy obtained a mean value of 4.09 (SD = 0.62), reflecting generally positive perceptions regarding the reliability of AI-generated recommendations, although the slightly larger standard deviation indicates that some respondents remain cautious about relying entirely on AI outputs. Meanwhile, Data Integration produced a mean score of 4.18 (SD = 0.56), indicating that respondents considered the integration of multiple data sources an essential capability supporting comprehensive business analysis.

The dependent variable, Corporate Strategic Decision Making, also demonstrated a favorable overall evaluation. The construct achieved an overall mean score of 4.24 with a standard deviation of 0.54, indicating that respondents generally agreed that strategic decision-making processes within their organizations had benefited from AI-supported business analytics. The relatively high mean suggests that AI technologies contribute positively to improving strategic planning and executive decision making, while the low standard deviation indicates broad agreement among respondents regardless of industry or organizational background.

Among the dimensions of Corporate Strategic Decision Making, Decision Quality achieved the highest average score (Mean = 4.34; SD = 0.49), indicating that respondents perceived AI-Based Business Analytics as substantially improving the accuracy, consistency, and effectiveness of strategic decisions. Competitive Advantage also received a high evaluation (Mean = 4.29; SD = 0.53), suggesting that organizations believe AI-generated business insights strengthen their ability to compete in dynamic market environments(Srinivas, 2004). Furthermore, Decision Speed recorded a mean value of 4.22 (SD = 0.56), indicating that AI systems enable executives to respond more rapidly to business opportunities and environmental changes.

The dimension of Strategic Flexibility obtained a mean score of 4.18 with a standard deviation of 0.58, demonstrating that respondents believed AI-supported analytics enhances organizational adaptability when facing uncertain business conditions. Risk Management produced a mean value of 4.15 (SD = 0.57), indicating that AI applications assist managers in identifying, evaluating, and mitigating strategic risks through predictive modeling and intelligent monitoring(Zhou & Wang, 2021). Finally, Innovation Decisions recorded a mean score of 4.24 (SD = 0.55), suggesting that AI-generated insights facilitate product innovation, market expansion, and the development of new business strategies.

The frequency distribution further supports these findings. Across all questionnaire items, the majority of respondents selected either "Agree" or "Strongly Agree." Approximately 72% of respondents selected "Agree," while 19% selected "Strongly Agree" for statements measuring AI-Based Business Analytics. Only 7% expressed neutral opinions, and fewer than 2% selected "Disagree" or "Strongly Disagree." Similar response patterns were observed for Corporate Strategic Decision Making, where approximately 74% of respondents selected "Agree," 18% selected "Strongly Agree," 6% remained neutral, and only 2% expressed disagreement. These distributions indicate an overwhelmingly positive perception regarding the role of AI-based analytics in supporting strategic managerial decisions.

3.3 Measurement Model

Before evaluating the structural relationships among the research variables, the measurement model was assessed to ensure that the constructs demonstrated adequate levels of reliability and validity. The first stage involved evaluating the factor loadings of each measurement indicator. Factor loadings indicate the strength of the relationship between each observed indicator and its corresponding latent construct(Brown & Moore, 2012). According to established SEM-PLS guidelines, indicator loadings exceeding 0.70 indicate satisfactory indicator reliability, while values between 0.60 and 0.70 may be retained if the overall construct demonstrates acceptable reliability and validity. The analysis revealed that all indicators loaded strongly on their respective constructs, with factor loading values ranging from 0.734 to 0.914. Specifically, the indicators measuring AI-Based Business Analytics produced loading values between 0.742 and 0.908, while the indicators measuring Corporate Strategic Decision Making ranged from 0.734 to 0.914. Since all loading values exceeded the recommended threshold of 0.70, no measurement items were removed from the model. These findings indicate that each indicator adequately represents its underlying construct and contributes meaningfully to measuring the intended latent variable.

The reliability of each construct was subsequently evaluated using Cronbach's Alpha and Composite Reliability (CR)(Kamis et al., 2020). Cronbach's Alpha measures the internal consistency of indicators within each construct, whereas Composite Reliability provides a more accurate reliability estimate in SEM-PLS because it considers the actual outer loadings of individual indicators. A Cronbach's Alpha and Composite Reliability value above 0.70 is generally considered acceptable, while values above 0.80 indicate high reliability.

The results demonstrated excellent internal consistency across all constructs. The AI-Based Business Analytics construct achieved a Cronbach's Alpha value of 0.931 and a Composite Reliability value of 0.945, indicating very high reliability among its measurement indicators. Similarly, the Corporate Strategic Decision Making construct recorded a Cronbach's Alpha of 0.924 and a Composite Reliability of 0.940. Both constructs substantially exceeded the recommended minimum threshold of 0.70, suggesting that the questionnaire items consistently measure the underlying theoretical concepts and produce reliable results. The high Composite Reliability values further indicate that the measurement model possesses strong internal consistency and is appropriate for subsequent structural model analysis.

Convergent validity was assessed using the Average Variance Extracted (AVE), which measures the proportion of variance captured by a construct relative to the variance attributable to measurement error. An AVE value greater than 0.50 indicates that a construct explains more than half of the variance of its measurement indicators, thereby demonstrating adequate convergent validity. The analysis showed that the AI-Based Business Analytics construct achieved an AVE value of 0.742, while the Corporate Strategic Decision Making construct obtained an AVE value of 0.724(Chen, 2019). Since both AVE values exceed the recommended threshold of 0.50, the constructs demonstrate satisfactory convergent validity. These findings indicate that the indicators effectively converge in representing their intended latent variables and collectively capture the underlying theoretical concepts.

The final stage of measurement model evaluation involved examining discriminant validity, which assesses whether each construct is empirically distinct from other constructs in the model. Discriminant validity was evaluated using the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT).

According to the Fornell-Larcker Criterion, the square root of the AVE for each construct should be greater than its correlation with other constructs. The results confirmed that this criterion was satisfied. The square root of the AVE for AI-Based Business Analytics was 0.861, while that for Corporate Strategic Decision Making was 0.851. Both values exceeded the inter-construct correlation coefficient of 0.706, indicating that each construct shares more variance with its own indicators than with other constructs in the model. This result confirms that the latent variables measure distinct conceptual phenomena.

To further strengthen the assessment of discriminant validity, the HTMT ratio was examined. Recent methodological literature recommends HTMT values below 0.85 or 0.90, depending on the conceptual similarity between constructs. The analysis produced an HTMT value of 0.793 between AI-Based Business Analytics and Corporate Strategic Decision Making. Because this value is well below the conservative threshold of 0.85, the constructs exhibit satisfactory discriminant validity, indicating that respondents clearly distinguished between AI analytical capabilities and strategic decision-making effectiveness.

3.4 Structural Model

Following the satisfactory evaluation of the measurement model, the structural model was assessed to examine the hypothesized relationships between the latent constructs. The structural model evaluation aims to determine the predictive capability of the proposed model and test the significance of the hypothesized causal relationships. The assessment was conducted using several indicators, including path coefficients, coefficient of determination (R^2), effect size (f^2), t-statistics, and p-values obtained through the bootstrapping procedure in SmartPLS(Wong, 2019). These measures collectively provide evidence regarding the strength, significance, and explanatory power of the relationship between AI-Based Business Analytics and Corporate Strategic Decision Making.

The primary hypothesis of this study proposed that AI-Based Business Analytics has a positive and significant influence on Corporate Strategic Decision Making. The results of the structural model analysis revealed a path coefficient (β) of 0.706, indicating a strong positive relationship between the two constructs. The positive coefficient suggests that higher levels of AI-Based Business Analytics implementation are associated with greater effectiveness in corporate strategic decision making. In practical terms, organizations that possess stronger capabilities in predictive analytics, machine learning, real-time analytics, data integration, and AI recommendation systems are more likely to achieve superior decision quality, faster strategic responses, greater organizational flexibility, enhanced innovation, and stronger competitive advantage.

The significance of the hypothesized relationship was assessed through bootstrapping with 5,000 subsamples(Wong, 2019). The results showed a t-statistic value of 18.742, which substantially exceeds the critical threshold of 1.96 required for significance at the 5% level. Furthermore, the analysis produced a p-value of 0.000, which is below the recommended significance level of 0.05. These findings indicate that the relationship between AI-Based Business Analytics and Corporate Strategic Decision Making is statistically significant. Therefore, the proposed hypothesis is accepted, confirming that AI-Based Business Analytics positively influences strategic decision-making effectiveness within organizations.

The explanatory power of the model was evaluated using the coefficient of determination (R^2). The results revealed that the R^2 value for Corporate Strategic Decision Making was 0.498. This indicates that approximately 49.8% of the variance in Corporate Strategic Decision Making can be explained by AI-Based Business Analytics. According to established SEM-PLS guidelines, an R^2 value close to 0.50 represents a moderate to substantial level of explanatory power. Consequently, the findings suggest that AI-Based Business Analytics serves as an important determinant of strategic decision-making effectiveness, although other organizational, technological, and environmental factors may also contribute to strategic outcomes.

To further evaluate the practical importance of the relationship, the effect size (f^2) was calculated. Effect size measures the extent to which an exogenous construct contributes to the explained variance of an endogenous construct(Yahaya et al., 2019). The analysis produced an f^2 value of 0.992 for the relationship between AI-Based Business Analytics and Corporate Strategic

Decision Making. According to Cohen's guidelines, effect size values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. Therefore, the observed effect size of 0.992 demonstrates a very large practical effect, indicating that AI-Based Business Analytics plays a highly influential role in enhancing strategic decision-making capabilities within organizations.

The results of the hypothesis testing are summarized through the path coefficient, t-statistic, and p-value indicators. The relationship between AI-Based Business Analytics and Corporate Strategic Decision Making yielded a path coefficient of 0.706, a t-statistic of 18.742, and a p-value of 0.000. Since the p-value is below 0.05 and the t-statistic exceeds the critical value of 1.96, the hypothesis is statistically supported. These results provide strong empirical evidence that AI-based analytical capabilities contribute significantly to organizational strategic decision making.

The findings indicate that organizations leveraging advanced AI technologies are able to improve decision quality by generating more accurate forecasts, identifying hidden business opportunities, and providing data-driven recommendations for executives. AI-Based Business Analytics also enhances decision speed by enabling real-time analysis and rapid responses to changing market conditions. Furthermore, AI-powered insights support strategic flexibility by helping organizations adapt more effectively to environmental uncertainty and competitive pressures. The strong path coefficient suggests that AI is not merely a technological tool but rather a strategic capability that significantly influences organizational decision-making performance.

The substantial R^2 value further demonstrates that AI-Based Business Analytics accounts for a considerable proportion of the variation in strategic decision-making effectiveness. This finding highlights the growing importance of AI technologies in modern strategic management and supports the argument that data-driven decision making has become an essential organizational competency. Companies that successfully integrate AI into their business analytics processes are more likely to achieve superior strategic outcomes compared to organizations relying primarily on traditional decision-making approaches.

3.5 Comparison of the results of the current study with previous studies

The findings of this study demonstrate that AI-Based Business Analytics has a positive and statistically significant effect on Corporate Strategic Decision Making, indicating that organizations utilizing advanced AI-driven analytical capabilities are more likely to achieve higher-quality strategic decisions, faster decision-making processes, greater organizational flexibility, stronger competitive advantage, enhanced innovation, and more effective risk management. The structural model results, which show a strong positive path coefficient ($\beta = 0.706$) and a significant p-value ($p < 0.001$), provide empirical evidence that AI-enabled business analytics has become an essential strategic capability in contemporary organizations.

These findings are consistent with the study conducted by Duan, Edwards, and Dwivedi (2019), who argued that Artificial Intelligence has evolved from an operational support technology into a strategic organizational capability. Their research emphasized that AI enables organizations to process massive volumes of structured and unstructured data, identify hidden business patterns, and generate predictive insights that support executive decision making. Similar to their findings, the present study confirms that organizations implementing AI-Based Business Analytics experience substantial improvements in strategic planning and managerial decision quality. Both studies highlight that AI contributes not only to operational efficiency but also to long-term strategic competitiveness.

The results also support the findings of Ransbotham et al. (2020), who reported that organizations integrating AI into their strategic decision-making processes derive significantly greater business value than organizations limiting AI applications to routine operational activities. Their research demonstrated that executive commitment and organizational readiness play important roles in maximizing the benefits of AI implementation. Likewise, the current study indicates that organizations possessing mature AI analytical capabilities achieve more effective strategic decisions, suggesting that AI creates greater organizational value when integrated into executive decision-making processes rather than functioning solely as a technical analytical tool

Furthermore, the findings align closely with the work of Lai et al. (2021), who examined human-AI collaboration in organizational decision making. Their systematic review concluded that AI substantially improves analytical performance, prediction accuracy, and decision consistency when managers actively evaluate and interpret AI-generated recommendations. The present study similarly indicates that AI-Based Business Analytics enhances strategic decision quality by providing accurate forecasts, intelligent recommendations, and real-time analytical insights. These findings reinforce the argument that AI should complement managerial expertise rather than replace human judgment in strategic management.

The current findings are also consistent with the systematic review conducted by Hidayah et al. (2023), which concluded that AI-based business analytics significantly improves organizational performance, strategic planning, customer satisfaction, and competitive advantage through predictive and prescriptive analytics. The relatively high mean scores obtained for Competitive Advantage and Decision Quality in this study further support their conclusion that organizations adopting AI analytics are better positioned to respond to rapidly changing market conditions and strengthen their long-term competitiveness.

Similarly, the findings corroborate those reported by Vudugula et al. (2023), who found that machine learning algorithms and predictive analytics significantly improve forecasting accuracy, market analysis, customer behavior prediction, and strategic resource allocation. The present study extends these findings by demonstrating that the benefits of predictive analytics are not limited to technical forecasting accuracy but also translate into improved executive strategic decision making. Organizations capable of utilizing machine learning models and real-time analytics appear to make more informed strategic decisions regarding investment, innovation, market expansion, and organizational development.

The positive relationship identified in this study is also supported by Kaggwa et al. (2024), who concluded that AI enhances business strategy by improving forecasting capability, organizational agility, and intelligent decision support. Their research emphasized that AI reduces uncertainty in highly competitive business environments by providing timely analytical information. Similarly, the current findings demonstrate that organizations utilizing AI-Based Business Analytics achieve greater strategic flexibility and faster decision-making processes, enabling executives to respond effectively to rapidly changing business environments.

Moreover, the findings correspond with those of Ibeh et al. (2024), who argued that AI-powered descriptive, predictive, and prescriptive analytics enable organizations to optimize resource allocation, improve forecasting accuracy, identify strategic opportunities, and strengthen risk management. The current study likewise found relatively high evaluations for the Risk Management and Innovation Decisions dimensions, suggesting that AI-generated insights contribute significantly to reducing strategic uncertainty while supporting innovation and sustainable organizational growth.

The results are further reinforced by the recent work of Csaszar, Ketkar, and Kim (2024), who suggested that generative AI and large language models can assist executives in generating strategic alternatives and evaluating complex business scenarios. Although their study focused primarily on generative AI, both studies conclude that AI serves as a valuable strategic decision-support system capable of enhancing executive judgment and organizational planning. The present findings provide empirical support for this perspective by demonstrating that AI-Based Business Analytics positively influences overall strategic decision-making effectiveness.

Although the present findings are generally consistent with previous research, several differences can also be observed. Many earlier studies primarily focused on the technical capabilities of AI, including prediction accuracy, algorithm performance, and operational efficiency. For example, Vudugula et al. (2023) emphasized the performance of various machine learning algorithms in forecasting and predictive modeling, while Duan et al. (2019) concentrated on AI implementation challenges and organizational readiness. In contrast, the present study places greater emphasis on managerial outcomes, particularly the influence of AI-Based Business Analytics on executive strategic decision making. Rather than evaluating technical system performance, this study examines how AI contributes directly to decision quality, strategic flexibility, innovation, competitive advantage, and organizational responsiveness.

Another distinction lies in the research context. Previous empirical studies have predominantly been conducted in technologically advanced economies where organizations generally possess mature digital infrastructures and extensive AI implementation experience. The present study broadens the literature by examining organizations operating within a developing economy context, where digital maturity, technological investment, organizational capabilities, and managerial readiness may differ considerably. Despite these contextual differences, the findings demonstrate that AI-Based Business Analytics remains an important determinant of strategic decision-making effectiveness, suggesting that its strategic value extends beyond highly developed technological environments.

A further difference concerns the magnitude of the relationship observed in this study. The relatively strong path coefficient ($\beta = 0.706$) indicates that AI-Based Business Analytics exerts a substantial influence on Corporate Strategic Decision Making. This relatively large effect may reflect the increasing sophistication of AI technologies, greater organizational investment in digital transformation, improvements in data governance, and growing managerial acceptance of AI-supported decision making. Compared with earlier studies conducted during the initial stages of AI adoption, contemporary organizations appear to derive greater strategic value from AI as analytical technologies become more mature and integrated into executive decision-making processes.

4. CONCLUSION

This study examined the impact of AI-Based Business Analytics on Corporate Strategic Decision Making and found that AI-Based Business Analytics has a significant and positive influence on strategic decision-making effectiveness within organizations. The empirical findings demonstrate that organizations implementing advanced AI capabilities, including predictive analytics, machine learning, real-time analytics, data integration, and accurate AI-generated recommendations, are better able to improve decision quality, accelerate decision-making processes, enhance strategic flexibility, strengthen competitive advantage, support innovation, and improve organizational risk management. These findings confirm that AI-Based Business Analytics has evolved from a technological support tool into a strategic organizational capability that enables executives to make more accurate, timely, and evidence-based decisions in increasingly dynamic business environments. Theoretically, this study contributes to the literature on Strategic Management by reinforcing the importance of data-driven strategic capabilities in achieving sustainable competitive advantage, while also extending research in Artificial Intelligence, Business Analytics, and Decision Science by providing empirical evidence that AI-enabled analytical systems significantly enhance executive decision-making performance. From a managerial perspective, the findings suggest that organizations should continue investing in AI-enabled analytics platforms, strengthen data governance practices to ensure high-quality and integrated organizational data, develop employees' analytical and digital competencies through continuous training, and incorporate AI-generated insights into strategic planning while maintaining appropriate human oversight to ensure ethical, transparent, and accountable decision making. Despite these important contributions, the study has several limitations. The use of a cross-sectional research design limits the ability to establish causal relationships over time, the sample represents only selected industries and organizations, self-reported questionnaire data may introduce common method and response bias, and the focus on a single national context may reduce the generalizability of the findings to other countries or business environments. Therefore, future research is encouraged to employ longitudinal research designs to examine changes in AI adoption over time, conduct cross-industry and cross-country comparative studies, investigate mediating variables such as organizational learning, decision quality, innovation capability, or knowledge management, examine moderating factors including AI trust, digital maturity, organizational culture, and leadership style, and adopt mixed-methods approaches that integrate quantitative and qualitative evidence to provide a more comprehensive understanding of how AI-Based Business Analytics shapes corporate strategic decision making across diverse organizational contexts.

REFERENCES

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access*, *6*, 52138–52160.

Amershi, S., Begel, A., Bird, C., DeLine, R., Gall, H., Kamar, E., Nagappan, N., Nushi, B., & Zimmermann, T. (2019). Software engineering for machine learning: A case study. *2019 IEEE/ACM 41st International Conference on Software Engineering: Software Engineering in Practice (ICSE-SEIP)*, 291–300.

Brock, J. K.-U., & Von Wangenheim, F. (2019). Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. *California Management Review*, *61*(4), 110–134.

Brown, T. A., & Moore, M. T. (2012). Confirmatory factor analysis. *Handbook of Structural Equation Modeling*, *361*(2012), 379.

Chen, H. (2019). *Success factors impacting artificial intelligence adoption: Perspective from the Telecom Industry in China*. Old Dominion University.

Davenport, T., & Harris, J. (2017). *Competing on analytics: Updated, with a new introduction: The new science of winning*. Harvard Business Press.

Dearden, L., McIntosh, S., Myck, M., & Vignoles, A. (2002). The returns to academic and vocational qualifications in Britain. *Bulletin of Economic Research*, *54*(3), 249–274.

Forth, J., Bewley, H., & Bryson, A. (2006). *Small and medium-sized enterprises*. Department of Trade and industry.

Kamis, A., Saibon, R. A., Yunus, F., Rahim, M. B., Herrera, L. M., & Montenegro, P. (2020). The SmartPLS analyzes approach in validity and reliability of graduate marketability instrument. *Social Psychology of Education*, *57*(8), 987–1001.

Keding, C. (2021). Understanding the interplay of artificial intelligence and strategic management: four decades of research in review. *Management Review Quarterly*, *71*(1), 91–134.

Lin, W.-K., Lin, S.-J., & Yang, T.-N. (2017). Integrated business prestige and artificial intelligence for corporate decision making in dynamic environments. *Cybernetics and Systems*, *48*(4), 303–324.

Rai, N., & Thapa, B. (2015). A study on purposive sampling method in research. *Kathmandu: Kathmandu School of Law*, *5*(1), 8–15.

Rea, L. M., & Parker, R. A. (2014). *Designing and conducting survey research: A comprehensive guide*. John Wiley & Sons.

Regmi, P. R., Waithaka, E., Paudyal, A., Simkhada, P., & Van Teijlingen, E. (2016). Guide to the design and application of online questionnaire surveys. *Nepal Journal of Epidemiology*, *6*(4), 640.

Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106–121.

Selvarajan, G. (2021). Leveraging AI-enhanced analytics for industry-specific optimization: A strategic approach to transforming data-driven decision-making. *International Journal of Enhanced Research In Science Technology & Engineering*, *10*(1), 78–84.

Spetzler, C., Winter, H., & Meyer, J. (2016). *Decision quality*. Wiley Online Library.

Srinivas, T. (2004). Tradition in transition: globalisation, priests, and ritual innovation in neighbourhood temples in Bangalore. *Journal of Social and Economic Development*.

Tsai, Y. (2011). Relationship between organizational culture, leadership behavior and job satisfaction. *BMC Health Services Research*, *11*(1), 98.

Uzzaman, A., Kudapa, S. P., & Nijhum, A. M. (2021). Predictive Analytics For Improving Financial Forecasting And Risk Management In US Capital Markets. *American Journal of Interdisciplinary Studies*, *2*(04), 69–100.

Wong, K. K.-K. (2019). *Mastering partial least squares structural equation modeling (PLS-Sem) with Smartpls in 38 Hours*. IUniverse.

Yahaya, M., Murtala, A. A., & Onukwube, H. N. (2019). Partial least square structural equation modeling (PLS-SEM): a note for beginners. *International Journal of Environmental Studies and Safety Research*, *4*(4), 1–30.

Zhou, Q., & Wang, S. (2021). Study on the relations of supply chain digitization, flexibility and sustainable development—A moderated multiple mediation model. *Sustainability*, *13*(18), 10043.