HUIT Journal of Science ***26*** *(3E) (2026) 131-145*

DOI: https://doi.org/10.62985/j.huit_ojs.vol26.no3E.470

APPLYING THE PLS-SEM MODEL TO ANALYZE THE RELATIONSHIP BETWEEN FACTORS AFFECTING THE INTENTION AND ACTUAL USE OF AI TOOLS (CHATGPT) IN THE WORKPLACE IN HO CHI MINH CITY

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Received: 2 March 2026; Revised: 15 April 2026; Accepted: 4 May 2026

ABSTRACT

This study examines the factors influencing intention to use and actual use of ChatGPT among students and office workers in Ho Chi Minh City. The proposed framework integrates the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), and the Theory of Planned Behavior (TPB), supplemented by local contextual factors related to digital infrastructure. A quantitative survey yielded 251 valid responses, which were analyzed using partial least squares structural equation modeling (PLS-SEM). The results indicate that intention to use has a strong positive effect on actual use (β = 0.810), while contextual factors strongly influence attitude (β = 0.793). Personal innovativeness (β = 0.416) has a stronger effect on intention than attitude does. Perceived ease of use is not statistically significant, suggesting that ease of use may function as a baseline expectation for generative AI rather than as a differentiating factor. The study contributes by incorporating local contextual conditions into established adoption models and offers implications for responsible AI adoption in educational institutions and organizations.

Keywords: ChatGPT, intention to use, actual use, PLS-SEM, technology adoption.

1. INTRODUCTION

Decision No. 131/QĐ-TTg of the Prime Minister approves a national scheme to strengthen information-technology application and digital transformation in education and training through 2025, with an orientation to 2030. The scheme positions digital capacity as an important driver of educational innovation and national competitiveness [1].

Against this policy background, generative AI tools are increasingly used in both education and work. Ho Chi Minh City is a relevant research setting because it is a major economic and educational center with a diverse population of students and office workers and a rapidly developing digital infrastructure.

Despite the growing body of international and domestic research on ChatGPT adoption, four gaps remain in the Ho Chi Minh City context. First, widely used models such as TAM and UTAUT2 rarely incorporate local conditions, including digital infrastructure, socioeconomic differences, and labor-market demands. Second, many studies rely on homogeneous samples from a single institution or discipline, which limits generalizability. Third, few studies compare students with office workers, although the two groups face different adoption conditions and usage requirements. Fourth, prior research often emphasizes model testing and risk description but provides limited group-specific managerial and policy implications.

This study addresses these gaps by applying PLS-SEM to analyze factors affecting intention to use and actual use of ChatGPT among students and office workers in Ho Chi Minh City. The model combines TAM, UTAUT2, and TPB with perceived usefulness, perceived ease of use, social influence, hedonic motivation, personal innovativeness, and local contextual factors. The study provides both theoretical evidence and practical guidance for promoting effective and ethical AI adoption.

Research Objectives

This study identifies and measures the factors influencing intention to use and actual use of ChatGPT among students and office workers in Ho Chi Minh City. Based on the empirical findings, managerial and policy implications are proposed for AI adoption in the context of digital transformation.

Research Approach

The study follows four steps: (i) extending the TAM-UTAUT2 framework by incorporating local contextual factors; (ii) collecting empirical data from students and office workers in Ho Chi Minh City; (iii) testing the proposed relationships using PLS-SEM and multi-group analysis; and (iv) developing practical implications for education and workplace settings.

2. THEORETICAL BACKGROUND

Three theoretical frameworks underpin the proposed model. TAM identifies perceived usefulness and perceived ease of use as central antecedents of technology acceptance [2]. UTAUT2 extends acceptance research through performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit [3]. TPB proposes that behavior is primarily determined by intention, which is shaped by attitude, subjective norms, and perceived behavioral control [4]. Integrating these frameworks provides a basis for examining both individual perceptions and contextual conditions associated with ChatGPT adoption.

3. RESEARCH METHODOLOGY

The study used a mixed research process with qualitative scale refinement followed by a quantitative survey. The preliminary stage involved scale development and expert consultation. The main stage collected survey data and evaluated the measurement and structural models using PLS-SEM.

The initial questionnaire contained 36 observed variables. After PU4 was removed because of excessive collinearity, 35 indicators remained in the final model. The minimum sample requirement was 175 observations under the five-observations-per-indicator rule. A total of 251 valid responses were retained, exceeding this minimum. Data analysis included descriptive statistics, reliability and validity assessment, structural-model evaluation, bootstrapping, multi-group analysis, and predictive assessment using SmartPLS 4 [5].

Proposed Research Model

Based on the literature review, the study proposes an integrated model combining TAM, UTAUT2, and TPB, with local contextual factors representing digital infrastructure and the Industry 4.0 environment.

The model contains six exogenous constructs: perceived usefulness, perceived ease of use, social influence, hedonic motivation, personal innovativeness, and contextual factors. Attitude and intention to use are endogenous mediating constructs, while actual use is the final endogenous construct.

Attitude is predicted by perceived usefulness, perceived ease of use, and contextual factors. Intention to use is predicted by hedonic motivation, personal innovativeness, social influence, and attitude. Actual use is predicted by intention to use and social influence. Gender and respondent group (students versus office workers) are examined using multi-group analysis. Figure 1 presents the proposed model.

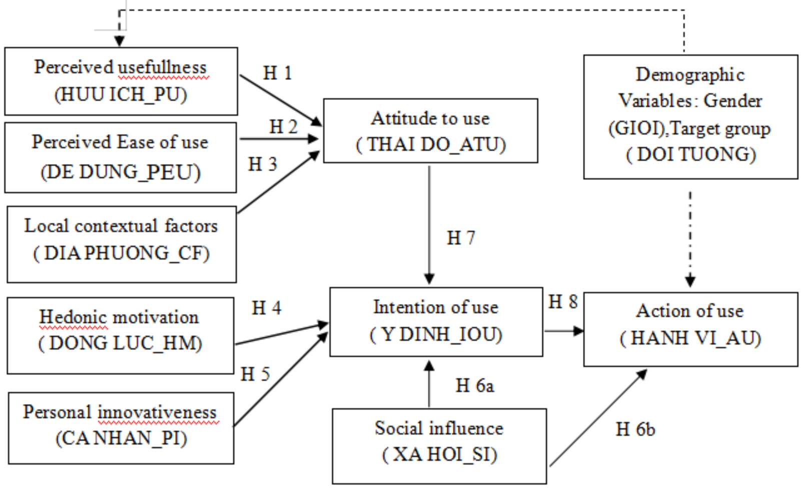

Figure 1. Proposed research model of intention to use and actual use of ChatGPT

Source: Authors' proposed model.

Based on the integrated theoretical framework and prior empirical studies, the following eight hypotheses are proposed:

H1: Perceived usefulness (PU) positively affects attitude toward using ChatGPT (ATU) in work and study contexts [2], [6]-[9].

H2: Perceived ease of use (PEU) positively affects attitude toward using ChatGPT (ATU) in work and study contexts [2], [10], [11].

H3: Local contextual factors (CF), including digital infrastructure and the Industry 4.0 environment, positively affect attitude toward using ChatGPT (ATU) [3], [9], [12], [13].

H4: Hedonic motivation (HM) positively affects intention to use ChatGPT (IOU) [3], [10], [13], [14].

H5: Personal innovativeness (PI) positively affects intention to use ChatGPT (IOU) [6], [11], [15], [16].

H6: Social influence (SI) positively affects (a) intention to use ChatGPT (IOU) and (b) actual use of ChatGPT (AU) [3], [17]-[19].

H7: Attitude toward using ChatGPT (ATU) positively affects intention to use ChatGPT (IOU) [2], [3], [9], [16].

H8: Intention to use ChatGPT (IOU) positively affects actual use of ChatGPT (AU) [9], [16].

The hypotheses were tested in SmartPLS 4 using 5,000 bootstrap resamples to evaluate the significance of direct and indirect effects in the measurement and structural models.

The 251 valid responses comprised 131 women (52.19%) and 120 men (47.81%). The respondent groups included 163 students (64.94%) and 88 office workers (35.06%). Gender and respondent group were subsequently examined using multi-group analysis.

4. RESULTS AND DISCUSSION

The analysis evaluates indicator reliability and collinearity, internal consistency, convergent and discriminant validity, structural relationships, group differences, and out-of-sample predictive performance.

4.1. Assessment of Indicator Reliability and Collinearity

Indicator reliability was assessed using outer loadings, while collinearity was examined using the variance inflation factor (VIF). Outer loadings of 0.708 or higher and VIF values below 5 were used as assessment criteria [5].

In the initial estimation, PU4 had a VIF of 5.187 and was removed. After re-estimation, all remaining VIF values were below 5, and all outer loadings were at least 0.708. The retained indicators therefore met the stated reliability and collinearity criteria.

Table 1. Assessment of outer loadings and VIF values

Criterion	ATU 1-5	AU 1-3	HM 1-5	IOU 1-3	PEU 1-4	PI 1-4	SI 1-4	CF 1-3	PU 1,2,3,5
Outer loading	> 0.708								
VIF	< 5								

Source: Authors' calculations.

All remaining indicators were retained for the subsequent measurement-model assessment.

4.2. Assessment of the Reflective Measurement Model

The reflective measurement model was assessed in terms of internal consistency, convergent validity, and discriminant validity. Internal consistency was evaluated using Cronbach's alpha and composite reliability (CR); convergent validity was evaluated using outer loadings and average variance extracted (AVE); and discriminant validity was evaluated using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT) [5, p. 49].

4.2.1. Internal Consistency and Convergent Validity

For the reflective constructs, Cronbach's alpha and CR values of at least 0.70 and AVE values of at least 0.50 were used as evaluation criteria [5]. Table 2 reports the results.

Table 2. Reliability and convergent validity of reflective constructs

Construct	Cronbach’s Alpha	Composite reliability (CR)	Average variance extracted (AVE)
HANHVI_AU	0.910	0.944	0.848
THAIDO_ATU	0.928	0.946	0.777
YDINH_IOU	0.815	0.891	0.734

Source: Authors' calculations.

The reported Cronbach's alpha, CR, and AVE values exceed the recommended thresholds, supporting internal consistency and convergent validity for the reflective constructs.

4.2.2. Discriminant Validity

Discriminant validity was examined using the Fornell-Larcker criterion and HTMT [5]. Under the Fornell-Larcker criterion, the square root of AVE for each reflective construct should exceed its correlations with other constructs.

Table 3 shows that the square roots of AVE for actual use (0.921) and attitude (0.881) exceed their relevant inter-construct correlations. For intention to use, however, the square root of AVE (0.856) is slightly lower than its correlation with actual use (0.877), indicating a potential discriminant-validity concern that requires additional HTMT assessment.

Table 3. Fornell-Larcker criterion

Construct	CANHAN_PI	DEDUNG_PEU	DIAPHUONG_CF	DONGLUC_HM	HANHVI_AU	HUUICH_PU	THAIDO_ATU	XAHOI_SI	YDINH_IOU
CANHAN_PI									
DEDUNG_PEU	0.516								
DIAPHUONG_CF	0.558	0.660							
DONGLUC_HM	0.549	0.573	0.657						
HANHVI_AU	0.539	0.617	0.683	0.623	0.921				
HUUICH_PU	0.564	0.697	0.636	0.564	0.654				
THAIDO_ATU	0.541	0.622	0.877	0.605	0.705	0.630	0.881		
XAHOI_SI	0.263	0.314	0.445	0.286	0.514	0.429	0.493		
YDINH_IOU	0.717	0.615	0.667	0.641	0.877	0.643	0.701	0.452	0.856

Source: Authors' calculations.

HTMT values below 0.85 or 0.90 generally support discriminant validity. When HTMT exceeds the selected threshold, a bias-corrected bootstrap confidence interval can be examined; an interval containing 1.000 does not support discriminant validity [5]. Table 4a reports HTMT values, and Table 4b reports bias-corrected 95% confidence intervals based on 5,000 resamples.

Table 4a. Heterotrait-monotrait ratio (HTMT) values

HTMT	HANHVI_AU	THAIDO_ATU
HANHVI_AU		
THAIDO_ATU	0.767	
YDINH_IOU	1.003	0.805

Table 4b. Bias-corrected 95% confidence intervals for HTMT

Relationship	M	Bias	2.5%	97.5%
THAIDO_ATU -> HANHVI_AU	0.769	0.002	0.704	0.821
YDINH_IOU -> HANHVI_AU	1.004	0.001	0.972	1.029
YDINH_IOU -> THAIDO_ATU	0.803	-0.001	0.740	0.862

Source: Authors' calculations.

The HTMT value between intention to use and actual use is 1.003. Its 95% confidence interval (0.972, 1.029) includes 1.000; therefore, discriminant validity between these two constructs is not established. By contrast, the confidence intervals for attitude-actual use and intention-attitude do not include 1.000. The intention-actual use overlap should be treated as a limitation and indicates that the conceptual distinction and indicators of these constructs require further review.

4.3. Structural Model Assessment

The structural model was evaluated using the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and selected model-fit indices. The results are presented in Tables 5-8.

R^2 measures the in-sample explanatory power of each endogenous construct. Values of approximately 0.75, 0.50, and 0.25 may be described as substantial, moderate, and weak in many PLS-SEM applications, while adjusted R^2 accounts for the number of predictors [5].

Table 5. Coefficients of determination (R^2)

Construct	R^2	Adjusted R^2
HANHVI_AU	0.787	0.785
THAIDO_ATU	0.778	0.775
YDINH_IOU	0.691	0.685

Source: Authors' calculations.

The adjusted R^2 values are 0.785 for actual use, 0.775 for attitude, and 0.685 for intention to use. Thus, intention to use and social influence explain 78.5% of the variance in actual use; perceived usefulness, perceived ease of use, and contextual factors explain 77.5% of the variance in attitude; and hedonic motivation, personal innovativeness, social influence, and attitude explain 68.5% of the variance in intention to use.

The f^2 statistic evaluates the contribution of each predictor to an endogenous construct. Values of 0.02, 0.15, and 0.35 are commonly interpreted as small, medium, and large effects, respectively [20].

Table 6. Effect sizes (f^2)

Predictor	HANHVI_AU	THAIDO_ATU	XAHOI_SI	YDINH_IOU
CANHAN_PI				0.352
DEDUNG_PEU		0.001		
DIAPHUONG_CF		1.437		
DONGLUC_HM				0.072
HANHVI_AU				
HUUICH_PU		0.025		
THAIDO_ATU				0.125
XAHOI_SI	0.082			0.052
YDINH_IOU	2.456			

Source: Authors' calculations.

Perceived ease of use has a negligible effect on attitude ($f^2 = 0.001$). Contextual factors have a large effect on attitude ($f^2 = 1.437$), personal innovativeness has a large effect on intention ($f^2 = 0.352$), and intention has a large effect on actual use ($f^2 = 2.456$). The remaining effects are small to moderate.

Table 7. Model-fit indices

Fit index	Saturated model	Estimated model	Interpretation
SRMR	0.067	0.074	< 0.08
d_ULS	2.797	3.443	Compare with HI95/HI99
d_G	1.703	1.763	Compare with HI95/HI99
Chi-square	1931.222	1968.821	Descriptive
NFI	0.791	0.787	Closer to 1

Source: Authors' calculations.

The standardized root mean square residual is acceptable for both the saturated model (SRMR = 0.067) and the estimated model (SRMR = 0.074), using the 0.08 guideline. The d_ULS and d_G values require comparison with bootstrapped HI95 or HI99 cutoffs, which are not reported in Table 7. The NFI value of 0.787 is below the commonly desired level close to 0.90 and should therefore be interpreted cautiously rather than as conclusive evidence of overall fit [21, p. 65].

Predictive relevance was assessed using blindfolding with an omission distance of D = 7. Q^2 values greater than zero indicate predictive relevance for the corresponding endogenous constructs.

Table 8. Predictive relevance (Q^2)

Construct	Construct crossvalidated redundancy	Construct crossvalidated communality
CANHAN_PI		0.606
DEDUNG_PEU		0.617
DIAPHUONG_CF		0.260
DONGLUC_HM		0.688
HANHVI_AU	0.661	0.653
HUUICH_PU		0.643
THAIDO_ATU	0.591	0.654
XAHOI_SI		0.500
YDINH_IOU	0.484	0.458

Source: Authors' calculations.

All reported Q^2 values are greater than zero, indicating in-sample predictive relevance for the endogenous constructs.

4.4. Hypothesis Testing and Impact Relationships

4.4.1. PLS-SEM Structural Model

Figure 2 presents the estimated PLS-SEM model. Outer weights and loadings show the relationships between indicators and constructs, while path coefficients (β) show the structural relationships among the constructs.

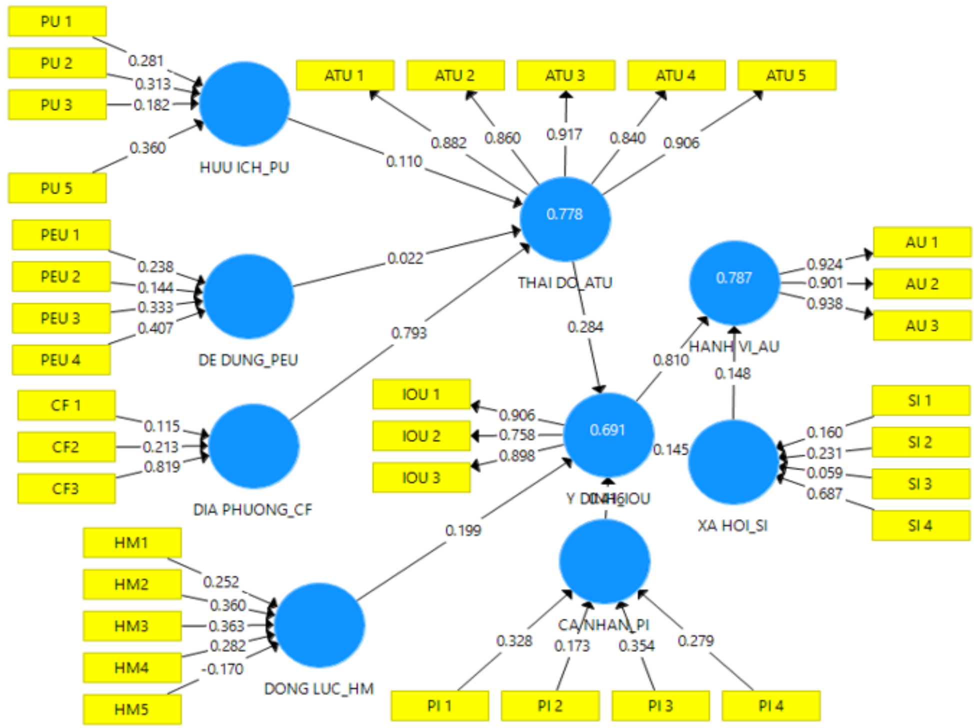

Figure 2. Estimated PLS-SEM model for intention to use and actual use of ChatGPT

Source: Authors' calculations.

4.4.2. Path Coefficients

The structural paths quantify the hypothesized relationships among perceived usefulness, perceived ease of use, contextual factors, hedonic motivation, personal innovativeness, social influence, attitude, intention to use, and actual use.

Path coefficients (β) indicate the direction and magnitude of relationships among the latent constructs. Their statistical significance was evaluated using bootstrap p-values.

Outer weights and outer loadings describe the relationships between constructs and their indicators, whereas structural path coefficients describe relationships among constructs. These quantities should therefore be interpreted separately.

Direct and indirect effects were estimated using 5,000 bootstrap resamples. The results are reported in Tables 9 and 10.

Table 9. Direct effects in the structural model

Path	Mean estimate (M)	p-value	Hypothesis
CANHAN_PI -> YDINH_IOU	0.413	0.000	H5
DEDUNG_PEU -> THAIDO_ATU	0.022	0.265	H2
DIAPHUONG_CF -> THAIDO_ATU	0.789	0.000	H3
DONGLUC_HM -> YDINH_IOU	0.208	0.000	H4
HUUICH_PU -> THAIDO_ATU	0.110	0.001	H1
THAIDO_ATU -> YDINH_IOU	0.279	0.000	H7
XAHOI_SI -> HANHVI_AU	0.149	0.000	H6b
XAHOI_SI -> YDINH_IOU	0.149	0.000	H6a
YDINH_IOU -> HANHVI_AU	0.810	0.000	H8

Source: Authors' calculations.

All direct paths except perceived ease of use to attitude have p-values below 0.05 and are statistically significant.

The path from perceived ease of use to attitude is not statistically significant ($\beta = 0.022$, $p = 0.265$). Thus, perceived ease of use does not explain meaningful additional variance in attitude after the other predictors are included.

Contextual factors have the strongest direct effect on attitude, whereas personal innovativeness has the strongest exogenous effect on intention to use. Intention to use is the dominant predictor of actual use.

Table 10. Indirect effects in the structural model

Indirect path	Mean estimate (M)	p-value	Hypothesis chain
CANHAN_PI -> YDINH_IOU -> HANHVI_AU	0.334	0.000	H5 -> H8
DONGLUC_HM -> YDINH_IOU -> HANHVI_AU	0.169	0.000	H4 -> H8
DEDUNG_PEU ->THAIDO_ATU ->YDINH_IOU ->HANHVI_AU	0.006	0.268	H2 -> H7 -> H8
DIAPHUONG_CF->THAIDO_ATU->YDINH_IOU->HANHVI_AU	0.179	0.000	H3 -> H7 -> H8
THAIDO_ATU -> YDINH_IOU -> HANHVI_AU	0.227	0.000	H7 -> H8
HUUICH_PU -> THAIDO_ATU -> YDINH_IOU -> HANHVI_AU	0.025	0.005	H1 -> H7 -> H8
XAHOI_SI -> YDINH_IOU -> HANHVI_AU	0.120	0.000	H6a -> H8
DEDUNG_PEU -> THAIDO_ATU -> YDINH_IOU	0.008	0.267	H2 -> H7
DIAPHUONG_CF -> THAIDO_ATU -> YDINH_IOU	0.220	0.000	H3 -> H7
HUUICH_PU -> THAIDO_ATU -> YDINH_IOU	0.031	0.005	H1 -> H7

Source: Authors' calculations.

The indirect paths beginning with perceived ease of use are not statistically significant. The remaining reported indirect effects are significant at $p < 0.05$.

4.4.3. Hypothesis Testing Results

The direct-effect results support H1 and H3-H8. H2 is not supported because the path from perceived ease of use to attitude is not statistically significant.

The indirect effects of perceived ease of use on intention and actual use through attitude are also not statistically significant. No direct path from perceived ease of use to actual use was hypothesized.

The hypothesis decisions are summarized as follows:

H1 is supported: perceived usefulness positively affects attitude toward using ChatGPT.

H3 is supported: contextual factors positively affect attitude toward using ChatGPT.

H4 is supported: hedonic motivation positively affects intention to use ChatGPT.

H5 is supported: personal innovativeness positively affects intention to use ChatGPT.

H6a and H6b are supported: social influence positively affects intention to use and actual use of ChatGPT.

H7 is supported: attitude toward using ChatGPT positively affects intention to use ChatGPT.

H8 is supported: intention to use ChatGPT positively affects actual use of ChatGPT.

4.5. Effects of Demographic Variables on ChatGPT Use

Permutation tests, PLS multi-group analysis (PLS-MGA), and parametric tests were used to examine differences by gender and respondent group. A difference was treated as robust when all three tests yielded $p < 0.05$ [5, pp. 153, 156].

Table 11 reports the p-values for the three comparison methods. The analysis used 500 bootstrap resamples for the group comparisons.

For gender, robust differences are observed for the paths from perceived ease of use to attitude, contextual factors to attitude, and intention to use to actual use.

For respondent group, a robust difference is confirmed for the path from personal innovativeness to intention to use. The table also flags the path from contextual factors to attitude, but its permutation p-value is not reported; robustness of that comparison cannot be verified from the available values.

The remaining paths do not show differences that are significant across all three comparison methods.

Table 11. Multi-group comparisons by gender and respondent group

Path	G: MGA	G: Para.	G: Perm.	G robust	R: MGA	R: Para.	R: Perm.	R robust
PI -> IOU	0.372	0.371	0.380	No	0.021	0.015	0.008	Yes
PEU -> ATU	0.033	0.035	0.022	Yes	0.124	0.067	0.008	No
CF -> ATU	0.001	0.001	0.002	Yes	0.003	0.000	N/R	N/V
HM -> IOU	0.484	0.484	0.467	No	0.151	0.127	0.141	No
PU -> ATU	0.263	0.190	0.223	No	0.106	0.069	0.013	No
ATU -> IOU	0.137	0.142	0.112	No	0.089	0.046	0.007	No
SI -> AU	0.155	0.139	0.131	No	0.144	0.140	0.177	No
SI -> IOU	0.199	0.204	0.198	No	0.070	0.047	0.009	No
IOU -> AU	0.023	0.018	0.013	Yes	0.112	0.085	0.070	No

Source: Authors' calculations.

4.6. Predictive Ability of the Model

Out-of-sample predictive performance was evaluated using PLS-Predict. Root mean square error (RMSE), mean absolute error (MAE), and Q^2 predict values from the PLS-SEM model were compared with those from a linear-model benchmark. Lower prediction error indicates better predictive performance.

All Q^2 predict values are greater than zero. However, the PLS-SEM model has a lower RMSE than the linear benchmark for only 5 of the 11 indicators, which is fewer than half. The model therefore shows relatively weak out-of-sample predictive performance compared with the linear benchmark, despite substantial in-sample explanatory power.

RMSE is most appropriate when prediction errors are approximately normally distributed, whereas MAE is more robust when that assumption is not met [21, p. 69]. In this study, both error measures lead to the same general conclusion that predictive performance is limited.

Table 12. PLS-Predict comparison between the PLS-SEM and linear models

Indicator	PLS			LM		
	RMSE	MAE	Q^2 predict	RMSE	MAE	Q^2 predict
AU 1	0.674	0.543	0.457	0.632	0.487	0.524
AU 2	0.632	0.495	0.452	0.636	0.494	0.445
AU 3	0.647	0.505	0.488	0.543	0.411	0.639
ATU 1	0.498	0.372	0.585	0.516	0.397	0.554
ATU 2	0.556	0.431	0.558	0.568	0.444	0.539
ATU 3	0.404	0.300	0.745	0.366	0.247	0.791
ATU 4	0.564	0.442	0.514	0.574	0.432	0.497
ATU 5	0.514	0.381	0.572	0.533	0.406	0.540
IOU 1	0.660	0.506	0.423	0.632	0.486	0.471
IOU 2	0.532	0.419	0.583	0.442	0.330	0.712
IOU 3	0.668	0.512	0.432	0.597	0.463	0.545

Source: Authors' calculations.

4.7. Discussion

The strong effect of intention to use on actual use ($\beta = 0.810$) is consistent with the central role assigned to behavioral intention in UTAUT2 and TPB [3], [4]. Personal innovativeness has a stronger exogenous effect on intention than attitude does, highlighting the importance of individual readiness to experiment with emerging technologies [6], [11], [15], [16]. Contextual factors have the strongest effect on attitude ($\beta = 0.793$), indicating that infrastructure and the local operating environment are important conditions for AI adoption [12], [13]. The non-significant effect of perceived ease of use may indicate that ease of use is increasingly treated as a baseline expectation for conversational AI; a similar absence of effect has been reported in recent AI-adoption research [16]. These results should nevertheless be interpreted alongside the discriminant-validity concern between intention and actual use and the model's limited out-of-sample predictive performance.

5. CONCLUSION AND POLICY IMPLICATIONS

The model explains substantial in-sample variance in attitude, intention to use, and actual use of ChatGPT among students and office workers in Ho Chi Minh City. Intention to use is the strongest predictor of actual use, contextual factors strongly shape attitude, and personal innovativeness is an important antecedent of intention. Perceived ease of use is not statistically significant. Although the structural results provide useful explanatory evidence, the intention-actual use discriminant-validity issue and relatively weak out-of-sample prediction require cautious interpretation.

The following implications are proposed:

For educational institutions

Educational institutions should integrate AI literacy and responsible-use guidance into teaching and learning. Students should be given structured opportunities to apply AI tools in assignments and research while being required to verify outputs, cite AI use where appropriate, protect confidential data, and maintain academic integrity. Practical training and reliable digital infrastructure are essential.

For organizations and businesses

Organizations should provide role-specific AI training, clear governance rules, and approved use cases for reporting, communication, analysis, and other work processes. Adoption should be encouraged through support and demonstration of value rather than through indiscriminate mandatory use. Human review should remain responsible for consequential decisions and external communications.

Policy recommendations

Policymakers and organizational leaders should support digital infrastructure, workforce reskilling, data protection, ethical-use standards, and collaboration between educational institutions and employers. Incentive mechanisms should reward demonstrably effective and responsible use of AI rather than frequency of use alone.

Limitations

The study uses a cross-sectional convenience sample limited to students and office workers in Ho Chi Minh City. The included constructs do not fully capture psychological, ethical, health-related, organizational, or task-specific influences on AI use.

The high HTMT value and confidence interval containing 1.000 for intention to use and actual use indicate insufficient discriminant validity between these constructs. In addition, PLS-Predict shows relatively weak out-of-sample performance compared with the linear benchmark. Future research should refine the intention and actual-use measures, use probability or longitudinal sampling, include additional demographic and organizational variables, and test the model in other regions and occupational settings.

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APPENDIX

SURVEY QUESTIONNAIRE ON INTENTION TO USE AND USE BEHAVIOR OF AI (CHATGPT)

A. GENERAL INFORMATION

Please provide the following information:

Question 1: Gender: 1 = Male; 2 = Female

Question 2: Respondent group/occupation

1 = Student; 2 = Office worker or freelancer

B. SURVEY QUESTIONNAIRE

Please mark X next to the response that best represents your level of agreement with each statement: 1 = Strongly disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly agree.

The constructs are perceived usefulness (PU), perceived ease of use (PEU), hedonic motivation (HM), personal innovativeness (PI), local contextual factors/digital infrastructure (CF), social influence (SI), attitude toward use (ATU), intention to use (IOU), and actual use (AU).

No.	Symbol	Explanation
	PU	**1. Perceived usefulness (PU)**
1	PU 1	I believe ChatGPT is useful in my work/study.
2	PU 2	Applying ChatGPT helps me increase my chances of success in my work/studies.
3	PU 3	Applying ChatGPT helps me complete tasks or projects/assignments faster in my work/studies.
4	PU 4	Applying ChatGPT helps me increase productivity/efficiency in my work/studies.
5	PU 5	Applying ChatGPT helps stimulate my creativity.
	PEU	**2. Perceived ease of use (PEU)**
6	PEU1	I find ChatGPT to have a simple interface.
7	PEU2	I can easily use the features of the ChatGPT application.
8	PEU3	I find ChatGPT easy to use on my phone and computer.
9	PEU4	Using ChatGPT makes my work/studies simpler.
	HM	**3. Hedonic motivation (HM)**
10	HM1	I feel more comfortable using ChatGPT in my work/study.
11	HM2	I feel happier using ChatGPT in my work/study.
12	HM3	I feel more enthusiastic in my work/study when using ChatGPT.
13	HM4	I am satisfied with the results I achieve when using ChatGPT in my work/study.
14	HM5	I feel confident with the knowledge I gain when using ChatGPT.
	PI	**4. Personal innovativeness (PI)**
15	PI 1	I enjoy experimenting with new software and technology.
16	PI 2	When I hear about a new software and technology, I will look for ways to use it.
17	PI 3	I don't hesitate to experiment with ChatGPT to apply it in my work/study.
18	PI 4	In my work, I often experiment with new technologies to create an image of self-innovation in the eyes of colleagues/friends.

No.	Symbol	Explanation
	CF	**5. Local contextual factors - digital infrastructure (CF)**
19	CF 1	Using ChatGPT helps me learn more about the current state of technology in the local area where I operate
20	CF 2	Language barriers are no longer a problem when I use ChatGPT.
21	CF 3	Using ChatGPT helps me learn more about local customs and traditions and avoid unnecessary ethical risks in the local area where I operate.
	SI	**6. Social influence and other people's opinions (SI)**
22	SI 1	People who are important to me (family, friends, teachers) think I should use ChatGPT.
23	SI 2	Many of my colleagues/friends use ChatGPT.
24	SI 3	People whose opinions I value and who influence my behavior recommend that I use ChatGPT
25	SI 4	My workplace/school encourages me to use ChatGPT to support my work/study and research
	ATU	**7. Attitude to use (ATU)**
26	ATU1	I have a positive feeling about the benefits that ChatGPT brings to my work/study.
27	ATU2	I appreciate the features that ChatGPT brings to my work/study
28	ATU3	Using ChatGPT in work/study is the right and necessary action.
29	ATU4	Using ChatGPT is a reasonable idea in work/study for me.
30	ATU5	I find myself working/studying better with the support of ChatGPT.
	IOU	**8. Intention of use (IOU)**
31	IOU1	I intend to continue using ChatGPT in work/study in the future.
32	IOU2	I am not hesitant to experiment with updated ChatGPT technologies.
33	IOU3	I intend to prioritize using ChatGPT in the near future.
	AU	**9. Actual use (AU)**
34	AU 1	I always try my best and use ChatGPT frequently
35	AU 2	I plan to use ChatGPT in my studies and work in the future
36	AU 3	I will encourage friends and family to use ChatGPT in their work

Thank you for taking the time to complete this questionnaire.