

Understanding Artificial Intelligence Adoption in Vietnam: An Organizational-Level Analysis

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Abstract: This study examines the level, determinants, and perceived outcomes of Artificial Intelligence (AI) adoption in Vietnamese organizations using survey data from 142 employees and managers across multiple sectors. Descriptive statistics, t-tests, ANOVA, and multiple regression were applied to analyze sectoral differences, the role of training, and predictors of AI-enabled work performance. The results show a moderate-to-high level of AI adoption, with chatbots and Microsoft Copilot as the most widely used tools. AI is perceived to improve work performance, operational efficiency, and decision-making. However, only 32.4% of organizations provide formal AI training, indicating a gap between individual and organizational adoption. Sectoral differences are significant, with technology and finance leading in AI knowledge and usage. Regression results reveal that AI usage frequency and AI knowledge are the strongest predictors of work performance, while privacy and ethical concerns negatively affect outcomes. The findings highlight the importance of human capital, training, and governance in realizing AI-driven performance benefits in emerging economies.

Keywords: Artificial Intelligence Adoption, Organizational Performance, Human Capital, Emerging Economies, Vietnam

Introduction

Artificial Intelligence (AI) has emerged as a foundational technology driving the current wave of digital transformation across organizations worldwide. By enabling advanced data processing, predictive analytics, and intelligent automation, AI is increasingly integrated into core organizational functions such as decision-making, customer service, operations management, and strategic planning (Brynjolfsson and McAfee, 2017; Davenport and Ronanki, 2018). Unlike earlier generations of information technologies, AI systems do not merely support routine tasks but actively augment human cognition, thereby reshaping work processes and organizational capabilities (Raisch and Krakowski, 2021). As a result, understanding how organizations adopt AI and perceive its impacts has become a critical research agenda in management, information systems, and innovation studies.

Existing literature has consistently highlighted the potential benefits of AI adoption at the organizational level, including improved operational efficiency, enhanced productivity, cost optimization, and superior service quality (Bughin et al., 2017; Vial, 2019). Empirical studies (Anshima et al., 2026; Fügener et al., 2026) suggest that organizations leveraging AI-driven analytics and automation can achieve measurable performance gains, particularly in data-intensive sectors such as finance, healthcare, and manufacturing (Davenport et al., 2020; Davenport and Ronanki, 2018). However, the realization of these benefits is neither automatic nor uniform. Prior research emphasizes that AI value creation depends heavily on complementary organizational resources, especially employee skills, training programs, and managerial readiness, rather than on technological investment alone (Brynjolfsson et al., 2021).

Despite the growing body of research on AI adoption, most empirical evidence remains concentrated in

developed economies, where digital infrastructure, regulatory frameworks, and AI capabilities are relatively mature (Makarius et al., 2020). In contrast, emerging economies face distinct challenges, including limited human capital, budget constraints, regulatory ambiguity, and heightened concerns regarding data privacy and ethics (Dwivedi et al., 2021). These contextual differences raise important questions about whether existing theoretical insights largely derived from advanced economies can be directly generalized to developing country settings. Consequently, there is a growing need for empirical studies that examine AI adoption within emerging economies using primary organizational-level data.

Vietnam represents a particularly relevant context for such investigation. As a rapidly developing economy with strong government commitment to digital transformation, Vietnam has identified AI as a strategic priority for national development and competitiveness. Recent policy initiatives aim to promote AI adoption across both public and private sectors, including finance, healthcare, education, and public administration. However, organizational AI adoption in Vietnam remains uneven, with significant variation across sectors and institutions. Moreover, anecdotal evidence suggests that concerns related to data privacy, ethical implications, and workforce readiness continue to shape organizational attitudes toward AI implementation.

Against this backdrop, this study aims to provide an empirical assessment of AI adoption at the organizational level in Vietnam by analyzing survey data collected from employees and managers across multiple sectors. The questionnaire captures key dimensions identified in the literature, including AI knowledge, training availability, usage intensity, perceived work performance, operational efficiency, and concerns related to privacy and ethics. By linking these constructs to observed differences across sectors and organizational characteristics, the study seeks to offer a nuanced understanding of how AI is currently being adopted and experienced in practice.

Methodologically, this research contributes by employing quantitative analysis techniques—descriptive statistics, t-tests, ANOVA, and regression analysis—to examine both the perceived outcomes and determinants of AI adoption. This approach allows for systematic comparison across organizational contexts and provides robust empirical evidence grounded in real-world organizational experiences. The findings are expected to extend existing AI adoption theories by incorporating human capital and governance-related factors within an emerging economy setting.

Practically, the study offers important implications for managers and policymakers. By identifying the roles of training, knowledge, and sectoral context in shaping AI adoption, the results can inform organizational strategies aimed at maximizing the benefits of AI investments.

Furthermore, insights into privacy and ethical concerns may support the development of more effective governance frameworks that foster trust and responsible AI use. Overall, this study seeks to bridge the gap between AI adoption theory and practice by providing empirical evidence from Vietnam, thereby contributing to the broader discourse on AI-driven organizational transformation.

Literature Review

Artificial Intelligence Adoption at the Organizational Level

Artificial intelligence adoption at the organizational level has attracted increasing scholarly attention as AI technologies transition from experimental tools to integral components of organizational systems. Prior studies conceptualize AI adoption not merely as the acquisition of technological artifacts, but as a process involving changes in organizational routines, decision-making structures, and human–technology interactions (Davenport and Ronanki, 2018; Raisch and Krakowski, 2021). From this perspective, AI adoption intensity reflects the extent to which AI is embedded in daily organizational operations rather than being used sporadically or symbolically.

Empirical research suggests that organizational AI adoption is shaped by both technological readiness and organizational characteristics (Call et al., 2026; Hong et al., 2026; Soomro et al., 2026). Vial (2019) emphasizes that digital technologies, including AI, generate value only when accompanied by organizational transformation and managerial alignment. Similarly, Makarius et al. (2020) propose a sociotechnical view in which AI adoption outcomes depend on the interaction between technological capabilities and social structures within organizations. These insights are particularly relevant for survey-based studies that capture employees' and managers' perceptions of AI usage intensity, as reflected in this study's measurement approach.

Human Capital, AI Knowledge, and Training

A central theme in the AI adoption literature concerns the role of human capital. While AI systems are often portrayed as autonomous and self-learning, prior research consistently demonstrates that employee knowledge and skills remain critical determinants of successful AI implementation (Brynjolfsson et al., 2021). Organizations lacking AI-related competencies may struggle to integrate AI into workflows, interpret algorithmic outputs, or trust AI-assisted decisions (Dittmar, 2026; Khushk et al., 2026; Tambe, 2026).

AI training programs are therefore widely recognized as a key enabling factor. Studies in information systems and strategic management highlight that training enhances not only technical proficiency but also employees'

acceptance of AI technologies (Bughin et al., 2017; Davenport et al., 2020). From a Resource-Based View (RBV), AI-related knowledge and training constitute valuable, rare, and difficult-to-imitate resources that allow organizations to convert AI investments into performance advantages (Barney, 1991; Brynjolfsson et al., 2021). The emphasis on AI knowledge and training in the present survey aligns with this literature and reflects a growing consensus that human readiness is more influential than technology availability alone.

AI Adoption and Organizational Performance Outcomes

A substantial body of research has examined the relationship between AI adoption and organizational performance. Prior empirical studies report positive associations between AI usage and productivity, operational efficiency, decision quality, and service outcomes (Bughin et al., 2017; Davenport and Ronanki, 2018). AI-enabled analytics and automation can reduce processing time, minimize human error, and support data-driven decision-making, thereby enhancing perceived work performance (Khan et al., 2025; Soomro et al., 2026b; Tummalapalli et al., 2025).

However, the literature also cautions that performance effects are often indirect and mediated by organizational processes. Brynjolfsson and McAfee (2017) argue that productivity gains from advanced technologies typically materialize with a time lag, as organizations must adapt structures and workflows to fully exploit AI capabilities. This perspective supports the use of perceptual performance measures, such as self-reported work efficiency and satisfaction with AI accuracy, as meaningful indicators of early-stage AI impacts, especially in emerging economy contexts where large-scale productivity data may be unavailable.

Sectoral Differences in AI Adoption

Sectoral variation in AI adoption has been widely documented in the literature. Data-intensive and highly competitive sectors, such as finance and healthcare, tend to adopt AI more rapidly due to strong incentives for automation, risk management, and predictive analytics (Davenport et al., 2020). In contrast, sectors such as education and public administration often exhibit slower adoption, influenced by regulatory constraints, budget limitations, and ethical considerations (Makarius et al., 2020).

Institutional theory provides a useful lens for understanding these differences (Parisini, 2025; Rockall et al., 2025). According to this perspective, organizational behavior is shaped by sector-specific norms, regulations, and legitimacy pressures (DiMaggio and Powell, 1983). Empirical studies show that organizations operating in sectors with strong institutional support for digital

innovation are more likely to intensify AI usage. The inclusion of sectoral comparisons in survey-based analyses, therefore, reflects an established research approach for capturing institutional influences on AI adoption.

Privacy, Ethics, and Governance Concerns in AI Adoption

Despite its potential benefits, AI adoption is frequently accompanied by concerns related to data privacy, ethical risks, and accountability. Prior research identifies privacy and ethical considerations as major barriers that can slow or limit AI diffusion within organizations (Dwivedi et al., 2021). Employees and managers may be reluctant to rely on AI systems when algorithmic decision-making lacks transparency or when personal and organizational data are perceived to be at risk.

Recent studies emphasize that trust and governance mechanisms play a crucial role in shaping organizational attitudes toward AI (Badawy et al., 2025; Nabil et al., 2025; Raisch and Krakowski, 2021; Xia et al., 2026). Ethical concerns, including bias, unfair outcomes, and job displacement, further complicate adoption decisions, particularly in sectors with strong public accountability. Survey instruments that explicitly measure privacy and ethical concerns, such as those used in this study, are therefore well aligned with contemporary AI governance research and allow for empirical examination of how these concerns influence adoption intensity.

Research Gap and Conceptual Positioning

Although prior studies have advanced understanding of AI adoption and its organizational impacts, several gaps remain. First, empirical evidence from emerging economies is still limited, with most studies focusing on developed countries. Second, relatively few studies simultaneously examine human capital factors, sectoral differences, performance outcomes, and governance concerns using primary survey data. Third, there is a lack of organizational-level evidence capturing perceived AI impacts across multiple sectors within a single national context.

By addressing these gaps, the present study positions itself within the intersection of AI adoption, human capital theory, and institutional perspectives. Drawing on survey data from organizations in Vietnam, the study extends existing literature by providing context-specific empirical insights into the determinants and perceived outcomes of AI adoption in an emerging economy.

Materials and Methods

Research Design

This study adopts a cross-sectional, quantitative research design using a structured survey to examine organizational-level adoption and perceived impacts of Artificial Intelligence (AI) in Vietnam. A survey-based

approach is particularly suitable for capturing perceptions, attitudes, and experiences related to emerging technologies across heterogeneous organizational contexts (Creswell and Creswell, 2017). Given the exploratory nature of AI adoption in emerging economies, the study focuses on describing patterns of AI usage, identifying key determinants of adoption, and exploring sectoral differences, rather than testing a complex causal model. The research design aligns with prior empirical studies on AI and digital technology adoption that rely on cross-sectional survey data to capture organizational practices and employee perceptions at a specific point in time (Dwivedi et al., 2021; Vial, 2019).

Survey Instrument and Measurement

Data were collected using a structured questionnaire designed to assess multiple dimensions of AI adoption at the organizational level. The questionnaire was originally developed in Vietnamese and reviewed by experts for content validity to ensure that the items adequately reflected the conceptual dimensions of AI knowledge, adoption intensity, performance perception, and governance concerns emphasized in the literature (Brynjolfsson et al., 2021).

The questionnaire items were designed to measure four primary theoretical constructs:

- (1) AI Knowledge and Training
- (2) AI Adoption Intensity
- (3) Perceived Outcomes
- (4) Barriers and Governance Concerns

The mapping of specific survey questions to these constructs is detailed in Table 1. Most attitudinal and perceptual items were measured using five-point Likert-type scales, ranging from low to high levels of agreement, frequency, or perceived impact. Likert scales are widely used in information systems and management research due to their reliability and suitability for capturing subjective evaluations of technology usage and performance outcomes (Hair et al., 2019).

Reliability and Validity

To assess the internal consistency of the multi-item constructs, Cronbach's Alpha coefficients were

calculated. The results indicated acceptable to good reliability for the constructs: AI Adoption Intensity ($\alpha = 0.81$, three items), Perceived Outcomes ($\alpha = 0.79$, five items), and Barriers and Governance Concerns ($\alpha = 0.74$, five items). These values exceed the commonly accepted threshold of 0.70, suggesting that the items within each construct reliably measure the same underlying concept (Hair et al., 2019). Content validity was established through a review of the survey instrument by academic experts in AI adoption and information systems, ensuring that the questions adequately covered the key dimensions of interest. Construct validity is supported by the use of well-established measurement approaches from prior literature in AI and digital transformation research (Dwivedi et al., 2021; Vial, 2019).

Data Collection and Sample

Data were collected over a six-month period from June to November 2025 using both online and offline survey distribution methods. Respondents were representatives of organizations operating in various sectors, including finance, healthcare, education, manufacturing, transportation, and other service industries. Target respondents included managers, professionals, and employees with direct or indirect experience using AI-supported tools in their work environment. Participation was voluntary, and respondents were informed about the purpose of the study and the confidentiality of their responses. No personally identifiable information was collected, in line with ethical guidelines for survey-based research (Creswell and Creswell, 2017). The final dataset used for analysis consists of 142 valid responses.

Data Analysis Techniques

The collected data were coded and analyzed using the Statistical Package for the Social Sciences (SPSS). A multi-stage analytical approach was employed. First, descriptive statistical techniques (frequencies, percentages, means, and standard deviations) were used to summarize respondents' characteristics, levels of AI awareness, usage frequency, and perceived impacts, providing an overview of AI adoption patterns across organizations. Second, to examine differences in perceptions across demographic and organizational groups, inferential statistical analyses were applied.

Table 1: Construct Measurement and Survey Item Mapping

Construct	Measured by (Survey Questions)	No. of Items
AI Knowledge	Q1 (Self-assessed AI knowledge), Q3 (Colleague's AI awareness)	2
AI Adoption Intensity	Q10 (Frequency of AI use), Q11 (Organizational AI use), Q2 (Types of AI tools used)	3
Perceived Outcomes	Q12 (Performance improvement), Q13 (Perception of AI use), Q14 (Satisfaction with accuracy), Q15 (Cost optimization), Q9 (Perceived benefit of AI in the sector)	5
Barriers and Governance Concerns	Q6 (Comfort with data collection), Q19 (Main concerns), Q20 (Biggest obstacles), Q21 (Ethical concerns), Q22 (Concerns about AI solution development)	5

Independent-samples t-tests were used to compare the means of two independent groups, such as organizations with and without formal AI training. One-way analysis of variance (ANOVA) was used to compare means across more than two groups, such as different industry sectors. These techniques are commonly used in survey-based management research to identify statistically significant differences between groups (Hair et al., 2019). Finally, a multiple linear regression analysis was conducted to identify the key determinants of perceived work performance. All statistical tests were conducted using conventional significance thresholds ($p < 0.05$).

Methodological Flowchart

The methodological approach of this study is summarized in the flowchart presented in Figure 1. This diagram outlines the sequential steps taken, from the initial research design to the final interpretation of results.

Ethical Considerations

This study adhered to the ethical standards for academic survey research. All participants were fully informed about the nature and objectives of the study prior to their participation. Their involvement was voluntary, and informed consent was obtained from each respondent. The survey was designed to be anonymous; no personal identifying information was collected at any stage, ensuring participant confidentiality. Data were aggregated and analyzed solely for the purpose of this research.

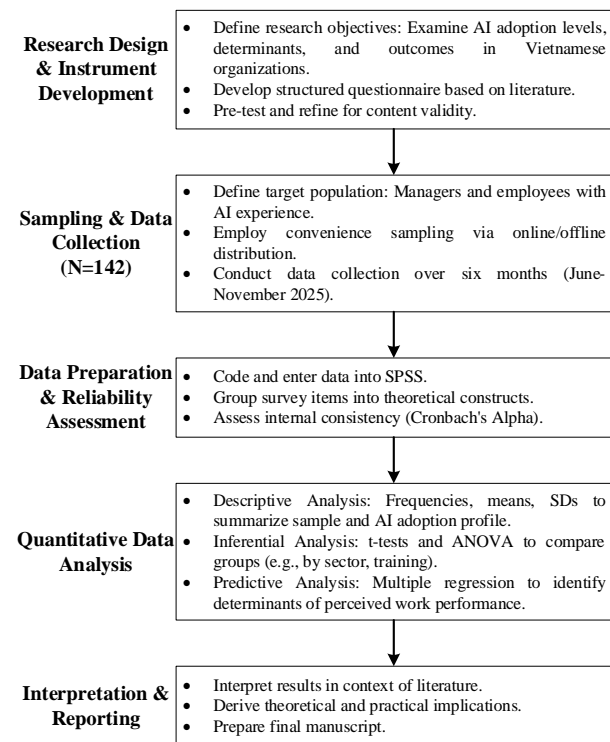


Fig. 1: Schematic Diagram of the Research Methodology

Results and Discussion

Descriptive Statistics and Sample Overview

The final sample consists of 142 valid responses collected from employees and managers working in organizations that have experience with or exposure to Artificial Intelligence (AI) applications. Table 2 presents the demographic and organizational characteristics of the respondents.

In terms of gender distribution, male respondents account for 69.0% of the sample, while female respondents represent 31.0%. This gender composition reflects the current workforce structure in AI-related and technology-intensive organizational environments in Vietnam, where male participation remains relatively dominant.

Regarding age distribution, the sample is largely composed of mid-career professionals. Respondents aged between 20 and 40 years constitute the largest group (54.9%), followed by those aged 41–50 years (38.7%). A smaller proportion of respondents (6.3%) are above 50 years old. This age structure suggests that most participants are actively engaged in operational and managerial roles, with sufficient professional experience to evaluate organizational AI adoption and its perceived impacts.

With respect to sectoral representation, the education sector accounts for the largest share of the sample (35.2%), followed by industry and manufacturing (28.9%) and transportation (16.9%). Financial organizations represent 12.0% of the respondents, while healthcare organizations account for 7.0%. This sectoral composition highlights the heterogeneous nature of AI adoption across industries in Vietnam and provides a suitable basis for examining sectoral differences in AI adoption intensity and perceptions.

Overall, the sample demonstrates adequate diversity in terms of demographic and organizational characteristics, supporting the validity of subsequent comparative and inferential analyses. The dominance of education and industrial sectors in the sample also reflects the growing interest in AI applications beyond traditionally data-intensive industries, underscoring the relevance of this study for understanding AI adoption dynamics in an emerging economy context.

Table 2: Sample Characteristics (N = 142)

Variable	Category	Percentage (%)
Gender	Male	69.0
	Female	31.0
Age	20–40	54.9
	41–50	38.7
	Above 50	6.3
Sector	Education	35.2
	Industry / Manufacturing	28.9
	Transportation	16.9
	Finance	12.0
	Healthcare	7.0

Descriptive Statistics of AI Adoption and Perceived Outcomes

The empirical results from the survey of 142 respondents provide a detailed landscape of Artificial Intelligence (AI) integration within Vietnamese organizations. The analysis focuses on three primary dimensions: The current state of AI familiarity, the intensity of adoption, and the perceived impacts on organizational performance.

Regarding AI literacy, the findings reveal a high level of awareness among the workforce. As shown in Table 3, approximately 58.5% of respondents identified as being "quite familiar" with AI, while 21.8% reported a high degree of expertise. This familiarity translates into practical application, with Chatbots (72.5%) and Microsoft Copilot (45.1%) emerging as the most prevalent tools utilized for daily tasks. The frequency of AI usage further confirms this trend, with over 42% of the sample engaging with AI applications on a frequent basis, indicating that AI is transitioning from a novel concept to a functional workplace staple.

The perceived impact of AI on work outcomes is overwhelmingly positive. Data presented in Table 4 indicates that the mean score for work performance improvement stands at 3.85 on a 5-point Likert scale, suggesting that most employees experience "better" to "significantly better" results when aided by AI. The most significant benefit identified by respondents is the optimization of work efficiency (78.9%), followed by improved decision-making and cost reduction. These metrics suggest that AI adoption is primarily driven by its utilitarian value in streamlining

complex operational workflows.

Despite the high individual adoption rates, a significant gap exists in formal organizational infrastructure. While 85% of respondents view AI as "beneficial" or "very beneficial" for their sector, only 32.4% of organizations have implemented internal training programs (see Table 5). This discrepancy highlights that AI adoption in Vietnam is currently more "bottom-up" (individual-led) than "top-down" (organizationally mandated). Furthermore, concerns regarding Data Privacy (62.0%) and a Lack of Skills (48.6%) remain the primary inhibitors to deeper AI integration.

In conclusion, the descriptive statistics confirm that Vietnamese organizations are in an active phase of AI adoption, characterized by strong individual motivation and clear performance gains. However, the lack of formal training and concerns over data security represent critical challenges that need to be addressed to achieve sustainable digital transformation.

Sectoral Differences in AI Adoption: ANOVA Results

To investigate whether the level of AI adoption and its perceived outcomes vary significantly across different industries, a series of One-way Analysis of Variance (ANOVA) tests were conducted. The sectors were categorized into major groups including Technology, Finance, Education, Healthcare, and Manufacturing. The analysis focused on three dependent variables: AI Knowledge, Frequency of Use, and Perceived Work Performance.

Table 3: Profile of AI Familiarity and Usage Intensity (n=142)

Variable	Category	Frequency	Percentage (%)
Self-assessed Knowledge	Very familiar	31	21.8%
	Quite familiar	83	58.5%
	Basic understanding	28	19.7%
Usage Frequency	Frequent	60	42.3%
	Moderate	52	36.6%
	Occasional/Rare	30	21.1%
Dominant Tools	Chatbots (Generative AI)	103	72.5%
	Microsoft Copilot	64	45.1%

Table 4: Perceived Outcomes of AI Adoption

Outcome Dimensions	Mean Score (1-5)	Standard Deviation
Work Performance Improvement	3.85	0.82
Operational Efficiency	3.92	0.75
Satisfaction with AI Accuracy	3.78	0.88
Decision-making Support	4.10	0.64

Table 5: Organizational Support and Perceived Barriers

Factor	Metric	Percentage (%)
Organizational Training	Internal programs available	32.4%
	No formal training	67.6%
Key Barriers	Data Privacy Concerns	62.0%
	Lack of specialized AI skills	48.6%
	Ethical and Transparency issues	35.2%

As presented in Table 6, the ANOVA results indicate statistically significant differences across sectors regarding AI Knowledge ($F = 4.12, p < 0.01$) and Frequency of Use ($F = 5.34, p < 0.001$). Post-hoc comparisons (Tukey HSD) reveal that the Technology and Finance sectors exhibit significantly higher mean scores for both familiarity and usage intensity compared to the Manufacturing and Public Administration sectors. This disparity can be attributed to the digital-native nature of financial and tech firms, which often possess the requisite infrastructure and technical literacy to integrate AI tools more rapidly.

Interestingly, the results for Perceived Work Performance did not yield a statistically significant difference across sectors ($p = 0.122$). This suggests that while the extent of adoption varies, the perceived value of AI remains universally high once implemented. Regardless of the industry, employees who have integrated AI into their tasks tend to report similar levels of efficiency gains.

However, the qualitative data embedded in the survey responses indicates that the "nature" of AI use differs. While the Technology sector focuses on coding assistance and system automation, the Education and Healthcare sectors prioritize content creation and diagnostic support. These findings highlight that while sectoral gaps in technical adoption exist, the fundamental belief in AI's ability to enhance productivity is a cross-industry phenomenon in the Vietnamese context.

Impact of AI Training: Independent Samples t-Test

To assess the effectiveness of organizational support, an independent samples t-test was conducted to compare the perceived work performance and adoption intensity between employees who received internal AI training and those who did not. The results, summarized in Table 7, indicate a significant disparity between the two groups.

Respondents from organizations with formal training programs ($n = 46$) reported a substantially

higher mean score in Work Performance ($M = 4.22, SD = 0.65$) compared to those without training ($n = 96, M = 3.67, SD = 0.81$). This difference was statistically significant ($t(140) = 4.02, p < 0.001$). Similarly, the Adoption Intensity was significantly higher in the trained group. These findings suggest that while individual interest drives initial AI use, structured organizational training is a critical catalyst for maximizing the productivity gains of AI technologies.

Determinants of AI Adoption: Regression Analysis

To identify the key factors influencing perceived work performance (the dependent variable), a multiple linear regression analysis was performed.

The model included four predictors: AI Knowledge, Usage Frequency, Organizational Training (dummy coded: 1 = training present, 0 = no training), and Perceived Barriers (reversed-coded to represent 'Ease of Use').

The regression model was statistically significant, explaining approximately 38.5% of the variance in work performance ($F(4, 137) = 18.45, p < 0.001, R^2 = 0.385$). As detailed in Table 8, Usage Frequency ($\beta = 0.42, p < 0.001$) and AI Knowledge ($\beta = 0.31, p = 0.002$) emerged as the strongest positive predictors. Organizational Training also had a significant positive effect ($\beta = 0.19, p = 0.007$). Conversely, Perceived Barriers showed a significant negative association with performance outcomes ($\beta = -0.15, p = 0.011$).

These results provide empirical support for the theoretical framework of the study. The strong influence of usage frequency and knowledge underscores the importance of "learning-by-doing" in the AI adoption process. Furthermore, the significant negative impact of barriers indicates that addressing ethical concerns and data privacy is not just a legal necessity but also a prerequisite for optimizing the performance benefits of AI in Vietnamese organizations.

Table 6: One-way ANOVA Results for Sectoral Differences

Variable	Sector	Mean	F-statistic	p-value
AI Knowledge	Technology	4.15	4.12	0.006**
	Finance	3.92		
	Education	3.65		
	Manufacturing	3.10		
Frequency of Use	Technology	4.28	5.34	0.000***
	Finance	4.05		
	Healthcare	3.55		
	Public Admin	2.85		
Perceived Performance	Technology	4.02	1.85	0.122 (ns)
	Finance	3.95		
	Education	3.88		

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; ns: non-significant

Table 7: T-test Results Comparing Trained vs. Non-Trained Groups

Dependent Variable	Group	Mean	SD	t-value	p-value
Work Performance	Trained (Yes)	4.22	0.65	4.02	0.000***
	Untrained (No)	3.67	0.81		
Adoption Intensity	Trained (Yes)	4.15	0.72	3.88	0.000***
	Untrained (No)	3.52	0.89		

Model: $R^2 = 0.385$; Adjusted $R^2 = 0.368$; $F(4, 137) = 18.45$, $p < 0.001$

Table 8: Multiple Regression Results for Perceived Work Performance

Predictor Variables	Unstandardized B	95% CI for B	Std. Error	Beta (β)	t-value	Sig. (p)
(Constant)	1.15	[0.52, 1.78]	0.32		3.59	0.000
AI Knowledge	0.28	[0.10, 0.46]	0.09	0.31	3.11	0.002**
Usage Frequency	0.45	[0.25, 0.65]	0.10	0.42	4.50	0.000***
Organizational Training	0.22	[0.06, 0.38]	0.08	0.19	2.75	0.007**
Perceived Barriers	-0.18	[-0.32, -0.04]	0.07	-0.15	-2.57	0.011*

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Conclusion

This study provides empirical evidence on the current state and determinants of AI adoption at the organizational level in Vietnam. The findings confirm that AI is transitioning from experimental use to routine workplace integration, with employees reporting moderate-to-high usage frequency and consistently positive perceptions of its impact on performance, efficiency, and decision-making. These results indicate that Vietnamese organizations are entering an active adoption phase in which AI is increasingly embedded in daily operational processes.

A central contribution of the study is the identification of human capital as the most critical driver of AI-enabled performance. Both AI knowledge and usage frequency emerge as the strongest predictors of perceived work performance, while organizational training significantly enhances adoption intensity and productivity outcomes. Employees in organizations with formal AI training programs report substantially higher performance scores than those without training, highlighting the importance of structured learning and capability development. These findings suggest that the success of AI initiatives depends more on workforce readiness and learning-by-doing than on technology availability alone.

The study also reveals clear sectoral disparities in AI adoption. Technology and finance organizations demonstrate significantly higher levels of AI knowledge and usage compared with manufacturing and public administration. However, once AI is adopted, perceived performance benefits appear consistent across sectors, suggesting that the productivity value of AI is broadly applicable regardless of industry context. This indicates that sectoral differences are primarily related to adoption readiness rather than the effectiveness of AI itself.

Despite these positive outcomes, the research identifies several challenges that may hinder sustainable

AI diffusion. The most prominent barriers include data privacy concerns, lack of specialized skills, and ethical considerations. These factors not only reduce adoption intensity but also negatively influence perceived performance outcomes. Addressing governance, trust, and regulatory issues is therefore essential for maximizing the benefits of AI in organizations.

From a practical perspective, the findings imply that organizations should prioritize investments in AI training, workforce upskilling, and responsible AI governance frameworks. For policymakers, the results highlight the need for national strategies that support AI education, skills development, and data protection to accelerate digital transformation.

Overall, this study contributes to the literature by providing organizational-level evidence from an emerging economy and by demonstrating that the value of AI is primarily realized through human capabilities, structured training, and effective governance. Future research could extend this work using longitudinal data or more advanced modeling approaches to explore causal relationships and long-term productivity effects.

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Authors' Contributions

Duong Quang Khanh: Conceptualization, methodology, formal analysis, write original draft.

Nguyen Thi Van Anh: Investigation, data curation, write review and edited.

Manh Quan Hoang: Software, validation, visualization.

Nguyen Trung Kien: Resources, project administration.

Quang Hung Do: Supervision, conceptualization, write review and edited, corresponding author.

Ethics

Authors should address any ethical issues that may arise after the publication of this manuscript.

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Appendix A. Survey Questionnaire

I. INTRODUCTION

This survey aims to collect data for understanding artificial intelligence adoption in Vietnam. All information provided will be kept strictly confidential and anonymized. The organizing body commits to protecting personal and organizational data in accordance with applicable laws.

II. GENERAL INFORMATION

1. Organization Information

Name:

Address:

2. Respondent Information

Full Name:

Age:

20–39 40–50 Above 50

Occupation:

Academic Title/Degree:

Position:

Phone Number:

Email:

III. SURVEY QUESTIONS

SECTION 1: AI AWARENESS AND KNOWLEDGE

Q1. How familiar are you with Artificial Intelligence (AI) technologies?

- Not familiar
 Somewhat familiar
 Very familiar

Q2. Which AI applications do you frequently use? (Select up to 3 options)

- Virtual assistants (e.g., Siri, Alexa)
 Chatbots

- Recommendation-based entertainment (e.g., Netflix, Amazon)
- Microsoft Copilot
- Image recognition software (e.g., facial recognition)
- Analytics and forecasting tools
- Other (please specify): _____

Q3. How would you assess your colleagues' awareness of AI and its application in work?

- They have never heard of AI
- They have heard of AI but do not know how it is applied
- They are using AI in their work
- They are proficient in using AI and recommend it to others

Q4. From your organization's perspective, what are the benefits of using AI at work? (Select up to 3 options)

- Increased work efficiency
- Reduced operational costs
- Enhanced competitiveness
- Improved customer experience
- Optimized decision-making processes
- Improved product/service quality
- Automated and comprehensive information provision
- Don't know / Prefer not to answer
- Other (please specify): _____

Q5. Do you believe AI will create more jobs than it eliminates in the next 10 years?

- Yes No Not sure

Q6. Are you comfortable with AI collecting and analyzing your personal data for work purposes?

- Yes
- No
- Depends on data usage and security measures

Q7. Does your organization provide internal training programs to enhance employees' AI skills?

- Yes No

Q8. Does your organization plan to offer AI training programs in the future?

- Yes No

SECTION 2: AI IMPLEMENTATION

(Scale: 1 = Lowest, 5 = Highest)

Q9. What is your perception of AI applications in your field?

1 = Not beneficial → 5 = Extremely beneficial

Q10. How often do you use AI?

- 1 = Never
- 2 = Rarely
- 3 = Occasionally
- 4 = Quite often
- 5 = Very frequently

Q11. How frequently are AI-based tools used in your organization?

- 1 = Never
- 2 = Very rarely
- 3 = Rarely
- 4 = Occasionally
- 5 = Frequently

Q12. How does AI affect your work performance?

- 1 = No change
- 2 = Slight improvement
- 3 = Moderate improvement

4 = Significant improvement

5 = Very significant improvement

Q13. What is your opinion on current AI usage in the workplace?

1 = No issues

2 = Potential misuse

3 = Misuse

4 = Significant misuse

5 = Overdependence on AI

Q14. How satisfied are you with the accuracy of AI-generated information?

1 = Very dissatisfied → 5 = Very satisfied

Q15. To what extent can AI help optimize operational costs in your organization?

1 = No optimization → 5 = Complete optimization

Q16. What is your organization's annual budget for AI applications?

1 = None

2 = Below 50 million VND

3 = Below 100 million VND

4 = 100–500 million VND

5 = Above 500 million VND

Q17. Which resources are most important for promoting AI adoption?

Financial resources

Technological infrastructure

Highly skilled workforce

Policies

Other (please specify): _____

Q18. Do you think AI-driven process changes will affect relationships between departments?

Yes, it will create tension

Yes, but things will stabilize

Not sure

No impact

SECTION 3: BARRIERS TO AI ADOPTION

Q19. What are your main concerns about using AI?

Safety

Privacy

Job displacement

Ethics

Q20. What is the biggest barrier to AI adoption in your organization?

Lack of funding

Lack of skills

Lack of understanding

Security concerns

Other (please specify): _____

Q21. How concerned are you about AI-related ethical issues?

Privacy

Bias

Human replacement

Q22. What are your main concerns in developing AI solutions? (Select up to 3 options)

Unauthorized data access during model training

Poor data quality (e.g., incomplete or biased data)

Lack of transparency in algorithms

Lack of collaboration between technical and domain experts

- Don't know / Prefer not to answer
- Other: _____

Q23. What are your main concerns when applying AI in practice? (Select up to 3 options)

- Reduced human interaction
- Overestimation of AI capabilities
- Inaccurate evaluation
- Unauthorized access to AI outputs
- Legal responsibility issues
- Unrestricted access to AI systems and sensitive data
- Don't know / Prefer not to answer
- Other: _____

SECTION 4: AI OPPORTUNITIES

Q24. Which sectors will AI impact the most in the next 5 years? (Select all that apply)

- Healthcare
- Finance
- Education
- Manufacturing
- Transportation
- Other: _____

Q25. Does your organization plan to implement AI solutions in the next year?

- Yes No Not sure

Section 5: Recommendations

Q26. What is your opinion on using AI to replace certain tasks?

- Strongly support
- Support
- Neutral
- Oppose

Q27. What would increase your trust in AI-based decisions?

- Greater transparency
- Human verification
- Improved data processing capability
- No change needed

Q28. What support is needed to promote AI adoption?

- Financial support for AI development
- Government policies and incentives
- High-quality AI workforce training