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DETERMINANTS OF EMPLOYEES' INTENTIONS TO ADOPT AI TOOLS: EVIDENCE FROM TECHNOLOGY FIRMS IN VIETNAM

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ABSTRACT

The rapid integration of artificial intelligence (AI) into organizational practices has intensified scholarly interest in employees' readiness and behavioral intentions toward AI adoption, particularly in emerging economies such as Vietnam. While prior studies have largely emphasized technological and organizational determinants, relatively limited attention has been paid to individual-level and contextual factors shaping AI adoption within developing digital environments. This study examines the determinants of employees' behavioral intentions to adopt AI tools in Vietnamese technology firms, drawing on an integrated framework that combines the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework, with the inclusion of personality traits and social influence. A quantitative research design was employed, using survey data collected from 231 employees working in technology-related roles across Vietnam. Structural Equation Modeling (SEM) was applied to test the proposed relationships among key constructs. The findings reveal that perceived ease of use plays a pivotal mediating role, significantly influenced by organizational support, environmental factors, and individual personality traits. Moreover, perceived usefulness and attitude toward using AI emerge as the strongest direct predictors of behavioral intention. Notably, and contrary to much of the existing literature, technological characteristics and social influence do not exhibit statistically significant effects on employees' adoption intentions in this context. These findings contribute empirical evidence from an emerging market and suggest that internal organizational readiness and individual psychological factors may outweigh purely technological considerations in shaping AI adoption. From a practical perspective, the study highlights the importance of employee-centered training, supportive organizational cultures, and targeted change management strategies for enhancing AI adoption in Vietnamese technology firms.

Keywords: Artificial intelligence adoption, behavioral intention, Technology Acceptance Model, TOE framework, Vietnamese technology firms.

1. INTRODUCTION

Artificial intelligence (AI) adoption in organizations has increasingly become a strategic concern, as firms seek to improve efficiency, innovation, and competitiveness through digital technologies. However, the successful implementation of AI tools depends not only on technological availability but also on employees' willingness and readiness to adopt them [1, 2]. Recent developments in digital transformation and the rise of generative AI have therefore shifted scholarly attention toward employee-centered adoption, emphasizing perceived benefits, behavioral intention, and user-related factors [3, 4].

Although prior studies have examined AI adoption through frameworks such as the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework [1, 5], the literature remains fragmented in two important ways. First, many studies focus primarily on technological and organizational determinants while giving less attention to individual characteristics and contextual influences. Second, evidence from emerging economies remains limited, despite the fact that adoption conditions in such contexts may differ substantially from those in more developed markets [6-9]. These gaps are particularly relevant in Vietnam's technology sector, where AI adoption is accelerating but remains uneven across firms and employees.

To address this limitation, this study investigates the determinants of employees' behavioral intentions to adopt AI tools in Vietnamese technology firms by integrating TAM and TOE with personality traits and social influence. Using survey data from 231 employees, the study examines how technological, organizational, environmental, and individual factors shape perceived ease of use, perceived usefulness, attitude, and behavioral intention toward AI adoption. In doing so, the study contributes to the literature by providing empirical evidence from an underexplored emerging-market context and by offering a more integrated understanding of AI adoption behavior at the employee level.

2. LITERATURE REVIEW

2.1. Theoretical Background: AI Adoption as Practice

AI adoption research is situated within the broader management literature on organizational openness to technology [10]. Originating in innovation studies examining the integration of internal and external expertise [11], this stream has recently focused on employee intentions toward AI tools [12]. Consistent with an adoption-as-practice perspective [13], this review synthesizes determinants and outcomes of AI adoption. The literature distinguishes technological, organizational, environmental, personal, and social influence factors, which are integrated through the Technology-Organization-Environment (TOE) framework and the Technology Acceptance Model (TAM).

2.2. Technological Factors

Technological factors encompass practices of assessing system attributes such as compatibility, usability, and reliability [1]. Empirical studies highlight that transparent attributes boost user assurance [14], positive prior experience fosters trust [15], and technical infrastructure predicts perceived usefulness [16]. Within TAM [1], these features serve as exogenous variables shaping behavioral intentions through Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Robust technical characteristics enhance PEOU by improving usability perceptions [2, 14], while system intricacy and integration capability directly shape PU by improving job performance [1, 16, 17]. Thus:

H1: Technology has a positive influence on Perceived Ease of Use.

H2: Technology has a positive influence on Perceived Usefulness.

2.3. Organizational Factors

Organizational factors involve practices of support, including resource allocation, training, and cultural openness [15, 18]. Perceived Organizational Support (POS) enhances acceptance [18], while policies reduce resistance [19], and training fosters positive attitudes [20]. Within the TOE framework, organizational context serves as an antecedent to both PEOU and PU. Support mechanisms such as training and resources reduce perceived complexity, thereby enhancing PEOU [21, 22]. Concurrently, infrastructure and leadership commitment improve system functionality and applicability, strengthening PU [23, 24]. Thus:

H3: Organization has a positive influence on Perceived Ease of Use.

H4: Organization has a positive influence on Perceived Usefulness.

2.4. Environmental Factors

Environmental factors encompass governance practices influenced by external regulations and competitive pressures [25]. Empirical evidence links national strategies [26] and market pressures [27] to adoption. Within TOE, these elements act as enablers or barriers. Government policies and institutional support reduce uncertainty, enhancing PEOU by alleviating cognitive barriers [22, 28]. Simultaneously, regulations and competitive demands highlight AI's practical benefits, shaping PU through external validation and reduced ambiguity [28]. Thus:

H5: Environment has a positive influence on Perceived Ease of Use.

H6: Environment has a positive influence on Perceived Usefulness.

2.5. Personal Factors

Personal factors include individual traits such as openness, self-efficacy, and trust, which differentiate adoption rates [29, 30]. Digital self-efficacy mediates intentions, while anxiety impedes acceptance [20, 31]. Within TAM and UTAUT (Unified Theory of Acceptance and Use of Technology), personal characteristics predict adoption behavior. Openness and conscientiousness correlate positively with PEOU by reducing perceived effort [32]. Innovativeness and technological self-efficacy enhance PU by boosting confidence in performance gains [32]. Thus:

H7: Personality has a positive influence on Perceived Ease of Use.

H8: Personality has a positive influence on Perceived Usefulness.

2.6. Social Influence Factors

Social influence involves norms and pressures shaping individual responses, with amplified effects in collectivist contexts such as Vietnam [3,33]. Trustworthy sources facilitate internalization, reducing perceived effort [34] and enhancing usefulness perceptions through validation [35]. Within UTAUT, social influence functions as a multifaceted antecedent. Normative support eases perceived complexity (H9), social validation enhances performance beliefs (H10), and interpersonal pressures directly drive usage intentions (H11) [36]. Thus:

H9: Social Influence has a positive influence on Perceived Ease of Use.

H10: Social Influence has a positive influence on Perceived Usefulness.

H11: Social Influence has a positive influence on Behavioral Intention to Use.

2.7. Perceived Ease of Use

PEOU, defined as the belief that system use requires minimal effort [1], fosters technology integration and reduces anxiety [14, 37]. Within TAM, PEOU exerts dual influences. It directly predicts PU, as easier systems appear more advantageous [2, 38]. It also directly influences Attitude Toward Using, as user-friendly systems foster positive dispositions [1, 38]. Thus:

H12: Perceived Ease of Use has a positive influence on Perceived Usefulness.

H13: Perceived Ease of Use has a positive influence on Attitude Toward Using.

2.8. Perceived Usefulness

PU, the belief that system use enhances job performance [1], is a central TAM determinant. It is influenced by PEOU and drives user acceptance across domains [14, 39]. Within TAM, PU exerts dual influences. It shapes Attitude Toward Using by translating performance gains into favorable evaluations [1]. It also directly predicts Behavioral Intention, with meta-analyses confirming its strong predictive power [2]. Thus:

H14: Perceived Usefulness has a positive influence on Attitude Toward Using.

H15: Perceived Usefulness has a positive influence on Behavioral Intention to Use.

2.9. Attitude

Attitude, defined as an individual's positive or negative evaluation of performing a behavior [40], mediates the relationship between cognitive perceptions and intentions in TAM and TRA [1]. As psychological readiness [14], positive attitudes toward technology significantly influence adoption decisions [41]. Thus:

H16: Attitude Toward Using positively influences Behavioral Intention to Use.

2.10. Conceptual Framework

The conceptual framework integrates the TOE and TAM models, positioning technological, organizational, environmental, personal, and social factors as exogenous variables influencing PEOU and PU. These perceptions, in turn, shape Attitude Toward Using, which ultimately determines Behavioral Intention to Use AI. This integrated model addresses the research gap by systematically examining the multi-level determinants of AI adoption within a single analytical framework, extending prior work that has largely examined these factors in isolation (Figure 1).

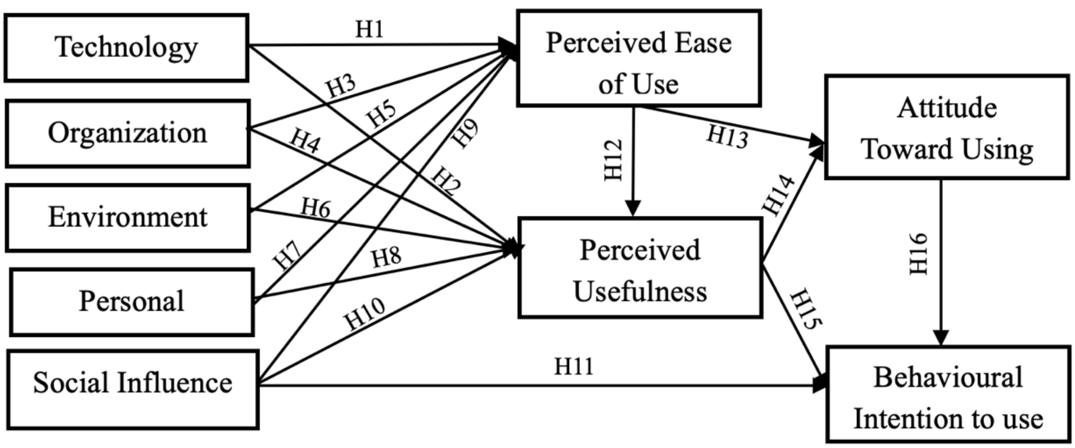

Figure 1. Conceptual Framework.

Source: Author's own work

3. METHODOLOGY

3.1. Research Design

This study employs a quantitative descriptive approach to investigate the determinants of employees' intentions to adopt AI tools in Vietnamese technology firms, integrating the Technology Acceptance Model (TAM) and the Technology-Organization-Environment (TOE) framework. This approach facilitates the measurement of relationships among latent constructs through structured data, enabling hypothesis testing and generalization to the target population. The study follows a pragmatic philosophy, prioritizing practical insights for organizational application, with a deductive strategy to verify theoretical relationships. A cross-sectional timeframe was utilized, collecting data at a single point to optimize resource efficiency while capturing current adoption intentions [42]. Survey methodology was selected for its ability to gather standardized responses from a dispersed sample, contrasting with qualitative methods that might offer depth but lack statistical generalizability. Analytical techniques include descriptive statistics for sample characterization, Exploratory Factor Analysis (EFA) for construct validation, Confirmatory Factor Analysis (CFA) for model fit assessment, and Covariance-Based Structural Equation Modeling (CB-SEM) using AMOS to test the proposed relationships among key constructs [43].

The target population encompasses employees in Vietnamese technology firms, including those in technical roles (e.g., IT specialists, product developers, data analysts) and non-technical roles (e.g., human resources, operations, customer service, marketing), all with varying levels of AI exposure, such as chatbots, predictive analytics, or automation tools. This broad inclusion ensures representation across functional areas impacted by AI integration. From an initial 276 responses, data cleaning removed 45 invalid entries (e.g., incomplete or inconsistent), yielding 231 valid cases.

A combination of convenience and snowball sampling techniques was employed to efficiently access employees working in technology-related firms. Snowball sampling facilitated participant recruitment through professional networks; however, this approach may introduce potential sampling biases, such as self-selection and network homogeneity, as respondents are more likely to share similar technological exposure, organizational contexts, or attitudes toward AI adoption. Consequently, the findings may not be fully generalizable to the broader Vietnamese technology sector, particularly to firms with lower levels of digital readiness or limited engagement with AI technologies. Nevertheless, these sampling methods are considered appropriate for exploratory research involving hard-to-reach professional populations. To partially mitigate these limitations, data were collected through multiple distribution channels and targeted respondents from diverse firms and job roles. The final sample size exceeded 200, satisfying the recommended minimum requirements for CFA and SEM analyses in terms of statistical power.

3.2. Data Collection and Analysis

Primary data were gathered from June 20 to August 12, 2025, via a self-administered online questionnaire deployed on Google Forms. To accommodate participants' language preferences, the survey was made available in both English and Vietnamese. It consisted of two parts: the first collected demographic information (e.g., age, gender, role, work experience) (Table 1), and the second presented construct-specific items measured on a 6-point Likert scale ranging from 1 (Strongly Disagree) to 6 (Strongly Agree), a design intended to reduce neutral responses and enhance data variability. The questionnaire was distributed through personal messages, social media groups, QR codes at industry events, and direct links shared via professional networks. A pilot test involving ten respondents was carried out to refine phrasing for clarity and cultural appropriateness, ensuring no ambiguous wording remained. Ethical safeguards included informed consent, assurance of respondent anonymity, voluntary participation, and secure data storage.

Table 1. Demographic Characteristics of Respondents

Variables	Components	Frequency	Percentage (%)
Gender	Female	119	51.5
	Male	91	39.4
	Other	21	9.1
	Total	231	100.0
Age	18 to 25 years old	119	51.5
	26 to 30 years old	73	31.6
	31 to 40 years old	31	13.4
	Over 40 years old	8	3.5
	Total	231	100.0
Highest Education Level	Middle School	0	0
	High School	7	3.0
	College	20	8.7
	University	195	84.4
	Master's Degree	9	3.9
	Total	231	100.0
Company department	Engineering / Development	20	8.7
	Product Management	9	3.9
	UI/UX Design	11	4.8
	Sales	17	7.4
	Marketing	25	10.8
	Customer Support / Customer Experience	26	11.3
	Operations	10	4.3
	Partnership / Merchant / Vendor Ops	12	5.2
	HR	20	8.7
	Admin / Office Management	14	6.1
	Finance – Accounting	19	8.2
	Research & Development	12	5.2
	QA Business / Audit	9	3.9
	Data / AI / Analytics	15	6.5
	Legal	12	5.2
	Total	231	100.0
Monthly Income	Under 5,000,000 VND	56	24.2
	5,000,000 VND - Under 10,000,000 VND	78	33.8
	10,000,000 VND - Under 20,000,000 VND	75	32.5
	20,000,000 VND - Under 30,000,000 VND	20	8.7
	30,000,000 VND - Under 40,000,000 VND	2	.9
	40,000,000 VND and above	0	0
	Total	231	100.0
Number of years working in the technology industry	Under 1 year	57	24.7
	1 to 3 years	107	46.3
	4 to 6 years	46	19.9
	7 to 10 years	8	3.5
	Over 10 years	13	5.6
	Total	231	100.0
Currently living	Ho Chi Minh	87	37.7
	Da Nang	90	39.0
	Ha Noi	54	23.4
	Other	0	0
	Total	231	100.0

Source: Data collected by the authors

3.3. Measures and Questionnaire Development

Measurement scales were adapted from established instruments to align with the study's context, ensuring content validity through expert review and pilot feedback. All items were modified to focus on AI tools in technology firms. The questionnaire structure and sources are as follows:

Table 2. Scales of Measurement

Construct	Code	Item	Source
Technology	T1	AI tools that I use are easy for data input and output	Developed by [22], adapted from [44].
	T2	The interface of the AI tools I use is user-friendly and accessible to everyone	
	T3	AI tools that I use operate stably during use	
	T4	Using AI improves information accessibility	
	T5	Information acquired by using AI is accurate and detailed	
	T6	Enough information can be gathered using AI	
	T7	Information acquired by using AI can be used throughout the course of the project	
Organization	ORGZ1	My organization does not have any resistance to using AI	Developed by [22], adapted from [44]
	ORGZ2	My organization understands the benefits of using AI	
	ORGZ3	My organization does not have psychological resistance to using new IT	
	ORGZ4	My organization has the technical capability to use new information technology	
	ORGZ5	My organization is aggressively pushing to use new information technology	
	ORGZ6	My organization provides proper education/training for AI utilization	
Environment	EV1	Concern for environmental questions is expressed in the company's mission statement	Developed by [45]
	EV2	Concern for environmental questions is expressed in the company's vision statement	
	EV3	Concern for environmental questions is mentioned in policies/directives	
	EV4	The company states environmental questions in its values	
	EV5	Establishes environmental goals and objectives	
Personality	P1	I do not have any resistance to using AI	Developed by [22], adapted from [44]
	P2	I am familiar with AI tools	
	P3	I understand the benefits of using AI	
	P4	I do not have psychological resistance to using a new information technology	
	P5	I am aggressive about using new information technology	
	P6	I have the technical capability to use new information technology	

Construct	Code	Item	Source
Social Influence	SI1	When I use personal social media, I often consult other people for help to choose the best alternative available as a career enhancement tool	Developed by [22], adapted by [46]
	SI2	When I use personal social media, I often ask my friends for useful information to use as a career enhancement tool	
	SI3	When I use personal social media as a career enhancement tool, I frequently gather information from friends or colleagues	
Perceived Ease of Use	PEOU1	It is easy to learn and stay proficient in using AI	Developed by [47]
	PEOU2	I can easily and skillfully use AI to handle work tasks	
	PEOU3	Overall, I think AI is easy to use.	
Perceived Usefulness	PU1	Using AI will reduce the time to finish tasks.	Developed by [22]
	PU2	Using AI will enhance my job performance	
	PU3	It would provide more chances to get promoted or raises if I can use AI.	
Behavioural Intention to use	BIU1	I would like to use AI in my work	Developed by [22], adapted by [41]
	BIU2	I expect that my frequency of using AI will increase in the future.	
	BIU3	I will definitely keep using advanced mobile services	Developed by [41], adapted by [48]
	BIU4	I expect to be using advanced AI services in the future as well.	
	BIU5	I expect that advanced AI services will make everything easier in the future	
	BIU6	I think others should use advanced AI services as well	
Attitude	AT1	I do not resist using AI in my work.	Developed by [22], adapted by [41]
	AT2	I like using AI in my work.	
	AT3	AI makes work more interesting.	Developed by [22], adapted by [41,49]

Source: Author's own work

4. RESULT

4.1. Descriptive Statistics

The analysis is based on 276 survey responses collected from employees in Vietnamese technology firms between June 20 and August 12, 2025, with 231 valid cases retained after data screening, yielding an effective response rate of 83.7%. The sample demographics indicate a predominantly young workforce, with 83.1% of respondents aged 18-30 years, 51.5% female, 84.4% holding bachelor's degrees, and 66.2% having 1-6 years of experience.

4.2. Measurement Model

4.2.1. Reliability and Exploratory Factor Analysis (EFA)

Reliability testing confirmed the robustness of the measurement scales, with Cronbach's Alpha coefficients exceeding 0.70 for all constructs and corrected item-total correlations above 0.30. To evaluate the dimensionality and construct validity of the measurement scales, exploratory factor analysis was performed separately for the independent, mediating, and dependent variables, employing principal component extraction with promax rotation. The adequacy of the factor analytic approach was confirmed by a Kaiser-Meyer-Olkin (KMO) measure of 0.776 for the independent variables, which exceeds the recommended threshold of 0.50, and a significant Bartlett's test of sphericity ($p < 0.001$) (Table A1, Appendix A). For the independent variables, five factors with eigenvalues greater than 1.0 were retained, collectively explaining 51.2% of the total variance. The rotated component matrix (Table B1, Appendix B) demonstrated that all retained items exhibited factor loadings exceeding 0.50 on their respective constructs, with no evidence of problematic cross-loadings. One item (T5) was removed due to a loading below the acceptable criterion. Equivalent patterns of satisfactory KMO values, significant Bartlett's tests, and clear factor structures were observed for the mediating and dependent variable sets. Collectively, the EFA results affirm the unidimensionality and discriminant validity of the scales, thereby providing a sound empirical basis for subsequent confirmatory factor analysis and structural equation modelling.

4.2.2. Confirmatory Factor Analysis (CFA)

The confirmatory factor analysis (CFA) was performed using AMOS to assess whether the observed indicators reliably measure their respective latent constructs. The model fit indices, reported in Table 3, indicate that the proposed measurement model adequately reproduces the sample covariance matrix. Specifically, the χ^2/df ratio of 1.437 falls well below the conservative threshold of 3, suggesting a close correspondence between the hypothesised model and the empirical data. The Comparative Fit Index (CFI = 0.929) and the Tucker-Lewis Index (TLI = 0.918) both exceed the recommended benchmark of 0.90, demonstrating that the model substantially improves upon a baseline independence model. The Root Mean Square Error of Approximation (RMSEA = 0.044) is below the conventionally accepted upper limit of 0.08, indicating a good approximate fit with minimal specification error. Moreover, the PCLOSE value (0.918) exceeds the conventional threshold of 0.05, indicating that the null hypothesis of close fit (RMSEA $\leq$ 0.05) cannot be rejected.

Table 3. Model Fit Summary

Index	Criteria	Results
χ^2/df	≤ 3	1.437
GFI	≥ 0.9	0.864
CFI	≥ 0.9	0.929
TLI	≥ 0.9	0.918
RMSEA	≤ 0.08	0.044
PCLOSE	≥ 0.05	0.918

Source: Author's calculation based on collected data using AMOS software

The Goodness of Fit Index (GFI = 0.864) falls marginally below the preferred 0.90 criterion. While this indicates that the model does not achieve optimal absolute fit, the discrepancy is modest and does not invalidate the overall adequacy of the measurement model, particularly given that all other indices meet or exceed conventional standards. Turning to the standardised factor loadings presented in Table C1 (Appendix C), all values exceed 0.50 and are statistically significant ($p < 0.001$). This threshold indicates that each observed item shares more than 25% of its variance with its corresponding latent construct, thereby demonstrating satisfactory convergent validity. In practical terms, this means that the survey items designed to measure Technology, Organisation, Environment, Personality, and other latent variables consistently and strongly reflect their intended theoretical constructs.

4.2.3. Structural Model Estimation and Hypotheses Testing

Structural Equation Modeling (SEM) tested the integrated TAM-TOE model, which explained 49.2% of the variance in PEOU, 24.2% of the variance in PU, 27.6% of the variance in AT, and 16.0% of the variance in BIU. Significant paths ($p < 0.05$) included Personality → PEOU ($\beta = 0.319$), Environment → PEOU ($\beta = 0.349$), Organization → PEOU ($\beta = 0.253$), Organization → PU ($\beta = 0.251$), PEOU → PU ($\beta = 0.288$), PEOU → AT ($\beta = 0.462$), PU → BIU ($\beta = 0.245$), and AT → BIU ($\beta = 0.225$). Non-significant paths were Technology → PEOU ($\beta = 0.054$, $p = 0.411$), Social Influence → PEOU ($\beta = -0.104$, $p = 0.142$), and others (Figure 2 and Table 4).

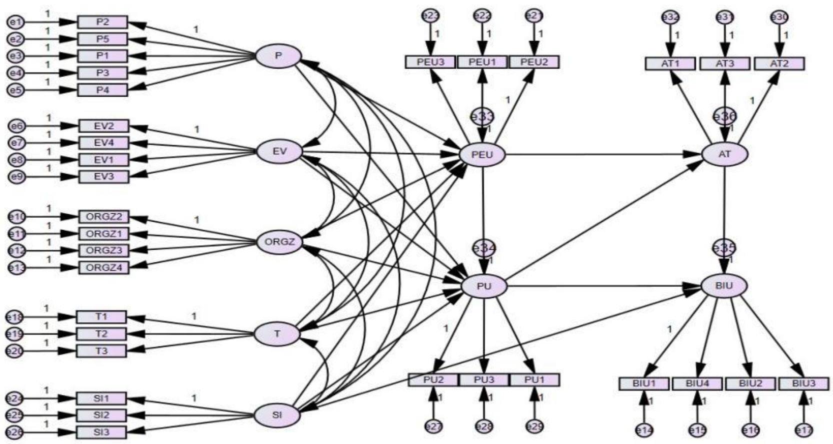

Figure 2. Structural Equation Modelling (SEM) Diagram (*Source: Author's own work)*

Table 4. Standardized Regression Weights

Structural Path	Estimate
PEOU <----- P	0.319
PEOU <----- EV	0.349
PEOU <----- ORGZ	0.253
PEOU <----- T	0.054
PEOU <----- SI	-0.104
PU <----- P	-0.107
PU <----- EV	0.050
PU <----- ORGZ	0.251
PU <----- T	0.116
PU <----- SI	0.116
PU <----- PEOU	0.288
AT <----- PU	0.127
AT <----- PEOU	0.462
BIU <----- SI	-0.104
BIU <----- PU	0.245
BIU <----- AT	0.225

Source: Author's calculation based on collected data using AMOS software

With respect to antecedents of PEOU, the results reveal that environmental factors ($\beta = 0.349$, $p < 0.001$) exert the strongest positive influence (supporting H5), followed by personality traits ($\beta = 0.319$, $p < 0.001$) (supporting H7) and organizational support ($\beta = 0.253$, $p < 0.001$) (supporting H3). These findings suggest that employees' perceptions of AI ease of use are shaped more by organizational readiness, external environmental conditions, and individual psychological predispositions than by purely technological attributes. In contrast, technology characteristics ($\beta = 0.054$, $p = 0.411$) (rejecting H1) and social influence ($\beta = -0.104$, $p = 0.142$) (rejecting H9) do not exhibit statistically significant effects on PEOU, indicating that technical features and peer pressure alone are insufficient to enhance perceived usability in this context.

Regarding PU, PEOU emerges as a significant predictor ($\beta = 0.288$, $p < 0.05$) (supporting H12), confirming a core assumption of the Technology Acceptance Model that ease of use enhances perceived usefulness. Additionally, organizational support directly influences PU ($\beta = 0.251$, $p < 0.05$) (supporting H4), underscoring the role of internal structures, resources, and managerial backing in shaping employees' evaluations of AI utility. Other TOE and individual factors, including environment, personality, technology, and social influence, do not demonstrate significant direct effects on PU (rejecting H2, H6, H8, H10).

In line with TAM, PEOU has a strong positive impact on Attitude toward use ($\beta = 0.462$, $p < 0.001$) (supporting H13), highlighting usability perceptions as the primary driver of favorable attitudes toward AI tools. Conversely, the direct effect of PU on attitude is not statistically significant ($\beta = 0.127$, $p = 0.247$) (rejecting H14), suggesting that functional usefulness alone may not be sufficient to shape attitudes unless accompanied by ease of interaction.

Finally, behavioral intention to use AI is jointly determined by Attitude ($\beta = 0.225$, $p < 0.05$) (supporting H16) and Perceived Usefulness ($\beta = 0.245$, $p < 0.05$) (supporting H15), indicating that both affective and cognitive evaluations play complementary roles in driving adoption intentions. Notably, social influence does not significantly affect BIU ($\beta = -0.104$, $p = 0.255$) (rejecting H11), further reinforcing the limited role of social pressure in this sample.

Table 5 presents the hypothesis testing results. The analysis supports 8 of the 16 proposed relationships at the conventional significance level ($p < 0.05$). These supported relationships mainly involve organizational factors, personality traits, the core constructs of the Technology Acceptance Model (TAM), and behavioral intentions to adopt AI tools.

Table 5. Hypothesis Testing Result

Hypothesis	β	p	Result
H1 - Technology has a positive influence on Perceived Ease of Use	0.054	0.411	Rejected
H2 - Technology has a positive influence on Perceived Usefulness	0.116	0.202	Rejected
H3 - Organization has a positive influence on Perceived Ease of Use	0.253	0.000	Supported
H4 - Organization has a positive influence on Perceived Usefulness	0.251	0.023	Supported
H5 - Environment has a positive influence on Perceived Ease of Use	0.349	0.000	Supported
H6 - Environment has a positive influence on Perceived Usefulness	0.050	0.640	Rejected
H7 - Personality has a positive influence on Perceived Ease of Use	0.319	0.000	Supported
H8 - Personality has a positive influence on Perceived Usefulness	-0.107	0.256	Rejected
H9 - Social Influence has a positive influence on Perceived Ease of Use	-0.104	0.142	Rejected
H10 - Social Influence has a positive influence on Perceived Usefulness	0.116	0.244	Rejected

H11 - Social Influence has a positive influence on Behavioural Intention to use	-0.104	0.255	Rejected
H12 - Perceived Ease of Use has a positive influence on Perceived Usefulness	0.288	0.029	Supported
H13 - Perceived Ease of Use has a positive influence on Attitude Toward Using	0.462	0.000	Supported
H14 - Perceived Usefulness has a positive influence on Attitude Toward Using	0.127	0.247	Rejected
H15 - Perceived Usefulness has a positive influence on Behavioural Intention to use	0.245	0.020	Supported
H16 - Attitude Toward Using has a positive influence on Behavioural Intention to use	0.225	0.036	Supported

Source: Author's calculation based on collected data using AMOS software

5. DISCUSSION

The results provided strong support for the positive influence of organisational support on both Perceived Ease of Use (H3) and Perceived Usefulness (H4). This finding means that when technology firms in Vietnam invest in training programmes, provide adequate technical resources, and demonstrate managerial commitment to AI integration, employees are more likely to find AI tools easy to use and genuinely beneficial for their work. The theoretical implication is that organisational readiness, which is a core component of the TOE framework [14,43], operates not merely as a contextual backdrop but as an active psychological mechanism that shapes employees' cognitive evaluations of new technology. This aligns with earlier work on Perceived Organisational Support [6,9] and extends it to the specific context of AI adoption in Vietnam. Practically, this suggests that Vietnamese firms seeking to accelerate AI adoption should prioritise internal capability-building over acquiring more sophisticated AI tools, because employee perceptions of usability and usefulness are shaped more by what the organisation does to support them than by the technical features of the AI systems themselves.

The study confirmed that personality traits positively influence Perceived Ease of Use (H7) but failed to find a significant effect on Perceived Usefulness (H8). This pattern is theoretically illuminating: individual characteristics such as openness to experience, digital self-efficacy, and low technological resistance [21] primarily determine how easily employees learn to interact with AI systems, rather than shaping their judgments about whether AI enhances job performance. The rejection of H8 implies that usefulness perceptions are not simply a byproduct of personality; they require direct, task-relevant experience with AI tools that demonstrate measurable productivity gains. For managers, this means that hiring employees with high technological readiness is beneficial for reducing usability barriers, but cultivating a belief in AI's value requires structured opportunities for hands-on experimentation and visible performance outcomes, which is a point also noted by [11] regarding the importance of facilitating conditions.

The study supported the positive influence of environmental factors on Perceived Ease of Use (H5) but rejected their influence on Perceived Usefulness (H6). This finding means that the national digital transformation strategy, AI policy initiatives, and institutional support effectively lower cognitive barriers [36], making AI tools feel more accessible and less intimidating to employees. However, the rejection of H6 indicates that external policies and market pressures alone do not convince employees that AI will improve their work performance. Perceived usefulness appears to be a more private, internally derived judgement that depends on personal experience rather than public signals. This distinction carries important policy implications: governments should not only build infrastructure and issue guidelines but also facilitate direct workplace exposure to AI applications, for example, through industry-wide demonstration projects or subsidised pilot schemes, so that employees gain tangible evidence of AI's performance benefits [17].

Contrary to classic TAM assumptions [31, 43], the study rejected the hypotheses that technology characteristics influence Perceived Ease of Use (H1) or Perceived Usefulness (H2). This means that in the Vietnamese technology sector, employees do not base their adoption intentions on the technical features of AI tools, such as interface design, reliability, or compatibility. A plausible interpretation, grounded in the manuscript's literature review, is that AI is still an emerging technology in Vietnam, and many employees lack sufficient hands-on experience to evaluate tools based on their intrinsic attributes. Instead, they rely on external cues from organisational support, environmental signals, and peer behaviour. This finding is consistent with [22], who noted that in the early stages of adopting new technology, users often rely more on external factors than on purely technological attributes. The rejection of H1 and H2 challenges the universal applicability of TAM's assumption that system characteristics are primary antecedents of user perceptions. In early-stage adoption contexts, external enabling conditions may temporarily substitute for direct technological evaluation.

One of the most unexpected findings is the complete lack of support for social influence on any outcome variable. Hypotheses proposing that social influence positively affects Perceived Ease of Use (H9), Perceived Usefulness (H10), and Behavioural Intention to Use (H11) were all rejected. This finding contradicts the UTAUT framework [44], which posits that subjective norms are particularly influential in collectivist societies such as Vietnam. The rejection of H9-H11 means that employees in Vietnamese technology firms do not rely on colleagues, supervisors, or wider social networks when forming their intentions to adopt AI. A compelling interpretation is that the sample, who are predominantly young, university-educated, and digitally native, prize individual autonomy and professional expertise over social conformity. In technology-intensive work environments, employees trust their own experimentation and performance evidence more than peer pressure or hierarchical expectations. This resonates with [24] argument that trustworthy sources can influence internalisation, but in this context, personal experience appears to override social influence. For practitioners, this implies that social marketing campaigns, leader-led endorsements, or peer-video testimonials may be ineffective; instead, firms should provide sandbox environments, clear performance dashboards, and self-directed learning pathways.

The study confirmed that Perceived Ease of Use positively influences Perceived Usefulness (H12) and Attitude (H13), reaffirming a core TAM proposition [29,43]. However, the rejection of the direct effect of Perceived Usefulness on Attitude (H14) is theoretically significant. This decoupling means that employees may recognise that AI tools improve task efficiency or accuracy without developing positive emotional feelings toward using the technology. This pattern may reflect underlying concerns not captured in the current model, such as fear of job displacement [46], privacy risks, or a sense of inadequacy when interacting with AI [22]. The rejection of H14 suggests that in uncertain technological contexts, usefulness beliefs alone are insufficient to generate favourable attitudes; ease of use and affective trust may be more decisive. Finally, both Attitude (H16) and Perceived Usefulness (H15) were confirmed as direct predictors of Behavioural Intention [32,46], indicating that adoption decisions are jointly determined by rational performance assessments and emotional dispositions, though the modest explanatory power of the model for intention suggests important unmeasured factors remain.

6. CONCLUSION

This study elucidates the determinants influencing employees' intentions to adopt artificial intelligence (AI) tools within Vietnam's technology firms, revealing that perceived ease of use serves as a pivotal mediator, shaping perceived usefulness and attitudes that, in turn, foster behavioral intentions. Organizational support, environmental contexts, and personality traits emerge as significant enablers of ease of use. At the same time, social influences exhibit negligible effects, partially affirming the integrated Technology Acceptance Model (TAM) and Technology-Organization-Environment (TOE) framework posited in the hypotheses. These findings address the research objectives by highlighting internal and contextual drivers rather than external social pressures, offering a nuanced understanding of adoption dynamics in an emerging-economy setting.

Collectively, these findings advance the literature in three ways. First, they provide empirical evidence from an emerging market where AI adoption conditions differ substantially from developed economies, challenging the universal applicability of assumptions embedded in Western-centric models. Second, they demonstrate that organisational support and individual personality traits outweigh technological characteristics and social influence in shaping AI adoption intentions, which is a configuration that may characterise early-stage digital transformation contexts. Third, the decoupling of perceived usefulness from attitude identified here suggests a need for theoretical refinement: in uncertain technological environments, cognitive evaluations and affective responses may operate through distinct pathways that interactive models should treat separately.

For practice, these results imply that Vietnamese technology firms should prioritise employee-centred training programmes, leadership-led AI advocacy, and user-friendly system design over purely technological investments or social pressure campaigns. For policy, the findings suggest that governments should focus on reducing ease-of-use barriers through infrastructure and standards while simultaneously creating mechanisms for employees to experience AI's performance benefits firsthand, such as through tax incentives for firms that implement pilot programmes or public recognition of organisations demonstrating measurable productivity gains from AI adoption.

Notwithstanding these contributions, the study is constrained by its reliance on convenience sampling, which limits generalizability beyond the sampled technology firms, and self-reported data are susceptible to biases. The cross-sectional design further precludes insights into the temporal dynamics of adoption factors. Addressing these limitations, future research could employ longitudinal methods to track evolving influences, expand samples across industries and firm sizes, or incorporate qualitative approaches to explore unexamined variables such as ethical concerns or cultural moderators. Ultimately, this investigation underscores the imperative of tailored strategies for harnessing AI to bolster economic resilience and inclusive growth in transitioning economies, especially in Vietnam.

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APPENDIX

Appendix A: Kaiser-Meyer-Olkin and Bartlett's test results for independent variables

Table A1. KMO and Bartlett's Test table of the independent variables

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.776
Bartlett's Test of Sphericity	Approx. Chi-Square	1862.426
	df	210
	Sig.	0.000

Source: Author's calculation based on collected data using SPSS software

Appendix B: Exploratory Factor Analysis: Rotated component loadings for independent variables

Table B1. Rotated Component Matrix for Independent Variables

Rotated Component Matrix					
	Component				
	1	2	3	4	5
P2	0.876				
P5	0.830				
P3	0.748				
P1	0.742				
P4	0.692				
EV2		0.819			
EV4		0.816			
EV1		0.756			
EV3		0.752			
ORGZ2			0.790		
ORGZ3			0.672		
ORGZ1			0.669		
ORGZ4			0.653		
T1				0.845	
T2				0.716	
T3				0.664	
T5				0.302	
SI3					0.632
SI2					0.627
SI1					0.618
Extraction Method: Principal Component Analysis. Rotation Method: Promax with Kaiser Normalization.					
a. Rotation converged in 5 iterations.					

Source: Author's calculation based on collected data using SPSS software

Appendix C: Confirmatory Factor Analysis: Unstandardized regression weights for measurement model

Table C1. Regression Weights

Item		Construct	Estimate	S.E.	C.R.	P
P2	<-----	P	1.000			0.000
P5	<-----	P	0.998	0.061	16.370	0.000
P1	<-----	P	0.820	0.064	12.893	0.000
P3	<-----	P	0.934	0.069	13.631	0.000
P4	<-----	P	0.836	0.074	11.283	0.000
EV2	<-----	EV	1.000			0.000
EV4	<-----	EV	1.063	0.075	14.184	0.000
EV1	<-----	EV	0.860	0.077	11.234	0.000
EV3	<-----	EV	0.978	0.077	12.734	0.000
ORGZ2	<-----	ORGZ	1.000			0.000
ORGZ1	<-----	ORGZ	0.830	0.090	9.260	0.000
ORGZ3	<-----	ORGZ	0.870	0.102	8.535	0.000
ORGZ4	<-----	ORGZ	0.854	0.099	8.640	0.000
BIU1	<-----	BIU	1.000			0.000
BIU4	<-----	BIU	0.858	0.128	6.712	0.000
BIU2	<-----	BIU	1.171	0.155	7.539	0.000
BIU3	<-----	BIU	0.975	0.135	7.241	0.000
T1	<-----	T	1.000			0.000
T2	<-----	T	0.967	0.106	9.137	0.000
T3	<-----	T	0.772	0.088	8.768	0.000
PEOU2	<-----	PEOU	1.000			0.000
PEOU1	<-----	PEOU	1.048	0.073	14.374	0.000
PEOU3	<-----	PEOU	0.966	0.072	13.364	0.000
SI1	<-----	SI	1.000			0.000
SI2	<-----	SI	1.208	0.224	5.392	0.000
SI3	<-----	SI	1.009	0.183	5.497	0.000
PU2	<-----	PU	1.000			0.000
PU3	<-----	PU	0.986	0.189	5.223	0.000
PU1	<-----	PU	1.335	0.247	5.339	0.000
AT2	<-----	AT	1.000			0.000
AT3	<-----	AT	1.840	0.412	4.461	0.000
AT1	<-----	AT	0.866	0.216	4.018	0.000

Source: Author's calculation based on collected data using AMOS software