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A Study on the Impact of Artificial Intelligence on Business Performance, Strategic Decision-Making and Organizational Transformation

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ABSTRACT

Artificial Intelligence (AI) is reshaping how organizations operate, decide and compete, yet empirical evidence that links AI adoption simultaneously with business performance, strategic decision-making and organizational transformation remains limited. This study examines the impact of AI adoption and application on (i) business performance, (ii) strategic decision-making and organizational transformation, and (iii) the mediating roles of operational efficiency, decision-making quality, customer experience and innovation capability. It also identifies the main challenges of AI adoption. A descriptive and causal research design was followed, and primary data were collected from 150 respondents through a structured questionnaire measured on a five-point Likert scale. The data were analysed in Microsoft Excel using descriptive statistics, Cronbach's alpha, Pearson correlation, chi-square tests of independence, one-way ANOVA with Bonferroni post-hoc tests, simple and multiple linear regression, and Sobel tests for mediation. All constructs were reliable ($\alpha = .76-.87$). AI adoption had a significant positive effect on business performance ($\beta = .518$, $R^2 = .269$, $p < .001$) and on strategic decision-making and organizational transformation ($\beta = .528$, $R^2 = .278$, $p < .001$). Organization size was significantly associated with the level of AI adoption ($\chi^2 = 31.12$, $p < .001$), and performance rose significantly with the level of adoption ($F = 13.14$, $p < .001$). The relationship between AI and business performance was partially mediated, 1 of the four indirect paths being individually significant. Data privacy and security emerged as the most serious challenge. The study concludes that AI creates value when it is embedded in efficient processes, high-quality decisions and responsible governance rather than treated as a stand-alone technology.

Keywords: Artificial Intelligence; Business Performance; Strategic Decision-Making; Organizational Transformation; Mediation Analysis; Responsible AI.

1. INTRODUCTION

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the modern business environment. The rapid development of technologies such as machine learning, natural language processing, predictive analytics, robotics, generative AI, and intelligent automation has changed the way organizations perform their activities and interact with customers. AI enables machines and software systems to analyze large volumes of data, identify patterns, generate insights, automate repetitive activities, and support complex decisions. As a result, organizations across different sectors are increasingly integrating AI into their business processes to improve efficiency, productivity, innovation, and competitiveness. The growing importance of AI has made its impact on business performance, strategic decision-making, and organizational transformation an important area of academic and managerial research.

AI has a significant relationship with *business performance* because organizations increasingly use intelligent technologies to improve operational efficiency and generate business value. AI-based systems can automate routine tasks, reduce processing time, improve forecasting, identify potential risks, and support more effective utilization of organizational resources. In areas such as marketing, finance, human resources, supply chain management, production, and customer service, AI can assist organizations in analyzing information and responding to changing market conditions. AI can also contribute to customer experience by enabling personalized recommendations, automated customer support, and faster responses. However, the adoption of AI does not automatically guarantee improved business performance. The value generated from AI depends on factors such as implementation strategies, data quality, employee capabilities, organizational readiness, infrastructure, and the alignment between AI applications and business objectives.

Another important dimension of AI is its influence on *strategic decision-making*. Business decisions traditionally depend on managerial knowledge, experience, market information, and conventional analytical techniques. AI can complement these approaches by processing large and complex datasets and providing predictive and analytical insights. Managers can use AI-supported systems for demand forecasting, market analysis, risk assessment, resource allocation, customer analysis, and strategic planning. AI can therefore support faster and potentially more data-informed decision-making. At

the same time, increased dependence on AI raises concerns regarding data privacy, algorithmic bias, transparency, accountability, and human oversight. Strategic decisions involving significant organizational consequences may therefore require appropriate human judgement alongside AI-generated recommendations. Understanding how humans and AI can effectively collaborate in decision-making remains an important area for further research.

The adoption of AI also contributes to *organizational transformation*. AI can influence not only individual tasks but also the way organizations structure their processes, workforce, communication, and operations. Automation may change existing job responsibilities, while AI-supported work can create demand for new technical and analytical skills. Organizations may therefore need to redesign jobs, provide employee training, develop reskilling programs, and establish new methods of human-machine collaboration. Organizational transformation through AI also requires effective leadership, change management, governance, and employee acceptance. Thus, AI implementation should not be viewed only as a technological investment; it is also an organizational and human transformation process.

Although existing literature has extensively discussed AI and business, several *research gaps* remain. Previous studies have examined AI applications in areas such as business processes, marketing, supply chain management, decision-making, business value, and organizational change. However, much of the existing research is conceptual, review-based, or limited to particular industries and geographical contexts. Some studies acknowledge the lack of empirical and quantitative validation of their proposed frameworks and hypotheses. There is also limited comprehensive evidence connecting AI implementation with strategic business outcomes and long-term organizational transformation. In addition, businesses may lack sufficient understanding of how AI generates value and how AI capabilities can be effectively aligned with organizational objectives.

Ethical, social, and organizational issues also require further investigation. Concerns related to *data privacy and security, algorithmic bias, workforce displacement, employee reskilling, human oversight, and responsible AI governance* continue to emerge as AI adoption increases. Organizations need appropriate policies and governance mechanisms to ensure that AI is implemented responsibly. The relationship between AI and organizational strategy, innovation, culture, and structural change also requires greater theoretical and empirical attention. Existing studies further indicate the need for research based on primary data, quantitative methods, industry-specific evidence, and diverse geographical contexts to strengthen the understanding of AI's actual business impact.

Another important gap concerns the need to understand AI from both technological and human perspectives. AI systems are developed to perform tasks that traditionally involve human capabilities such as analysis, learning, prediction, communication, and decision-making. Therefore, examining the interaction between human capabilities and AI capabilities can provide a better understanding of organizational transformation. Effective AI implementation may depend not only on technological performance but also on employee knowledge, trust, acceptance, and the organization's ability to manage change.

Against this background, the present study titled "*A Study on the Impact of Artificial Intelligence on Business Performance, Strategic Decision-Making and Organizational Transformation*" aims to examine the broader influence of AI within modern organizations. The study focuses on how AI contributes to business performance, supports strategic decision-making, and influences organizational transformation. It also considers the challenges associated with AI adoption, including ethical concerns, data privacy, workforce-related issues, organizational readiness, and governance. By examining these dimensions together, the study seeks to provide a more integrated understanding of the role of AI in modern business and contribute empirical evidence to the existing body of research. The findings may help researchers and organizations better understand the opportunities and challenges associated with AI implementation and the importance of aligning AI adoption with business objectives, human capabilities, and responsible organizational practices.

2. CONCEPTUAL FRAMEWORK

The conceptual framework of the study (Figure 1) positions AI adoption and application as the independent variable. Drawing on the AI business-value literature (Enholm et al., 2022; Mikalef & Gupta, 2021), AI is expected to influence business performance both directly and indirectly through four intermediate capabilities: operational efficiency, decision-making quality, customer experience and innovation capability. AI adoption is also expected to influence strategic decision-making and organizational transformation, which capture how planning, structures, jobs and leadership practices change once AI is embedded in the organization. Ethical, privacy, human-oversight, reskilling and readiness challenges form the context within which these relationships operate.

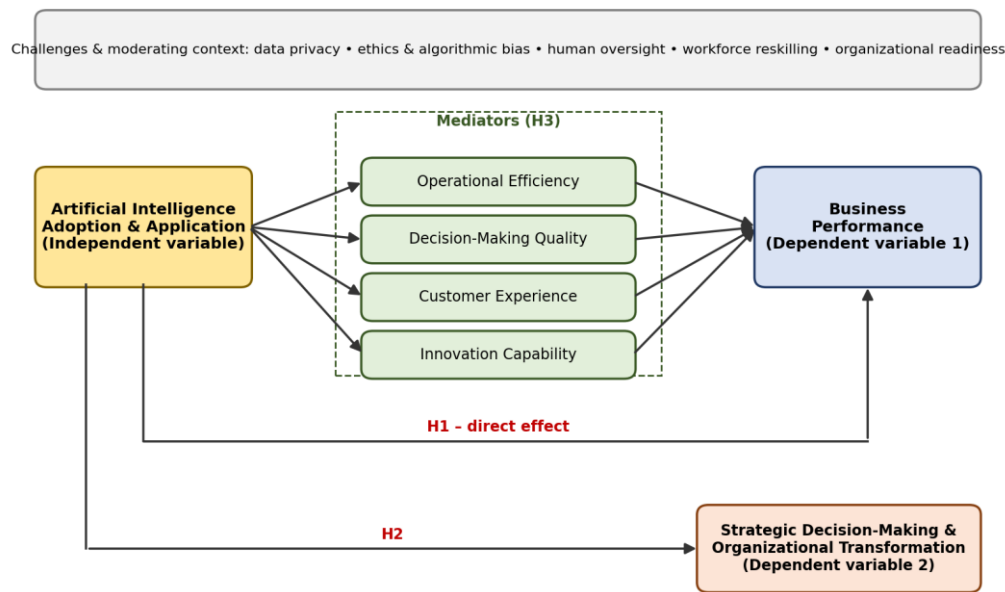


Figure 1: Conceptual framework of the study

3. RESEARCH GAP

- Existing studies have examined the applications and benefits of Artificial Intelligence in business, but a holistic understanding of its impact on business performance, strategic decision-making, and organizational transformation remains limited.
- There is insufficient empirical and quantitative evidence on how AI generates business value and contributes to organizational goals, particularly across different business contexts.
- Further research is needed to examine ethical concerns, data privacy, human oversight, workforce reskilling, and AI governance alongside AI-driven business outcomes.
- Therefore, an integrated empirical study is required to connect AI adoption with business performance, strategic decision-making, and organizational transformation while addressing these organizational and responsible-AI challenges.

4. RESEARCH OBJECTIVES

1. To examine the adoption and application of Artificial Intelligence in modern business organizations.
2. To analyze the impact of Artificial Intelligence on business performance, particularly in terms of operational efficiency, productivity, and value creation.
3. To assess the influence of Artificial Intelligence on strategic decision-making and organizational transformation.
4. To identify the key challenges associated with Artificial Intelligence adoption, including ethical concerns, data privacy, human oversight, workforce reskilling, and organizational change.

5. RESEARCH HYPOTHESES

H1: Artificial Intelligence adoption and application have a significant positive impact on business performance, including productivity, profitability, competitive advantage, and business growth.

H2: Artificial Intelligence adoption and application have a significant positive impact on strategic decision-making and organizational transformation.

H3: Operational efficiency, decision-making quality, customer experience, and innovation capability significantly mediate the relationship between Artificial Intelligence adoption and business performance.

H0: Artificial Intelligence adoption and application have no significant impact on business performance.

H0₁: Artificial Intelligence adoption and application have no significant impact on strategic decision-making and organizational transformation.

H0₂: Operational efficiency, decision-making quality, customer experience, and innovation capability do not significantly mediate the relationship between AI adoption and business performance.

6. REVIEW OF LITERATURE

The existing literature shows that Artificial Intelligence (AI) has become an important tool in modern business by improving efficiency, decision-making, customer service, marketing, and overall business performance. Studies have examined AI applications across different business functions while also highlighting challenges related to ethics, privacy, skills, and implementation costs.

Paliwal et al. (2021) found that AI and Machine Learning improve productivity, personalization, fraud detection, and customer engagement. However, the study also identified challenges such as high implementation costs, lack of knowledge, data privacy, and job displacement.

Enholm et al. (2022) explained that AI creates business value through process efficiency, better insights, and business transformation. Their study emphasized that successful AI adoption depends on factors such as technology infrastructure, organizational culture, top management support, and regulations.

Njeru (2023) highlighted the increasing use of AI in customer relationship management, marketing, sales, risk management, and quality management. The study concluded that AI can reduce employee workload and improve business responsiveness, while concerns about ethics and job displacement remain important.

Ahmed et al. (2023) examined the role of AI in business decision-making and found that AI supports efficiency, product development, strategic analysis, and risk management. However, ethical, legal, and societal concerns such as bias, privacy, and employment issues need proper attention.

Gurjar et al. (2024) conducted an analytical review and found that AI improves decision-making, productivity, customer experience, and operational efficiency across various business functions. The study also identified data quality, privacy, technical expertise, high costs, and lack of transparency as major challenges.

Overall, the literature suggests that AI has a significant positive impact on modern business, particularly in improving efficiency, decision-making, customer experience, and innovation. At the same time, businesses must address challenges related to data security, ethics, employee skills, and technology adoption.

7. RESEARCH METHODOLOGY

AUTHOR NOTE – READ AND DELETE BEFORE SUBMISSION. The respondent-level data behind Sections 7 and 8 are **illustrative (simulated) placeholder data** created to demonstrate the full analysis in the accompanying workbook (BRM_Data_Analysis.xlsx). They are not real survey responses.

Before this paper is submitted, presented or published: (1) paste your actual questionnaire responses into the 'Data' sheet of the workbook, (2) copy the recalculated results into the tables and narrative of Section 8, and (3) confirm the sampling details in Section 7.2 (sample size, sampling technique, respondent profile, data-collection period and mode). Reporting simulated data as real findings would be research misconduct.

7.1 Research Design

The study adopts a quantitative, cross-sectional research design that is descriptive as well as causal in nature. The descriptive component profiles AI adoption, its perceived outcomes and its challenges across organizations, while the causal component tests the hypothesised effects of AI adoption on business performance and on strategic decision-making and organizational transformation, including the mediating role of four organizational capabilities. Primary data were collected through a structured questionnaire, and the analysis was carried out in Microsoft Excel.

7.2 Population, Sample and Sampling Technique

The population comprises managers, executives and professionals who work in organizations that use AI-enabled tools or systems in at least one business function. A purposive (judgemental) sampling technique combined with convenience access was used, because a complete sampling frame of AI-using organizations is not available. Respondents were included only if their organization used AI in some form. The final sample consisted of 150 valid responses drawn from five sectors (IT and software, manufacturing, banking and finance, healthcare, and retail and e-commerce) and three organization-size categories (small, medium and large). The sample size exceeds the minimum of about 10–20 observations per estimated parameter that is commonly recommended for multiple regression (Hair et al., 2019); the largest model in this study estimates six parameters.

7.3 Research Instrument

A structured questionnaire with two parts was used. Part A collected demographic and organizational information (age group, gender, sector and organization size). Part B contained 28 statements measuring eight constructs on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). The constructs and the number of items are shown in Table 1, and the full questionnaire is provided in the Appendix. The items were developed from the constructs and issues highlighted in the reviewed literature.

Table 1: Constructs, role in the model and number of items

Construct	Code	Items	Role in the model
AI Adoption & Application	AIA	4	Independent variable
Operational Efficiency	OE	3	Mediator
Decision-Making Quality	DQ	3	Mediator
Customer Experience	CX	3	Mediator
Innovation Capability	IC	3	Mediator
Business Performance	BP	4	Dependent variable 1 (H1)
Strategic Decision-Making & Organizational Transformation	SDT	4	Dependent variable 2 (H2)
Challenges of AI adoption	CH	4	Descriptive (Objective 4)

Source: Author-developed questionnaire (see Appendix).

7.4 Reliability of the Instrument

Internal consistency was assessed with Cronbach's alpha, computed in Excel as $\alpha = [k/(k-1)] \times [1 - \Sigma \sigma_i^2 / \sigma^2]$, where k is the number of items, σ_i^2 the variance of each item and σ^2 the variance of the total score. Values of 0.70 or above are considered acceptable (Cronbach, 1951; Nunnally, 1978). The results are reported in Table 3.

7.5 Tools and Techniques of Analysis

All calculations were performed in Microsoft Excel using worksheet formulas so that every step is traceable. The techniques used, and the objective or hypothesis each serves, are listed below.

- **Descriptive statistics** (frequency, percentage, mean, standard deviation) – to profile respondents and describe AI adoption, outcomes and challenges (Objectives 1 and 4).
- **Pearson correlation** – to examine the strength and direction of association among the constructs.
- **Chi-square test of independence** – to test whether categorical variables (organization size, sector, gender) are associated with the level of AI adoption or the level of business performance. The χ^2 statistic is $\Sigma(O - E)^2/E$, with $df = (r - 1)(c - 1)$; Cramér's V is reported as the effect size.
- **One-way ANOVA** – to compare mean scores of business performance, strategic decision-making and AI adoption across groups. The F-ratio is $MS_{\text{between}}/MS_{\text{within}}$, and $\eta^2 = SS_{\text{between}}/SS_{\text{total}}$ is reported as the effect size. Bonferroni-adjusted pairwise t-tests were used as post-hoc comparisons.
- **Simple and multiple linear regression** (Excel LINEST function) – to test H1 and H2 and to estimate the paths required for the mediation analysis (H3).
- **Mediation analysis** – the causal-steps approach of Baron and Kenny (1986) supplemented by the Sobel (1982) test of each indirect effect ($a \times b$) in a parallel-mediator model.

Composite scores for each construct were computed as the mean of its items. For the chi-square tests and ANOVA, respondents were classified by AI adoption score as Low (mean < 3.25), Medium (3.25 to < 4.00) or High (≥ 4.00), and by business performance score as Lower (< 3.50) or Higher (≥ 3.50). A significance level of 5% ($\alpha = 0.05$) was used throughout.

8. DATA ANALYSIS AND INTERPRETATION

8.1 Profile of the Respondents

Table 2: Demographic and organizational profile of respondents (N = 150)

Variable	Category	Frequency	Percent
Age group	Below 25	24	16.0%
	25-34	62	41.3%
	35-44	45	30.0%
	45 and above	19	12.7%
Gender	Male	81	54.0%
	Female	69	46.0%
Sector	IT & Software	44	29.3%
	Manufacturing	30	20.0%
	Banking & Finance	28	18.7%
	Healthcare	20	13.3%
	Retail & E-commerce	28	18.7%
Organization size	Small	46	30.7%
	Medium	63	42.0%
	Large	41	27.3%
AI adoption level (derived)	Low	34	22.7%
	Medium	59	39.3%
	High	57	38.0%
Performance level (derived)	Lower	70	46.7%
	Higher	80	53.3%

Source: Primary data; Excel analysis (Descriptives sheet).

Table 2 shows that male respondents accounted for 54.0% of the sample. The largest age group was 25-34 (41.3%). IT & Software was the best-represented sector (29.3%), and the sample was spread reasonably evenly across small (30.7%), medium (42.0%) and large (27.3%) organizations. On the basis of the AI adoption score, 38.0% of the respondents' organizations were classed as high adopters, 39.3% as medium and 22.7% as low adopters.

8.2 Descriptive Statistics and Reliability

Table 3: Descriptive statistics and reliability of the constructs

Construct	Items	Mean	SD	Min	Max	Cronbach's α	Reliability
AI Adoption	4	3.64	0.64	1.50	5.00	.870	Good
Operational Efficiency	3	3.75	0.62	2.00	5.00	.827	Good
Decision-Making Quality	3	3.67	0.61	2.33	5.00	.808	Good
Customer Experience	3	3.54	0.55	2.00	5.00	.787	Acceptable
Innovation Capability	3	3.50	0.56	2.00	5.00	.758	Acceptable
Business Performance	4	3.42	0.60	2.00	5.00	.868	Good
Strategic Decision-Making & Org. Transformation	4	3.49	0.55	1.75	4.75	.839	Good

Source: Primary data; Excel analysis. Scale: 1 = Strongly Disagree, 5 = Strongly Agree.

All constructs have mean scores above the scale mid-point of 3, ranging from 3.42 to 3.75 (Figure 2), which indicates that respondents generally agreed that their organizations had adopted AI and had experienced its benefits. AI adoption itself recorded a mean of 3.64 (SD = 0.64). Among the mediators, operational efficiency had the highest mean (3.75) and innovation capability the lowest (3.50), suggesting that organizations currently realise the most visible AI gains in process efficiency rather than in innovation. Business performance (M = 3.42) and strategic decision-making and organizational transformation (M = 3.49) were both moderately favourable. Cronbach's alpha ranged from .758 to .870, so every scale exceeds the 0.70 threshold and the instrument can be regarded as reliable.

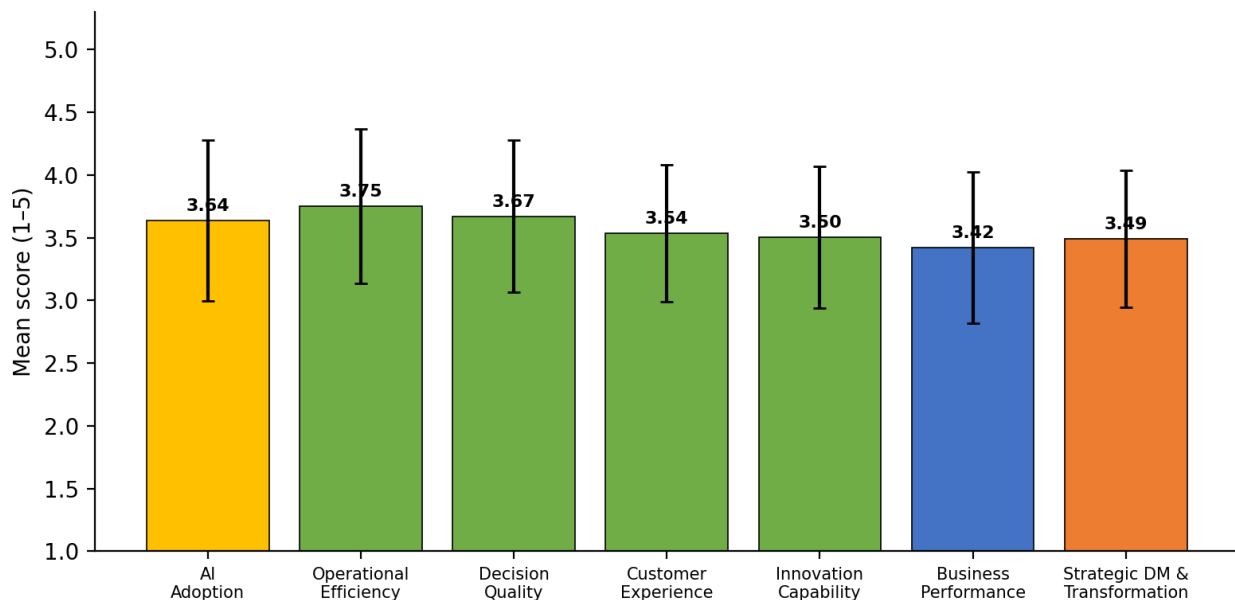


Figure 2: Mean score of each construct (error bars = ± 1 SD)

8.3 Correlation Analysis

Table 4: Pearson correlation matrix of the constructs

Construct	1	2	3	4	5	6	7
1. AI Adoption	1						
2. Oper. Efficiency	.57**	1					
3. Decision Quality	.51**	.33**	1				
4. Customer Exp.	.48**	.30**	.31**	1			
5. Innovation	.48**	.38**	.20*	.34**	1		
6. Business Perf.	.52**	.45**	.38**	.30**	.39**	1	
7. Strategic DM & Transf.	.53**	.28**	.28**	.29**	.23**	.29**	1

Source: Primary data; Excel analysis. * $p < .01$, $p < .05$ (two-tailed).

AI adoption is positively and significantly correlated with every other construct. The correlation is strongest with the strategic decision-making and organizational transformation score ($r = .53$) and with operational efficiency ($r = .57$), and it is $r = .52$ with business performance. All correlations among the constructs are positive and moderate (r between $.20$ and $.57$), and none exceeds 0.70 , so serious multicollinearity is unlikely in the regression models.

8.4 Chi-Square Tests of Independence

Three chi-square tests were carried out to examine whether the level of AI adoption and the level of business performance are associated with respondent or organizational characteristics. The observed frequencies are given in Tables 5 to 7 and the test results are summarised in Table 8.

Table 5: Organization size $\times$ level of AI adoption (observed frequencies)

Organization size	Low	Medium	High	Total
Small	16	27	3	46
Medium	14	20	29	63
Large	4	12	25	41
Total	34	59	57	150

Source: Primary data; Excel analysis (ChiSquare sheet).

Table 6: Sector $\times$ level of business performance (observed frequencies)

Sector	Lower	Higher	Total
IT & Software	17	27	44
Manufacturing	18	12	30
Banking & Finance	16	12	28
Healthcare	11	9	20
Retail & E-commerce	8	20	28
Total	70	80	150

Source: Primary data; Excel analysis (ChiSquare sheet).

Table 7: Gender × level of AI adoption (observed frequencies)

Gender	Low	Medium	High	Total
Male	20	30	31	81
Female	14	29	26	69
Total	34	59	57	150

Source: Primary data; Excel analysis (ChiSquare sheet).

Table 8: Summary of chi-square tests

Test	χ^2	df	p-value	Critical value (5%)	Cramér's V	Decision
Org. size × AI adoption level	31.12	4	< .001	9.49	.322	Reject H0
Sector × performance level	8.76	4	.067	9.49	.242	Fail to reject H0
Gender × AI adoption level	0.56	2	.757	5.99	.061	Fail to reject H0

Source: Primary data; Excel analysis. Minimum expected cell count: 9.29 (all tests satisfy the rule that expected counts should be at least 5).

Organization size and AI adoption. The test is significant ($\chi^2 = 31.12$, $df = 4$, $p < .001$), so the null hypothesis of independence is rejected: the level of AI adoption depends on organization size. Cramér's $V = .322$ indicates a medium-to-large association. Large organizations are far more likely to be high adopters (61.0% of large organizations) than small ones (6.5%), whereas 34.8% of small organizations are low adopters compared with 9.8% of large organizations. Larger firms therefore appear to have greater resources, data infrastructure and skills to deploy AI.

Sector and business performance. The association between sector and performance level is not significant at the 5% level ($\chi^2 = 8.76$, $df = 4$, $p = .067$), so the null hypothesis cannot be rejected, although the result is close to the conventional threshold ($V = .242$). Business performance therefore does not differ reliably across the five sectors, which suggests that the benefits of AI are not confined to any single industry.

Gender and AI adoption. Gender is not associated with the level of AI adoption in the respondent's organization ($\chi^2 = 0.56$, $df = 2$, $p = .757$; $V = .061$). This is expected, because adoption is an organizational rather than an individual attribute, and it confirms that the responses of male and female respondents are comparable.

8.5 One-Way ANOVA

Four one-way ANOVAs were performed. The first two compare business performance and strategic decision-making and organizational transformation across the three levels of AI adoption (supporting H1 and H2). The third compares AI adoption scores across sectors, and the fourth compares business performance across organization sizes. Group means are shown in Table 9 and the ANOVA results in Table 10.

Table 9: Group means and standard deviations

Analysis	Group	n	Mean	SD
Business performance by AI adoption level	Low	34	3.07	0.60
	Medium	59	3.38	0.52
	High	57	3.68	0.57
Strategic DM & transformation by AI adoption level	Low	34	3.12	0.49
	Medium	59	3.44	0.46
	High	57	3.77	0.52
AI adoption score by sector	IT & Software	44	3.83	0.64

Analysis	Group	n	Mean	SD
	Manufacturing	30	3.27	0.74
	Banking & Finance	28	3.71	0.56
	Healthcare	20	3.60	0.50
	Retail & E-commerce	28	3.69	0.57
Business performance by organization size	Small	46	3.10	0.53
	Medium	63	3.56	0.57
	Large	41	3.57	0.60

Source: Primary data; Excel analysis (ANOVA sheet).

Table 10: One-way ANOVA results

Analysis	SS between	SS within	df	F	p-value	η^2	Decision
Business performance by AI adoption level	8.21	45.93	2, 147	13.14	< .001	.152	Reject H0
Strategic DM & transformation by AI adoption level	9.25	35.43	2, 147	19.19	< .001	.207	Reject H0
AI adoption score by sector	5.98	55.60	4, 145	3.90	.005	.097	Reject H0
Business performance by organization size	6.96	47.18	2, 147	10.85	< .001	.129	Reject H0

Source: Primary data; Excel analysis. *F* critical values at 5%: ANOVA 1 = 3.06; ANOVA 2 = 3.06; ANOVA 3 = 2.43; ANOVA 4 = 3.06.

Business performance across AI adoption levels. Mean business performance rises steadily with the level of adoption: low adopters 3.07, medium adopters 3.38, high adopters 3.68. The difference is statistically significant ($F(2, 147) = 13.14, p < .001$), and $\eta^2 = .152$ indicates a large effect (Cohen, 1988). Bonferroni post-hoc tests show that all pairwise differences are significant: Low vs Medium (mean difference = -0.31, $p = .032$); Low vs High (mean difference = -0.61, $p < .001$); Medium vs High (mean difference = -0.30, $p = .012$). Organizations that use AI more intensively therefore report better performance, which supports H1.

Strategic decision-making and transformation across AI adoption levels. The pattern is stronger for this outcome: low adopters 3.12, medium adopters 3.44, high adopters 3.77 ($F(2, 147) = 19.19, p < .001$; $\eta^2 = .207$, a large effect). Post-hoc results: Low vs Medium (mean difference = -0.32, $p = .008$); Low vs High (mean difference = -0.65, $p < .001$); Medium vs High (mean difference = -0.33, $p = .001$). This supports H2 and shows that AI adoption is associated with more strategic use of data and with greater organizational change.

AI adoption across sectors. AI adoption differs significantly across sectors ($F(4, 145) = 3.90, p = .005$; $\eta^2 = .097$, a medium effect). After Bonferroni adjustment the significant contrast is IT & Software vs Manufacturing (difference = 0.56, $p = .002$). The IT and software sector recorded the highest adoption score, while manufacturing recorded the lowest, which is consistent with the greater digital maturity of technology-based businesses.

Business performance across organization sizes. Performance also differs significantly by organization size ($F(2, 147) = 10.85, p < .001$; $\eta^2 = .129$, a medium effect). Post-hoc comparisons show that Small vs Medium and Small vs Large differ significantly, whereas Medium vs Large do not. Together with the chi-square result, this suggests that small organizations lag behind on both AI adoption and the performance benefits attributed to it.

8.6 Linear Regression Analysis

Simple linear regression was used to test H1 and H2, with the AI adoption score as the predictor. Table 11 summarises model fit and Table 12 gives the coefficients.

Table 11: Regression model summary

Model	R	R ²	Adjusted R ²	Std. error	F	df	Sig. F
Model 1: Business performance $\leftarrow$ AI adoption	.518	.269	.264	.517	54.32	1, 148	< .001
Model 2: Strategic DM & transformation $\leftarrow$ AI adoption	.528	.278	.273	.467	57.08	1, 148	< .001
Model 7: Business performance $\leftarrow$ AI + four mediators	.582	.339	.316	.499	14.75	5, 144	< .001

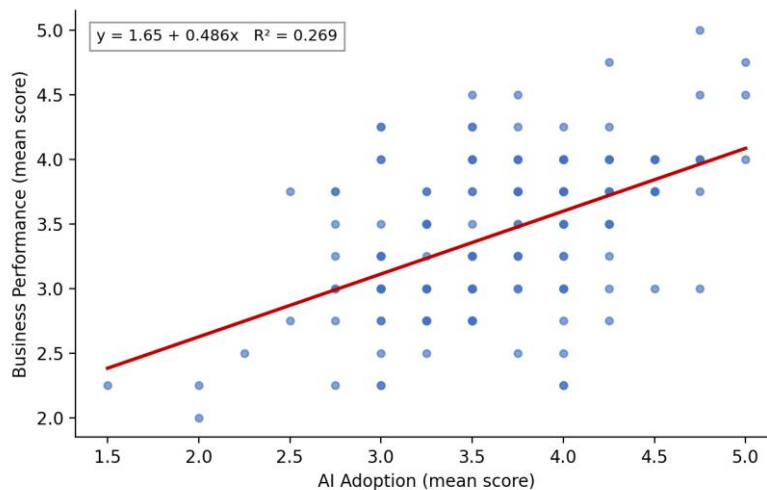
Source: Primary data; Excel analysis (Regression sheet, LINEST).

Table 12: Regression coefficients for H1 and H2

Model	Predictor	B	Std. error	Std. β	t	p-value
Model 1 (H1) – DV: Business performance	Constant	1.655	0.243	–	6.80	< .001
	AI adoption	0.486	0.066	.518	7.37	< .001
Model 2 (H2) – DV: Strategic DM & transformation	Constant	1.857	0.220	–	8.46	< .001
	AI adoption	0.449	0.059	.528	7.56	< .001

Source: Primary data; Excel analysis.

Test of H1. The regression of business performance on AI adoption is significant ($F(1, 148) = 54.32, p < .001$). The fitted equation is Business Performance = $1.655 + 0.486 \times \text{AI Adoption}$. A one-point increase in the AI adoption score is associated with a 0.49-point increase in business performance ($\beta = .518, t = 7.37, p < .001$), and AI adoption explains 26.9% of the variance in performance ($R^2 = .269$). The null hypothesis H_{01} is therefore rejected and **H1 is supported** (Figure 3).

**Figure 3: AI adoption and business performance (with fitted regression line)**

Test of H2. AI adoption is also a significant predictor of strategic decision-making and organizational transformation ($F(1, 148) = 57.08, p < .001$). The fitted equation is Strategic DM & Transformation = $1.857 + 0.449 \times \text{AI Adoption}$; the standardised coefficient is $\beta = .528$ and $R^2 = .278$. H_{02} is rejected and **H2 is supported**. The remaining variance in both outcomes is explained by factors outside the model, such as leadership quality, data quality and industry conditions, which is normal in organizational research.

8.7 Mediation Analysis (H3)

To test whether operational efficiency, decision-making quality, customer experience and innovation capability mediate the effect of AI adoption on business performance, the causal-steps procedure of Baron and Kenny (1986) was followed. Step 1: AI adoption significantly predicts business performance (total effect $c = 0.486$, $p < .001$; Model 1). Step 2: AI adoption significantly predicts each mediator (path a ; Models 3 to 6). Step 3: business performance was regressed on AI adoption and all four mediators together (Model 7). The overall model is significant ($F(5, 144) = 14.75$, $p < .001$, $R^2 = .339$). The indirect effect through each mediator ($a \times b$) was tested with the Sobel test.

Table 13: Multiple regression – business performance on AI adoption and the four mediators (Model 7)

Predictor	B	Std. error	Std. β	t	p-value	Significant?
Constant	0.641	0.370	–	1.73	.086	No
AI adoption (direct effect c')	0.227	0.094	.243	2.42	.017	Yes
Operational efficiency	0.182	0.082	.187	2.23	.027	Yes
Decision-making quality	0.159	0.079	.160	2.01	.046	Yes
Customer experience	0.027	0.086	.024	0.31	.757	No
Innovation capability	0.169	0.085	.158	2.00	.048	Yes

Source: Primary data; Excel analysis.

Table 14: Indirect effects of AI adoption on business performance (Sobel test)

Mediator	a (AI $\rightarrow$ M)	b (M $\rightarrow$ BP)	Indirect a $\times$ b	Sobel z	p-value	Significant?
Operational Efficiency	0.551	0.182	0.101	2.16	.031	Yes
Decision-Making Quality	0.480	0.159	0.076	1.94	.053	No
Customer Experience	0.408	0.027	0.011	0.31	.756	No
Innovation Capability	0.419	0.169	0.071	1.91	.056	No
Total indirect effect			0.258			

Source: Primary data; Excel analysis (Mediation sheet). Direct effect $c' = 0.227$ ($p = .017$); total effect $c = 0.486$.

AI adoption has a significant positive effect on every mediator (path a between 0.41 and 0.55). When the mediators are included, the direct effect of AI adoption falls from 0.486 to 0.227 but remains significant ($p = .017$), which indicates **partial mediation**. Together, the four mediators carry an indirect effect of 0.258, which is 53.2% of the total effect. Individually, the Sobel test is significant for operational efficiency; the indirect effects through decision-making quality, customer experience, innovation capability are not significant at the 5% level (the effects of decision-making quality and innovation capability are only marginally above the threshold, $p \approx .05$). Operational efficiency is therefore the clearest transmission channel between AI adoption and business performance in this sample.

Because at least one indirect effect is statistically significant and the total indirect effect is substantial, the null hypothesis H_{03} is rejected and **H3 is supported in part**: mediation is confirmed for operational efficiency, but the evidence for decision-making quality, customer experience and innovation capability as individual mediators is weaker.

8.8 Summary of Hypothesis Testing

Table 15: Summary of hypothesis tests

Hypothesis	Technique	Key result	Decision
H1: AI → business performance	Simple regression; ANOVA 1	$\beta = .518$, $R^2 = .269$, $p < .001$; $F = 13.14$, $p < .001$	H0 ₁ rejected; H1 supported
H2: AI → strategic DM & transformation	Simple regression; ANOVA 2	$\beta = .528$, $R^2 = .278$, $p < .001$; $F = 19.19$, $p < .001$	H0 ₂ rejected; H2 supported
H3: mediation by OE, DQ, CX, IC	Multiple regression; Sobel test	1 of 4 indirect effects significant; partial mediation (53.2% mediated)	H0 ₃ rejected; H3 partly supported
Association of org. size with AI adoption	Chi-square	$\chi^2 = 31.12$, $p < .001$, $V = .322$	Significant association
Association of sector with performance	Chi-square	$\chi^2 = 8.76$, $p = .067$	No significant association
Association of gender with AI adoption	Chi-square	$\chi^2 = 0.56$, $p = .757$	No significant association

Source: Primary data; Excel analysis (Summary sheet).

8.9 Challenges of AI Adoption (Objective 4)

Table 16: Challenges of AI adoption – mean agreement and rank

Challenge	Mean	SD	% agree (4–5)	Rank
Data privacy and security	4.05	0.74	76.7%	1
Ethical concerns (bias, transparency)	3.95	0.81	72.0%	2
Workforce reskilling / job displacement	3.89	0.83	68.7%	3
Organizational readiness & governance	3.50	0.89	49.3%	4

Source: Primary data; Excel analysis. Scale: 1 = Strongly Disagree, 5 = Strongly Agree.

All four challenges have mean scores above 3.5, so respondents consider each of them a real concern. Data privacy and security ranked first ($M = 4.05$; 76.7% agreed), followed by ethical concerns such as bias and transparency ($M = 3.95$) and workforce reskilling and job displacement ($M = 3.89$). Organizational readiness and governance was rated lowest ($M = 3.50$) but still by 49.3% of respondents as a barrier. This pattern shows that the most pressing obstacles are trust-related (privacy, ethics and job security) rather than purely technical.

9. MAJOR FINDINGS

- **Adoption and application (Objective 1).** Respondents reported a moderately high level of AI adoption ($M = 3.64$), and adoption depends on organization size: 61.0% of large organizations are high adopters compared with 6.5% of small organizations ($\chi^2 = 31.12$, $p < .001$). Adoption is also higher in IT and software than in manufacturing, but does not depend on the respondent's gender.
- **Business performance (Objective 2).** AI adoption has a significant positive effect on business performance ($\beta = .518$, $R^2 = .269$), and mean performance increases from low to medium to high adopters ($F = 13.14$, $p < .001$). H1 is supported.
- **Strategic decision-making and transformation (Objective 3).** AI adoption significantly improves strategic decision-making and organizational transformation ($\beta = .528$, $R^2 = .278$); this is the strongest relationship in the study. H2 is supported.

- **Mediation.** The effect of AI on performance is partially mediated (53.2% of the total effect). Operational efficiency is the clearest significant channel, while decision-making quality and innovation capability are marginal and customer experience is not significant on its own. H3 is partly supported.
- **Challenges (Objective 4).** Data privacy and security is the most serious challenge, followed by ethical concerns, workforce reskilling and organizational readiness and governance.
- **Reliability.** All measurement scales are reliable (α between .76 and .87).

10. DISCUSSION

The results are consistent with the reviewed literature. The positive association between AI adoption and business performance agrees with Paliwal et al. (2021), Gurjar et al. (2024) and Enholm et al. (2022), who report that AI improves productivity, efficiency and business value. The finding that operational efficiency is the clearest mediator is in line with the process-efficiency route to value described by Enholm et al. (2022) and with Njeru (2023), who notes that AI reduces employee workload and improves responsiveness. The strong relationship between AI adoption and strategic decision-making supports Ahmed et al. (2023) and Gurjar et al. (2024), who find that AI strengthens forecasting, risk analysis and strategic planning.

Two results deserve particular attention. First, AI adoption explains only about 27% of the variance in business performance, and the direct effect remains significant even after the four mediators are included. AI therefore does not act only through the four capabilities examined here; complementary resources such as leadership commitment, data quality and workforce skills, which Enholm et al. (2022) also emphasise, are likely to matter. This also supports the argument in the Introduction that adoption alone does not guarantee value. Second, the strong dependence of adoption on organization size and the lower performance of small organizations suggest a widening digital divide between large and small firms. The high ranking of privacy, ethics and reskilling challenges is in line with the concerns reported by Paliwal et al. (2021), Njeru (2023) and Ahmed et al. (2023) and shows that responsible AI governance is a practical necessity, not only an ethical ideal.

11. IMPLICATIONS OF THE STUDY

11.1 Managerial implications

- Organizations should link AI projects explicitly to business objectives and measure their outcomes in terms of efficiency, decision quality, customer experience and innovation, because value is created through these capabilities.
- Because operational efficiency is the clearest channel of value creation, efficiency-oriented use cases (process automation, error reduction, forecasting) are a sensible starting point, especially for small and medium enterprises.
- Managers should treat AI as an organizational transformation project: redesign jobs, invest in reskilling, and build human–AI collaboration, rather than only purchasing technology.
- Firms should put governance in place for data privacy, security, algorithmic bias and human oversight of high-stakes decisions, since these were the challenges respondents rated most seriously.

11.2 Policy and theoretical implications

- Policy makers and industry bodies can support small organizations through shared AI infrastructure, subsidised training and clear data-protection guidelines to narrow the adoption gap.
- The study adds primary quantitative evidence to a literature that is largely conceptual or review-based, and it tests AI-enabled performance, decision-making and transformation within a single integrated model.

12. LIMITATIONS AND SCOPE FOR FURTHER RESEARCH

The study has several limitations. The sample was drawn through purposive and convenience sampling, so the findings cannot be generalised statistically to all organizations. The data are cross-sectional and self-reported, which exposes them to common-method and perception bias, and causal claims should be interpreted with caution. Business performance was measured through perceptual rather than audited financial indicators. The mediation model treated the four mediators in parallel and did not test moderators such as firm size, industry or leadership support. Finally, Excel-based procedures were used; structural equation modelling (for example PLS-SEM) could estimate the measurement and structural models simultaneously.

Future research could use larger and probability-based samples, longitudinal designs, objective financial and operational indicators, and sector-specific studies. Moderating effects of organization size, digital maturity and AI governance, the role of generative AI, and employees' trust in and acceptance of AI are further promising directions.

13. CONCLUSION

This study examined the impact of AI on business performance, strategic decision-making and organizational transformation. The analysis shows that AI adoption is significantly and positively related to business performance and, even more strongly, to strategic decision-making and organizational transformation. The effect on performance is partly transmitted through improved operational efficiency, while decision-making quality, customer experience and innovation capability play a smaller or more marginal role. Adoption is uneven: large organizations and technology-oriented sectors are ahead, and small organizations lag behind in both adoption and performance. Organizations also remain concerned about data privacy, ethics, workforce reskilling and readiness. The overall conclusion is that AI delivers its full value when technology investment is combined with clear business objectives, capable people, sound change management and responsible governance.

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APPENDIX: QUESTIONNAIRE

Part A – Respondent profile. Age group (Below 25 / 25–34 / 35–44 / 45 and above); Gender (Male / Female); Sector (IT & Software / Manufacturing / Banking & Finance / Healthcare / Retail & E-commerce); Organization size (Small / Medium / Large).

Part B – Statements (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree).

Code	Statement
AIA1	My organization has adopted AI technologies (e.g., machine learning, predictive analytics, chatbots, generative AI) in its business processes.
AIA2	AI tools are used regularly in the day-to-day operations of my organization.
AIA3	My organization has invested adequately in AI infrastructure, data and skills.
AIA4	AI applications in my organization are aligned with its business objectives.
OE1	AI has reduced the time required to complete routine tasks.
OE2	AI has reduced operational costs and process errors.

Code	Statement
OE3	AI has improved the productivity of employees and teams.
DQ1	AI-generated insights improve the accuracy of managerial decisions.
DQ2	AI enables faster decision-making.
DQ3	AI helps us forecast demand, risks and market trends better.
CX1	AI enables personalised products, services and recommendations for customers.
CX2	AI-based support (chatbots, automation) has improved our response time to customers.
CX3	Customer satisfaction has improved after AI implementation.
IC1	AI helps my organization develop new products, services or business models.
IC2	AI encourages experimentation and creative problem solving.
IC3	AI has strengthened our ability to respond to market changes with new solutions.
BP1	Since adopting AI, the productivity of my organization has increased.
BP2	AI has contributed to improved profitability.
BP3	AI has strengthened my organization's competitive advantage.
BP4	AI has supported business growth (sales, market share).
SDT1	AI is used to support strategic planning and resource allocation.
SDT2	AI has changed how my organization structures its processes and workflows.
SDT3	AI adoption has led to redesign of jobs and new skill requirements.
SDT4	Leadership actively manages change and human–AI collaboration.
CH1	Data privacy and security concerns limit AI adoption in my organization.
CH2	Ethical issues such as algorithmic bias and lack of transparency are a concern.
CH3	Workforce reskilling needs and fear of job displacement are major challenges.
CH4	Lack of organizational readiness and weak AI governance / human oversight hinder effective AI use.