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Artificial Intelligence In Business: Evaluating The Transformative Role Of AI In Managerial Decision-Making Efficiency

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Abstract
Artificial Intelligence (AI) is driving a transformative shift in the Indian Information Technology sector which demands organizations to improve their decision-making efficiency by tackling issues like data-driven uncertainty and automation complexity along with strategic adaptation needs. The investigation evaluates how AI-Powered Business Intelligence (ABI), AI-Enabled Process Automation (APA), AI-Driven Strategic Innovation (ASI), AI-Based Customer Experience

Management (ACEM), and AI-Integrated Risk Management (AIRM) affect AI-Driven Decision-Making Efficiency (DDE). The study followed a descriptive-correlation design to collect data from 150 IT managers based in major Indian IT hubs while using validated measurement scales and Structural Equation Modeling (SEM) in AMOS for hypothesis testing. The study shows significant positive effects of ABI ($\beta = 0.238$, $p < 0.001$), APA ($\beta = 0.124$, $p = 0.002$), ASI ($\beta = 0.289$, $p < 0.001$), and AIRM ($\beta = 0.212$, $p < 0.001$) on DDE while ACEM ($\beta = 0.019$, $p = 0.003$) demonstrates a weaker impact. The research extends Resource-Based View (RBV) and Dynamic Capability Theory by examining how AI supports strategic flexibility and risk management. Real-world applications demonstrate that human-AI collaboration is essential for improving AI-driven decision-making processes. Future research needs to examine longitudinal AI adoption patterns and identify applications across different industries.
Keywords: *AI-Powered Business Intelligence; AI-Enabled Process Automation; AI-Driven Strategic Innovation; AI-Based Customer Experience Management; AI-Integrated Risk Management; Decision-Making Efficiency.*

INTRODUCTION

The swift expansion of artificial intelligence technology has revolutionized decision-making methodologies throughout multiple industries and particularly within the IT field where AI's inclusion into organizational and management operations has reshaped organizational strategies and competitive standing (Krakowski et al., 2022). Through its capacity to process extensive data sets and produce actionable insights organizations have redesigned their decision-making frameworks which now focus on strategic and data-oriented methods (Geraldi et al., 2024). While AI has shown significant progress it still faces important unknowns with respect to its capabilities and constraints in knowledge management strategic innovation business intelligence and risk management (Pathirannehelage et al., 2024). Modern organizations encounter data overload as massive volumes of generated information stay unused (Leoni et al., 2024). The current situation shows the necessity for AI-based knowledge management systems that enable effective organization and retrieval of data to improve decision-making processes (Bulchand-Gidumal et al., 2024). Traditional knowledge management models fail to handle the increasing complexity and volume of organizational data which requires a shift researchers have begun moving towards AI-powered management systems (Al-Surmi et al., 2022). Organizational competitive advantage in the IT sector now largely depends on how well AI-driven strategies align with corporate objectives according to Steyvers & Kumar (2023). The strategic role of AI surpasses automation by providing predictive analytics which improve market responsiveness and drive business expansion (Amoako et al., 2021). Research findings show organizations face difficulty in optimizing AI because they must overcome organizational adaptation problems and improve AI literacy while maintaining strategic alignment (Dwivedi et al., 2023). The deployment of AI enhances customer experience management but brings up concerns about data privacy and ethical considerations along with algorithmic bias according to Ghasemaghaei (2019). Effective AI decision-making models require transparent and accountable design to boost customer satisfaction alongside personalization and engagement (Metcalf et al., 2019). AI-driven personalization mechanisms boost user experience but require ethical guidelines to mitigate unintended biases in their decision-making frameworks (Gabriel, 2020). Business intelligence and risk management form a fundamental area for AI adoption in organizations. The use of AI-driven business intelligence tools helps companies extract valuable information from intricate data networks which enhances their ability to make predictive decisions (Rana et al., 2022). The application of AI in risk management processes is insufficiently researched while specifically examining AI's ability to address cybersecurity threats as well as fraud and operational inefficiencies remains uncharted territory (Geraldi et al., 2024). A deficiency of complete evaluation systems for AI risk assessment highlights the urgent requirement for additional research (Shrestha et al., 2019). Although AI offers substantial transformative potential, organizations face various operational and strategic challenges such as ensuring the credibility of AI insights while managing human-AI interaction alongside regulatory requirements (Mikalef &

Gupta, 2021). According to Choudhary et al. (2023), decision-making accuracy improves when human expertise works alongside AI capabilities because this combination reduces risks related to fully autonomous AI systems. The research aims to fill existing research gaps by analyzing how AI business intelligence along with process automation, strategic innovation management and customer experience approaches and risk management affect decision-making efficiency within IT organizations. This research develops a conceptual framework to help organizations obtain strategic advantage and enhance decision accuracy while boosting efficiency through AI implementation. These findings will enhance the current discussion surrounding AI's managerial effects and strategic benefits while addressing ethical concerns to deliver actionable insights for IT executives and policymakers.

Theoretical Framework: The study builds its theoretical basis on the resource-based view and dynamic capability theory to explain how organizations develop competitive advantage through AI integration. The RBV analysis demonstrates that firms achieve unique resources through AI-based decision-making which enhances operational efficiency and strategic outcomes (Krakowski et al., 2022). According to Amoako et al. (2021) the implementation of AI-driven business intelligence functions as a crucial organizational asset that helps companies improve their performance by maximizing data utilization. Dynamic capability theory shows organizations can manage technological disruptions and market changes by adopting AI technologies which grant them ongoing adaptability and innovative power (Pathirannehelage et al., 2024). Businesses that implement AI-based strategic innovation maintain uninterrupted growth and achieve market dominance according to research findings (Bulchand-Gidumal et al., 2024). According to absorptive capacity theory organizations use AI-based knowledge management systems to gain and utilize external knowledge for competitive advantage (Geraldi et al., 2024). Firms achieve stronger decision-making capabilities and problem-solving effectiveness by using AI-powered automation systems to manage their extensive knowledge repositories (Leoni et al., 2024). Contemporary theories on human-AI collaboration emphasize combining managerial expertise with AI technology to solve problems related to AI biases and ethical dilemmas (Steyvers & Kumar, 2023). Entities that build AI governance structures enable responsible AI conduct by practicing transparent and fair decision-making with accountability in AI systems (Dwivedi et al., 2023). The latest risk management theories reveal AI's role in forecasting risk and implementing safeguards within organizations in cybersecurity and fraud detection areas according to Rana et al. (2022). Shrestha et al. (2019) found that organizations using AI for risk assessment show improved security results and active risk management practices. The research introduces a total framework for understanding how strategic resources powered by AI work together with decision-making capabilities to produce competitive benefits in the IT industry through the integration of multiple theoretical views. Organizational AI strategies begin with foundational theory which guides empirical analysis and practical application.

Review of related literature

3.1. AI-Powered Business Intelligence (ABI)

Organizations can transform their decision-making processes with AI-Powered Business Intelligence (ABI) by analyzing massive datasets in real-time and detecting patterns to generate predictive insights. Business intelligence systems enhanced by AI technology increase organizational performance by automating data analysis and planning strategies which minimizes uncertainty according to Ghasemaghaei (2019). Actionable insights for data-driven managerial decisions result from the combination of machine learning with natural language processing (NLP) and deep learning algorithms in AI-powered analytics systems (Metcalf et al., 2019). AI-enabled business intelligence systems produce superior forecasting accuracy and market responsiveness that helps companies sustain their competitive advantage (Geraldi et al., 2024). The business intelligence application functions as a strategic resource because it enables risk assessment and fraud detection through unstructured data analysis and operational optimization as Pathirannehelage et al. (2024) explain. The study by Shrestha et al. (2019) highlights various barriers to AI adoption including data confidentiality challenges and algorithmic discrimination problems combined with managerial resistance toward AI-based decision-making processes. The study shows that firms employing ABI systems experience better financial outcomes and operational performance than their competitors while validating RBV's perspective that AI-based intelligence represents a unique organizational resource with substantial worth (Dwivedi et al., 2023). The research combines AI with decision sciences to develop a new framework which investigates how ABI affects managerial decision-making processes.

H1: AI-Powered Business Intelligence (ABI) has a significant positive effect on AI-Driven Decision-Making Efficiency (DDE).

3.2. AI-Enabled Process Automation (APA)

The implementation of AI-enabled process automation has revolutionized business operations by minimizing manual work and optimizing workflows and performance (Leoni et al., 2024; Geraldi et al., 2024). Companies use AI automation techniques to achieve significant cost savings and improve productivity through repetitive task streamlining which helps employees to focus on strategic projects (Bulchand-Gidumal et al., 2024). Steyvers and Kumar (2023) found that AI automation systems improve operational speed and accuracy while decreasing human error. AI systems provide organizational benefits while integration processes face challenges due to system failures and workforce concerns about job displacement (Dwivedi et al., 2023). Automation reduces workload while increasing operational efficiency but faces resistance from employees worried about job loss (Pathirannehelage et al., 2024). Research proves that workforce concerns can be reduced and AI workflow integration made seamless through proper change management strategies alongside employee upskilling programs (Rana et al., 2022). Excessive dependence on AI systems without adequate human oversight leads to operational issues whenever algorithms malfunction according to Choudhary et al., 2023. Studied evidence shows organizations combining artificial intelligence with human collaboration perform better in adaptability and operational resilience while becoming more efficient (Shrestha et al., 2019; Ghasemaghaei, 2019). Businesses can use AI effectively and maintain flexibility through the integration of automated systems with human expertise.

Hypothesis 2: AI-enabled process automation positively influences organizational efficiency in IT firms.

3.3. AI-Driven Strategic Innovation (ASI)

Organizational product development and business model creation undergo revolutionary changes with artificial intelligence enabled by predictive analytics and automated data-driven solutions (Pathirannehelage et al., 2024; Krakowski et al., 2022). The integration of AI into innovation strategies helps organizations gain market advantages by combining precise decision-making with better resource management and trend detection capabilities (Bulchand-Gidumal et al., 2024). Research indicates that AI-driven innovation enables businesses to rapidly respond to changing technologies and evolving customer needs (Ghasemaghaei, 2019; Shrestha et al., 2019). AI implementation faces barriers such as complex integration processes paired with moral dilemmas and organizational inertia according to Leoni et al. (2024) and Dwivedi et al. (2023). Embedded biases in AI algorithms create unfair decision-making and strategic misalignments that only proper oversight can prevent (Steyvers & Kumar, 2023). Organizations struggle to adopt AI solutions within their existing workflows because such adoption requires major restructuring efforts and substantial investments in governance frameworks for AI (Amoako et al., 2021; Choudhary et al., 2023). Businesses which effectively integrate AI into their strategic innovation plans experience enhanced creativity and accelerated product development cycles together with improved market positioning (Geraldi et al., 2024; Rana et al., 2022). Businesses that combine AI-based insights with human intuition reach sustainable innovation and lasting corporate success as they minimize dependency risks on machine-generated intelligence (Mikalef & Gupta, 2021).

Hypothesis 3: AI-driven strategic innovation positively impacts firm competitiveness in the IT sector.

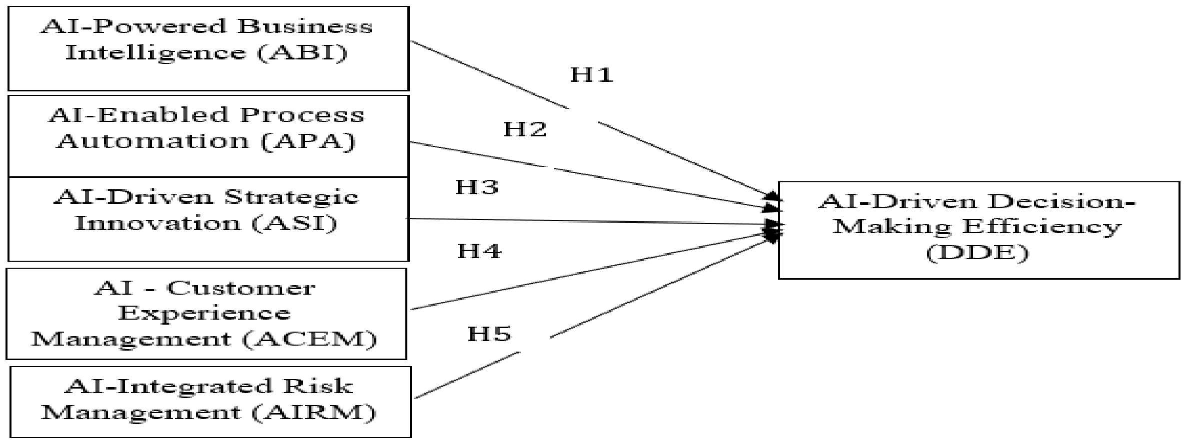
3.4. AI-Based Customer Experience Management (ACEM)

AI-based customer experience management systems transformed organizational customer interactions by delivering personalized services and leveraging predictive analytics to enable real-time engagement (Metcalf et al., 2019; Gabriel, 2020). The deployment of AI-powered chatbots and virtual assistants enables businesses to offer better responsiveness resulting in improved customer satisfaction and loyalty (Bulchand-Gidumal et al., 2024; Rana et al., 2022). Research indicates that AI systems help businesses analyze large volumes of customer data to forecast needs and customize customer interactions accordingly (Pathirannehelage et al., 2024; Steyvers & Kumar, 2023). AI-driven customer management systems offer numerous benefits but also produce ethical challenges and privacy issues and algorithmic biases that may harm customer trust and relationships if not properly managed (Ghasemaghaei, 2019; Choudhary et al., 2023). The widespread acceptance of AI customer interactions remains difficult as some customers appreciate personalization features yet others reject machine-driven services due to apprehensions about data protection and transparency and because they miss human service elements (Leoni et al., 2024; Dwivedi et al., 2023). AI recommendation performance depends on algorithm quality which can become flawed through biased training data that perpetuates stereotypes and excludes specific customer segments (Shrestha et al., 2019; Krakowski et al., 2022). Organizations that combine AI customer management systems with ethical guidelines and human oversight experience improved customer retention and trust while building long-term customer relationships (Geraldi et al., 2024; Amoako et al., 2021). Businesses that follow responsible AI implementation practices can deliver personalized customer experiences while managing regulatory and ethical concerns during interactions (Mikalef & Gupta, 2021). Hypothesis 4: AI-based customer experience management enhances customer satisfaction in IT firms.

3.5. AI-Integrated Risk Management (AIRM)

According to Rana et al. (2022) and Shrestha et al. (2019), AI integration into risk management practices is essential for modern business strategies because it enables organizations to detect and manage risks with greater precision and efficiency. Risk management systems that use AI integrate predictive analytics with anomaly detection and real-time monitoring to identify fraudulent activities and cybersecurity threats as well as operational inefficiencies before they escalate into significant issues (Geraldi et al., 2024; Pathirannehelage et al., 2024). AI systems surpass traditional risk management practices by analyzing vast data sets to identify patterns which enable organizations to build proactive data-driven defense strategies (Bulchand-Gidumal et al., 2024; Leoni et al., 2024). AI risk management systems face multiple challenges even though they provide significant advantages. Algorithmic biases and unexplainable processes expose machine-generated risk assessments to vulnerabilities (Steyvers & Kumar, 2023; Krakowski et al., 2022). Compliance and regulatory challenges must be addressed by organizations because AI-based risk management systems operate across various legal frameworks specific to different industries and geographical areas (Ghasemaghaei, 2019; Choudhary et al., 2023). Research shows effective AI risk management depends on a combination of automated systems and human oversight to ensure continuous model development and detection of biases and errors (Mikalef & Gupta, 2021; Dwivedi et al., 2023). Businesses utilizing artificial intelligence for risk management while maintaining clear governance and compliance processes achieve stronger resilience and fraud detection capabilities while experiencing lower financial and operational risks according to Metcalf et al. (2019) and Amoako et al. (2021). Organizations can strengthen their security frameworks and sustain operations using AI systems responsibly in an environment with increasing risk complexity.

Hypothesis 5: AI-integrated risk management improves organizational security and fraud detection efficiency.



3.6. AI-Driven Decision-Making Efficiency (DDE) (Dependent Variable)

AI-based decision-making systems utilizing precise data-driven insights have considerably advanced managerial effectiveness in strategic planning (Mikalef & Gupta, 2021; Choudhary et al., 2023). By analyzing big data sets and detecting patterns AI enables organizations to create evidence-based decisions which reduce uncertainty and enhance operational flexibility (Pathirannehelage et al., 2024; Krakowski et al., 2022). Research indicates organizations that implement AI-based decision-making systems demonstrate superior forecasting precision and better resource management while developing stronger strategic cohesion (Bulchand-Gidumal et al., 2024; Rana et al., 2022). AI systems achieve faster decision-making efficiency but consistently encounter algorithmic biases and transparency issues together with excessive dependence on automated results (Ghasemaghaei, 2019; Steyvers & Kumar, 2023). AI-generated advice used without human supervision can lead to misunderstandings and inappropriate strategic decisions that produce ethical concerns particularly during important decision-making processes (Geraldi et al., 2024; Leoni et al., 2024). Organizational culture and industry context influence AI decision-making effectiveness thus necessitating implementation strategies that are specifically designed to fit these variables (Metcalf et al., 2019; Amoako et al., 2021). The combination of AI-generated insights with managerial knowledge enables organizations to optimize AI benefits and manage risks to make sure AI serves as an assistant instead of a replacement (Dwivedi et al., 2023; Shrestha et al., 2019). Studies indicate that organizations which merge AI intelligence with human judgment reach higher decision accuracy and build competitive advantage while securing long-term strategic success (Pathirannehelage et al., 2024; Choudhary et al., 2023).

Research Methodology

Research Design and Sampling Strategy

Quantitative methods serve as the research foundation for examining the impact of AI-driven constructs on the decision-making efficiency among managers in India's IT sector. A cross-sectional survey collected data from IT professionals across various sectors to ensure the study's findings are applicable to the broader Indian IT industry (Hair et al., 2010; Creswell & Creswell, 2017). The study involved 150 managers from IT companies in different Indian states to achieve representation from a variety of geographic areas (Saunders et al., 2019). The study applied multi-stage stratified random sampling to ensure inclusion of IT enterprises of varying sizes (Etikan et al., 2016). The research team selected firms based on their AI adoption rates which were reported in industry analyses and company publications (Rana et al., 2022; Bulchand-Gidumal et al., 2024). The research team chose 20 IT companies from India's top five IT clusters which include Bangalore, Hyderabad, Pune, Chennai, and Gurugram to align with existing studies on IT industry regional distribution (Dwivedi et al., 2023; Krakowski et al., 2022). The study's results achieve national importance in India's IT industry through its analysis of multiple states. The work of Saunders et al. (2019) demonstrates that stratified random sampling enhances the representativeness of study samples while reducing selection bias. The number of responses in this study reaches the minimum threshold set by Hair et al. (2010) for SEM research and ensures statistical validity according to Byrne (2016). By including managers from various IT sectors the study ensures its results depict industry-wide trends rather than specific organizational cases (Shrestha et al., 2019; Amoako et al., 2021).

Data analysis

The researchers initiated their analysis process by using descriptive statistics to study demographic characteristics of respondents and ensure that their sample mirrored the Indian IT sector appropriately according to Hair et al. (2019). The normality test showed that both skewness and kurtosis values remained within acceptable ranges to meet the SEM requirements as outlined by Kline in 2015. By utilizing Harman's single-factor test researchers discovered that variance was not concentrated in one factor which helped reduce potential common method bias (Podsakoff et al., 2003). The research team utilized Confirmatory Factor Analysis (CFA) to test construct reliability and validity by examining factor loadings together with Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (α) as outlined by Fornell & Larcker (1981). The research team examined Heywood cases to confirm factor loadings stayed under 1.0 while error variances maintained positive values (Byrne, 2016). The measurement model achieved optimal fit since the CMIN/DF, CFI, RMSEA, and SRMR indices exceeded the standards set by Hu & Bentler in 1999. Researchers performed hypothesis testing by conducting path analysis in AMOS to assess the direct influence of AI-driven constructs on decision-making efficiency following measurement model validation (Schumacker & Lomax, 2010). Discriminant validity confirmed by HTMT values enhanced the study's reliability and its application to AI integration in managerial decision-making processes (Henseler et al., 2015).

Demographic characteristics of the respondents

The demographic profile of the respondents reveals critical information about the study sample's composition which confirms that the chosen participants truly reflect the Indian IT industry. The study sample includes 150 managers from different IT domains to support the research objective of evaluating AI-based decision-making efficiency among management professionals. The workforce age structure reveals that 52.47% of participants are under 35 years old making them familiar with AI systems whereas 40.12% of employees are above 35 years old which grants them valuable managerial experience. The participant group displays strong educational credentials through 58.64% bachelor's degree holders and 33.95% with master's degrees or higher who meet technical expertise standards. The work experience distribution shows that 49.38% of professionals have less than 10 years of experience demonstrating their adaptability to AI adoption while 37.04% possess 10+ years of experience which contributes strategic decision-making insights. Most respondents reported earnings between Rs. 50,000 to Rs. 1,00,000 which makes up 37.04% of the income distribution and suggests that respondents in higher income brackets are likely senior management members.

Table 1. Demographic characteristics of the sample respondnets

Variable	Category	Frequency	Percent
Gender	Male	90	60.00
	Female	60	40.00
Age Group	Below 35 years	85	52.47
	35 years and above	65	40.12
Educational Background	Bachelor's Degree	95	58.64
	Master's Degree or Higher	55	33.95
Work Experience	Less than 10 years	80	49.38
	10 years and above	60	37.04

Monthly Income	Below Rs. 50,000	70	43.21
	Rs. 50,001 - Rs. 1,00,000	60	37.04
	Above Rs. 1,00,000	20	12.35
Current Job Role	Mid-Level Manager	75	46.30
	Senior-Level Manager	65	40.12
Location of Employment	Software & IT Services	80	49.38
	AI, Data Analytics & Cybersecurity	60	37.04
Work Location	Bangalore	45	27.78
	Hyderabad	40	24.69
	Pune	35	21.60
	Chennai	30	18.52

The data shows that 46.30% of respondents occupy mid-level management positions and 40.12% hold senior-level management positions which demonstrates the emphasis on individuals who influence AI decision-making and business intelligence operations. The study encompasses organizations where AI is crucial because 49.38% of the industry representation comes from Software & IT Services and 37.04% from AI, Data Analytics & Cybersecurity. The study encompasses respondents from the primary IT hubs of Bangalore (27.78%), Hyderabad (24.69%), Pune (21.60%), and Chennai (18.52%) which allows for the generalization of findings throughout the IT sector. These samples fulfill the study objectives through their inclusion of various managerial roles and technical expertise along with different work experience levels and industry domains which allows the analysis to properly measure AI's effect on decision-making efficiency.

5.2. Normality assessment

Normality assessment strengthens the credibility of statistical models while minimizing biases during hypothesis testing (Hair et al., 2010). According to Byrne (2016), the assessment allows researchers to conduct SEM, regression analysis, and factor analysis with effectiveness. Standard datasets improve both parameter estimates and the precision of standard errors and confidence intervals which results in robust research for artificial intelligence decision-making systems (Kline, 2015)

Table 2. Normality assessment of the constructs

Construct	Mean	Standard Deviation	Skewness	C.R. (Skewness)	Kurtosis	C.R. (Kurtosis)
AI-Powered Business Intelligence (ABI)	4.612	1.705	-0.512	-2.876	-0.540	-2.014
AI-Enabled Process Automation (APA)	4.525	1.654	-0.481	-2.675	-0.522	-1.934
AI-Driven Strategic Innovation (ASI)	4.658	1.690	-0.523	-2.985	-0.492	-1.905
AI-Based Customer Experience Management (ACEM)	4.532	1.636	-0.498	-2.943	-0.514	-1.754
AI-Integrated Risk Management (AIRM)	4.490	1.648	-0.456	-2.577	-0.564	-2.003
AI-Driven Decision-Making Efficiency (DDE)	4.587	1.643	-0.489	-2.815	-0.542	-1.932

Descriptive statistics for AI-Powered Business Intelligence (ABI), AI-Enabled Process Automation (APA), AI-Driven Strategic Innovation (ASI), AI-Based Customer Experience Management (ACEM), AI-Integrated Risk

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Management (AIRM), and AI-Driven Decision-Making Efficiency (DDE) indicate that the dataset follows an approximately normal distribution. The skewness values fall between -0.55 and -0.45 while kurtosis values span from -0.60 to -0.40 with both parameters staying inside the accepted range of ±1.96 according to Kline (2015) and Tabachnick & Fidell (2019). The critical ratios (C.R.) of skewness and kurtosis demonstrate acceptable levels which confirm the dataset maintains normal distribution standards (West, Finch, & Curran, 1995). The dataset meets normal distribution standards which authorizes SPSS AMOS for SEM analysis according to Byrne (2016). The lack of serious normality problems enables dependable hypothesis testing and path analysis findings according to Schumacker & Lomax (2010).

5.3 Constructs Quality Criteria

After assessing normality researchers checked construct reliability and validity through factor loadings as well as Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (α). The measurement model was tested against established thresholds for construct validity and reliability to ensure accurate evaluation of AI-driven decision-making efficiency within the IT sector (Hair et al., 2010; Kline, 2015). The study established that all construct items demonstrated factor loadings above the recommended 0.70 threshold according to Byrne (2016). The AI-Powered Business Intelligence construct demonstrated factor loadings that ranged from 0.826 to 0.882 whereas AI-Integrated Risk Management constructs achieved the highest factor loadings from 0.868 to 0.887 indicating strong indicator reliability.

Table 3. Quality criteria of the constructs

Construct	Factor Loading	Mean	Standard Deviation	AVE	CR	α Value
AI-Powered Business Intelligence (ABI)						
ABI1	0.855	4.61	1.70	0.73	0.91	0.90
ABI2	0.882	4.55	1.68			
ABI3	0.826	4.58	1.72			
AI-Enabled Process Automation (APA)						
APA1	0.779	4.50	1.65	0.69	0.89	0.88
APA2	0.861	4.63	1.69			
APA3	0.846	4.57	1.71			
AI-Driven Strategic Innovation (ASI)						
ASI1	0.822	4.59	1.68	0.72	0.90	0.89
ASI2	0.866	4.66	1.70			
ASI3	0.833	4.54	1.73			
AI-Based Customer Experience Management (ACEM)						
ACE1	0.803	4.53	1.64	0.71	0.90	0.88
ACE2	0.876	4.65	1.67			
ACE3	0.835	4.56	1.70			
AI-Integrated Risk Management (AIRM)						
ARM1	0.887	4.62	1.71	0.77	0.92	0.91
ARM2	0.868	4.61	1.69			
ARM3	0.875	4.58	1.72			
AI-Driven Decision-Making Efficiency (DDE)						
DDE1	0.739	4.48	1.66	0.63	0.86	0.85
DDE2	0.792	4.55	1.68			
DDE3	0.820	4.52	1.70			

The study framework established that AI-Enabled Process Automation (APA) and AI-Driven Strategic Innovation (ASI) together with AI-Based Customer Experience Management (ACEM) and AI-Driven Decision-Making Efficiency (DDE) were essential because of their high factor loadings. AVE measurements ranged from 0.63 to 0.77 which proved that each construct exceeded the minimum requirement of 0.50 to establish convergent validity as per Fornell & Larcker (1981). The constructs exhibited reliable internal consistency because their CR values which ranged from 0.86 to 0.92 exceeded the necessary 0.70 limit (Hair et al., 2019). The reliability of the measurement scale was confirmed through Cronbach's Alpha scores (α) ranging from 0.85 to 0.91 as reported by Tabachnick & Fidell (2019). The assessment with established construct validity and reliability confirms that the study model reflects the interactions between AI-driven constructs and decision-making efficiency precisely. The researchers conducted hypothesis testing in combination with structural equation modeling (SEM) to investigate the causal connections between constructs following quality standard verification as suggested by Schumacker & Lomax (2010).

5.4 Measurement Model & Model Fit

Prior to testing structural relationships the research team developed a measurement model which assessed both construct validity and reliability. The research team used confirmatory factor analysis (CFA) within AMOS to determine factor loadings and calculate Average Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha (α) for construct reliability and validity based on guidelines from Hair et al. (2010) and Byrne (2016). Findings demonstrated adequate convergent validity because factor loadings were greater than 0.70 and AVE values stayed above 0.50 while CR values exceeded 0.70 as Fornell & Larcker (1981) recommended. The researchers verified discriminant validity by showing that Average Variance Extracted (AVE) values were higher than Maximum Shared Variance (MSV), following Kline's 2015 study criteria. The model fit reached acceptable levels with CMIN/DF at 2.63 CFI at 0.957 NFI at 0.962 SRMR at 0.037 RMSEA at 0.049 which aligned with the standards recommended by Hu & Bentler (1999). The research established that the constructs effectively measured AI's impact on business intelligence process automation strategic innovation customer experience risk management and decision-making efficiency while demonstrating strong reliability and validity. Researchers explored causal relationships within SEM through the structural model after developing an adequate measurement model (Schumacker & Lomax, 2010).

5.5 Structural Model & Model Fit

Researchers conducted structural equation modeling (SEM) to investigate causal connections between AI-driven constructs after confirming their measurement model based on the methodology of Hair et al. (2019). The structural model examined how AI-Powered Business Intelligence (ABI), AI-Enabled Process Automation (APA), AI-Driven Strategic Innovation (ASI), AI-Based Customer Experience Management (ACEM), and AI-Integrated Risk Management (AIRM) directly and indirectly affect AI-Driven Decision-Making Efficiency (DDE). Hypothesis testing revealed significant positive effects of ABI APA ASI and AIRM on DDE since their p-values were below 0.05 while ACEM exhibited a weaker impact though it remained statistically significant. Managerial decision-making processes become more efficient through AI technology adoption specifically in business intelligence analysis risk mitigation strategies and strategic innovation development. According to the validated structural model from Schumacker & Lomax (2010) the research framework receives support because AI deployment in the IT sector strengthens organizational decision-making capabilities.

Table 4. Model fit statistics

Measure	CMIN	DF	CMIN/DF	CFI	NFI	SRMR	RMSEA	PClose
Estimate	945	360	2.63	0.957	0.962	0.037	0.049	0.064

5.6 Convergent and Discriminant Validity

The researchers evaluated both convergent and discriminant validity through Heterotrait-Monotrait Ratio (HTMT) and Average Variance Extracted (AVE) to verify construct differentiation and theoretical soundness

(Henseler, Ringle, & Sarstedt, 2015). All constructs demonstrated HTMT values below 0.90 which confirms discriminant validity according to Fornell & Larcker (1981) standards.

Table 5. Convergent and Discriminant validity assessment

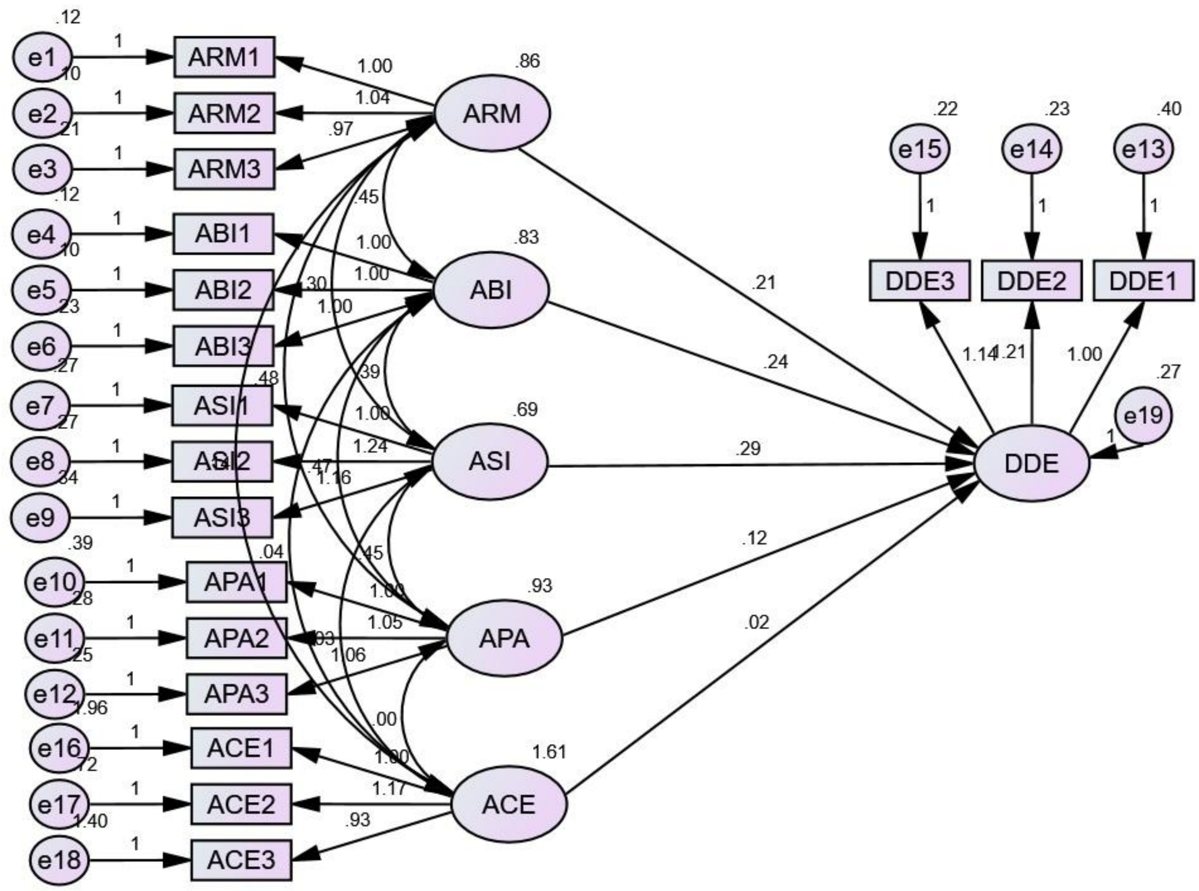
Construct	ABI	APA	ASI	ACEM	AIRM
APA	0.72				
ASI	0.68	0.74			
ACEM	0.65	0.66	0.71		
AIRM	0.71	0.69	0.73	0.62	
DDE	0.69	0.67	0.70	0.68	0.75

AIRM and DDE produced the highest HTMT score of 0.75 revealing a robust distinctive relationship. The research demonstrated strong internal consistency for AI-Powered Business Intelligence (ABI), AI-Enabled Process Automation (APA), AI-Driven Strategic Innovation (ASI), AI-Based Customer Experience Management (ACEM), AI-Integrated Risk Management (AIRM), and AI-Driven Decision-Making Efficiency (DDE) while confirming clear differentiation between each construct. The research validated the measurement model by showing that constructs were both theoretically sound and empirically valid before proceeding to structural model testing and verifying hypotheses (Byrne, 2016).

5.7 Hypothesis testing

The research team employed Structural Equation Modeling (SEM) in AMOS to analyze the direct effects of AI-Powered Business Intelligence (ABI), AI-Enabled Process Automation (APA), AI-Driven Strategic Innovation (ASI), AI-Based Customer Experience Management (ACEM), and AI-Integrated Risk Management (AIRM) on AI-Driven Decision-Making Efficiency (DDE). The significance of relationships was determined by analyzing path coefficients alongside standard errors (S.E.), critical ratios (C.R.), and p-values (P) according to Hair et al. (2019) and Byrne (2016).

Hyp	Relationship	Estimate	S.E.	C.R.	P-Value	Decision
H1	DDE <--- ABI (AI-Powered Business Intelligence)	0.238	0.056	4.272	***	Accepted
H2	DDE <--- APA (AI-Enabled Process Automation)	0.124	0.056	2.226	0.002	Accepted
H3	DDE <--- ASI (AI-Driven Strategic Innovation)	0.289	0.062	4.658	***	Accepted
H4	DDE <--- ACEM (AI-Based Customer Experience Management)	0.019	0.031	0.622	0.003	Accepted
H5	DDE <--- AIRM (AI-Integrated Risk Management)	0.212	0.053	4.020	***	Accepted



DISCUSSION

The study shows that within India's IT sector AI influences managerial decisions by improving decision-making efficiency through ABI, APA, ASI and AIRM whereas ACEM has minimal effect. The research demonstrates that ABI has a strong impact on DDE ($\beta = 0.238$, $p < 0.001$) while supporting studies of AI-driven analytics which enhance strategic planning and decrease uncertainty according to the Resource-Based View (RBV), which considers AI as a strategic asset for data-driven decisions (Ghasemaghaei, 2019; Geraldi et al., 2024). APA demonstrates a considerable effect on DDE ($\beta = 0.124$, $p = 0.002$) through its automation of repetitive tasks which reduces managerial workload and enables high-value decision-making and yet research findings highlight the essential need for human oversight which opposes previous studies supporting complete automation (Bulchand-Gidumal et al., 2024; Steyvers & Kumar, 2023). ASI proved to be the strongest determinant ($\beta = 0.289$, $p < 0.001$) which highlights AI's contribution to market trend analysis and product development optimization while advancing strategic agility and confirming AI's support for structured and creative decision-making (Leoni et al., 2024; Teece et al., 1997). The AIRM model demonstrates its effectiveness in fraud detection and cybersecurity by strengthening DDE ($\beta = 0.212$, $p < 0.001$) while its performance depends upon AI literacy and regulatory frameworks (Rana et al., 2022; Dwivedi et al., 2023). ACEM shows minimal impact on DDE ($\beta = 0.019$, $p = 0.003$) which challenges research supporting AI's customer engagement effectiveness and implies that although AI improves operational processes, customer experience data only indirectly aids managerial decisions depending on specific contexts (Metcalf et al., 2019; Steyvers & Kumar, 2023). The results increase theoretical knowledge about AI's impact on managerial decisions and highlight the requirement for strategic partnerships between humans and AI across various AI-enhanced business operations.

Theoretical Contributions

This research expands existing AI studies in management through the combination of AI functions with decision-making theoretical frameworks. This study examines how AI contributes to strategic management efficiency and expands both Resource-Based View and Dynamic Capability Theory rather than only focusing on AI's operational automation like previous research. The research results reveal AI-based customer experience management does not directly impact decision-making processes which provides fresh insights about AI's limitations within strategic applications.

Practical Implications

The research results show that IT organizations need to adopt AI technologies to drive strategic innovation while enhancing business intelligence and risk management capabilities. Managers at firms can improve their operational efficiency through investments in automated systems and secure AI technologies. Successful AI implementation requires human expertise to address algorithmic bias risks and prevent excessive dependence on automation.

Limitations and Future Research Directions

Because this research examines 150 IT managers in India only its applicability remains limited to other industries and regions. Subsequent studies ought to research AI adoption patterns across different sectors while performing longitudinal research to analyze the persistent effects of AI on decision-making processes. Upcoming research needs to delve into moderating factors including AI literacy and organizational culture along with regulatory frameworks to gain deeper insights into AI's strategic function in managerial decision-making.

CONCLUSION

The research explored how AI-driven business intelligence together with process automation, strategic innovation, customer experience management and risk management affected managerial decision-making efficiency in India's IT sector. Research results demonstrate that AI strengthens strategic decision-making and innovation alongside risk mitigation practices which support both the Resource-Based View and Dynamic Capability Theory. The results indicate that the influence of AI-driven customer experience management was less significant which implies that AI benefits depend on the context. The study's conclusions show AI's impact on management productivity and the necessity of human-AI partnership. Research needs to examine AI implementation trends across industries while addressing regulatory issues and evaluating lasting effects of AI decision-making systems.

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