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Factors Influencing IT Students' Willingness to Use Generative AI for Learning: A UTAUT-Based Study

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ABSTRACT

The rapid advancement of Generative Artificial Intelligence (GAI) has greatly influenced its adoption in various fields, particularly education. This study utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) to explore factors shaping the willingness of vocational school and college-level information technology students to use GAI for learning specialized subjects. Data were collected through an online survey via Google Forms, targeting 115 IT students in Khanh Hoa province, Vietnam. The analysis focuses on four key factors: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), with moderating variables such as gender, age, and learning year. The findings reveal that performance expectancy, social influence, and facilitating conditions have significant positive impacts on students' willingness to use GAI, while effort expectancy was not statistically significant. Among the factors, facilitating conditions had the strongest influence, followed by social influence and performance expectancy. No significant differences were observed across age or learning year, but female students demonstrated a greater reliance on support and resources than their male counterparts. These results underscore the transformative potential of GAI as an educational tool, highlighting the importance of integrating supportive resources and fostering a conducive learning environment. This study provides valuable insights into the factors driving GAI adoption among students, paving the way for future research and practical applications in education.

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1. Introduction

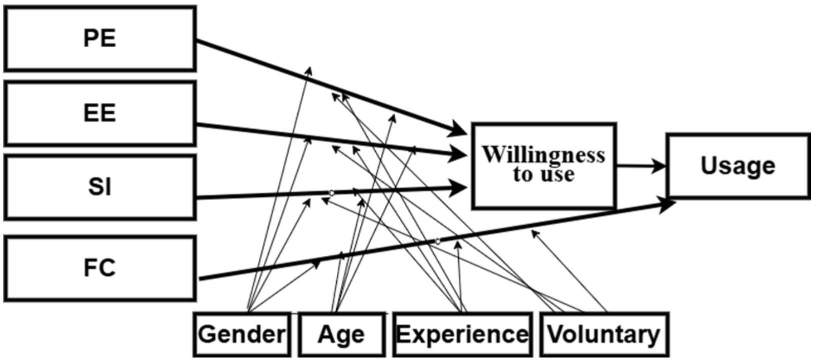

Figure 1. *Unified Theory of Acceptance and Use of Technology (UTAUT) model*

The new generation of Generative Artificial Intelligence (GAI), exemplified by technologies such as ChatGPT, has created a significant breakthrough in education. The launch of ChatGPT in 2022 not only marked a new era in AI applications but also unlocked immense potential in reshaping teaching and learning methods. In education, GAI has demonstrated strong capabilities in personalizing learning experiences, providing instant feedback, and generating adaptive learning content tailored to individual

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student needs. Specific applications include using GAI for analyzing learning data, supporting adaptive assessments, and simulating real-world learning scenarios. These capabilities not only enhance teaching effectiveness but also foster critical thinking and creativity among learners. As a result, research on GAI applications in education, particularly at early learning stages, has gained increasing attention ([1-8]).

One of the key factors determining the successful implementation of these emerging technologies is the willingness of teachers and students to accept and adopt them. To examine this, theoretical models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) have been widely applied. Compared to TAM, UTAUT is considered superior due to its ability to explain up to 70% of variance in technology acceptance behavior ([12]). The UTAUT model ([9-11]) includes four key constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). These factors are moderated by variables such as age, gender, and academic year, allowing for a more nuanced analysis of technology acceptance across different demographic groups.

Numerous studies have demonstrated the effectiveness of UTAUT in educational research. For instance, J. H. Bu (2022) applied UTAUT to analyze the acceptance of interactive whiteboards and digital learning devices (Figure 1), highlighting the influence of performance expectancy and facilitating conditions. Furthermore, researchers have adapted UTAUT to better fit specific research contexts. Studies on computer science education have incorporated additional variables such as Computer Anxiety (CA) and Self-Efficacy (SE) to refine technology acceptance models for educators ([13]). Similarly, mobile learning research has integrated factors like interaction, satisfaction, and innovation to explore technology adoption in dynamic educational settings ([14]).

Building on this strong theoretical foundation, the present study investigates the factors influencing the willingness of vocational school and college-level IT students to use GAI for learning specialized subjects. By applying UTAUT and adjusting its moderating variables to suit the educational context, this research aims to provide a comprehensive understanding of how GAI can be effectively integrated into education, contributing to the broader discourse on technological innovation in teaching and learning.

2. Model, Hypothesis and Methods

2.1. The UTAUT Model

Based on the analysis of previous studies and theoretical models of technology acceptance, this research adopts the UTAUT model as the fundamental theoretical framework. The literature review has shown that the UTAUT model has been widely applied by scholars to study technology acceptance and is considered more effective than earlier models like TAM. The original structure of UTAUT includes four main variables: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), along with moderating variables such as gender, age, and learning year (e.g., year 1, year 2). These four variables help explain and predict technology acceptance and usage behaviors from both individual and social perspectives (Figure 2).

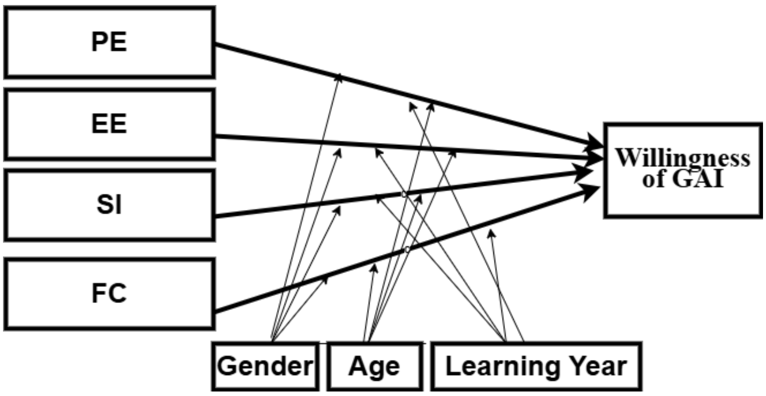

Figure 2. *The UTAUT model of inforamtion technology students' willingness to use GAI*

Performance Expectancy (PE) refers to the degree to which students believe that using GAI can enhance their learning efficiency and academic performance. Effort Expectancy (EE) indicates the extent to which students feel that using GAI for educational purposes is easy or difficult. Social Influence (SI) refers to the degree to which students perceive that important others (peers, instructors, or industry trends) expect them to use GAI. Facilitating Conditions (FC) reflect the availability of institutional, technical, and resource-based support that enables effective GAI adoption.

Based on the UTAUT model, this study explores the factors influencing the willingness of vocational school and college-level IT students to use Generative Artificial Intelligence (GAI) in learning specialized subjects. The key factors include performance expectancy, effort expectancy, social influence, and facilitating conditions. The dependent variable in this study is students’ acceptance of GAI, reflected through their intentions and behaviors toward using this technology in their studies. This study also adds moderating variables such as **gender -** Male and female students may have different perceptions of technology adoption, particularly regarding perceived ease of use (EE) and reliance on facilitating conditions (FC), **age -** Younger students may be more open to adopting new technologies, whereas older students may rely more on institutional support (FC) or social influence (SI), and **learning year (academic seniority) -** Students in higher learning years may have more experience with educational technologies, influencing their expectations of GAI’s benefits (PE) and ease of use (EE). These factors may influence how students perceive and use GAI. Other variables were excluded in favor of those more suited to the context of vocational school and college students.

2.2. Research Hypotheses

H1: Performance Expectancy (PE) has a significant positive impact on students' willingness to use GAI.

H2: Effort Expectancy (EE) has a significant negative impact on students' willingness to use GAI.

H3: Social Influence (SI) has a significant positive impact on students' willingness to use GAI.

H4: Facilitating Conditions (FC) has a significant positive impact on students' willingness to use GAI.

2.3. Hypotheses on Moderating Variables

H5: Age moderates the relationship between the independent variables and students' willingness to use GAI.

H6: Gender moderates the relationship between the independent variables and students' willingness to use GAI.

H7: Learning year moderates the relationship between the independent variables and students' willingness to use GAI.

In summary, this theoretical model aims to provide a deeper understanding of the factors influencing students' willingness to use GAI, thereby contributing to the enhancement of this technology’s application in education.

2.4. Methods

The study was conducted through the following steps:

Step 1: Selecting the Research Model

Apply the UTAUT (Unified Theory of Acceptance and Use of Technology) model to examine the factors influencing IT students' willingness to use Generative Artificial Intelligence (GAI) in their studies.

Step 2: Identifying Research Variables

Independent Variables: Includes the following factors:

– Performance Expectancy (PE)
– Effort Expectancy (EE)
– Social Influence (SI)

– Facilitating Conditions (FC)

Dependent Variable: Willingness to use GAI.

Step 3: Designing the Questionnaire

Develop a questionnaire based on scales from previous studies (V. Venkatesh & F. D. Davis, 2000; V. Venkatesh et al., 2003; V. Venkatesh & X. Zhang, 2010; J. H. Bu, 2022, S. Zhang et al., 2016, A. Birch & V. Irvine, 2009), and the practical application of GAI in education. Adjust the measurement questions to suit the target respondents, who are vocational and college IT students. Questionnaire Structure:

Part 1: Collect personal information from students.

– Gender: 106 male students (92.2%) and 9 female students (7.8%).

– Age: Ranges from 16 to 34; the largest group is 20 years old (33 students, accounting for 27.8%).

– Learning Year: 83 second-year students (72.2%) and 32 third-year students (27.8%).

Part 2: Evaluate factors affecting the willingness to use GAI, including questions on:

– Performance Expectancy (PE): 3 questions

– Effort Expectancy (EE): 3 questions

– Social Influence (SI): 3 questions

– Facilitating Conditions (FC): 4 questions

– Willingness to use GAI: 3 questions

All questions in this section use a 5-point Likert scale, ranging from "Strongly Disagree" to "Strongly Agree."

Step 4: Selecting the Survey Sample and Collecting Data

Choose a sample of 115 IT students from vocational and college institutions in Khanh Hoa Province, Vietnam. The survey was conducted online via Google Forms.

Step 5: Aggregating and Analyzing Data

Aggregate and analyze the collected data based on various aspects:

Reliability analysis (Table 1): The reliability of the scale is assessed using Cronbach's Alpha to check the internal consistency of the variables in the questionnaire. The formula for Cronbach's Alpha is as follows:

$$\alpha = \frac{N \times \bar{c}}{\bar{v} + (N-1) \times \bar{c}} \quad (1)$$

where:

N is the number of items (questions) in the scale.

$\bar{c}$: is the average inter-item covariance among the items.

$\bar{v}$: is the average variance of each item.

Validity analysis (Table 2, Table 3): The validity of the scale is assessed through the Kaiser-Meyer-Olkin (KMO) Measure and Bartlett’s Test of Sphericity to determine the suitability of the data for factor analysis (Table 2). The formula for KMO is as follows:

$$KMO = \frac{\sum_{i \neq j} r_{ij}^2}{\sum_{i \neq j} r_{ij}^2 + \sum_{i \neq j} a_{ij}^2} \quad (2)$$

where:

r_{ij}: Correlation coefficient between items i and j..

a_{ij}: Partial correlation coefficient between items i and j.

The KMO value ranges from 0 to 1. A higher KMO value (typically ≥ 0.5) indicates that the data is more suitable for factor analysis.

To determine whether the correlation matrix significantly differs from an identity matrix (i.e., to check if the variables are correlated), Bartlett's Test is used with the following formula:

$$\chi^2 = -(N - 1 - \frac{2p+5}{6}) \ln |R| \tag{3}$$

where:

χ^2 : is the Chi-square statistic for Bartlett's Test

N: is the sample size.

p: is the number of variables

|R|: is the determinant of the correlation matrix.

A large Chi-Square value with a small p-value (typically < 0.05) indicates that the correlation matrix significantly differs from an identity matrix, meaning the variables are correlated and the data is suitable for factor analysis.

To examine the relevance of each question to each factor (Table 3), we used factor analysis with factor loadings, variance interpretation rate, and cumulative variance interpretation rate.

Descriptive statistics (Table 4): Summarize the key characteristics of the survey data by calculating the mean and standard deviation of each variable.

Structural equation model (SEM) (Table 5, Table 6): Identify the factors influencing the willingness to use GAI. We use the Structural Equation Model (SEM) to examine and determine the relationships between variables in the research model. It is divided into two parts:

– Assess the model fit of the SEM (Table 5) based on the following indices: Chi-Square/df (χ^2/df) (assesses model fit), GFI (Goodness of Fit Index) (GFI is an index evaluating the overall model fit with the data, indicating the percentage of variance and covariance in the data explained by the model), CFI (Comparative Fit Index) (CFI compares the proposed model to an independent model (assuming no correlation between variables). CFI reflects the extent to which the model improves fit relative to the independent model), NFI (Normed Fit Index) (NFI assesses model fit by comparing the model to an independent model), TLI (Tucker-Lewis Index) (TLI, similar to CFI, compares the current model with an independent model but also adjusts for model complexity), and RMSEA (Root Mean Square Error of Approximation) (RMSEA measures the model's approximation error with the data. This index indicates the degree of discrepancy between the theoretical model and the actual data).

– Evaluate specific hypotheses in the SEM model (Table 6) based on the following: Normalised Path Coefficient: This coefficient shows the level of impact the independent variable has on the dependent variable. A positive coefficient indicates a positive influence, while a negative coefficient indicates a negative influence, SE - Standard Error: SE indicates the degree of uncertainty in the path coefficient estimate. The smaller the SE, the more accurate the estimate, C.R. Coefficient: A C.R. value greater than 1.96 or less than -1.96 indicates that the coefficient is statistically significant at the 0.05 level, P Value: The P Value shows the statistical significance of the path coefficient. If $p < 0.05$, the variable's influence is statistically significant, meaning the hypothesis is supported. If $p > 0.05$, the hypothesis is not supported, Hypothetical Judgement: Assesses whether the hypothesis is supported or not.

Adjustment effect test (Table 7, Table 8, Table 9): Check whether the demographic factors Age (Table 7), Gender (Table 8), and Academic Seniority (Table 9) influence the willingness to use GAI. The statistical coefficients used include t, which is used to determine if there is a statistically significant difference in the interaction between age, gender, learning year, and the independent variables; p, which indicates the statistical significance of the coefficients. If $p < 0.05$, the coefficient is considered statistically significant. Hypothetical Judgement: Hypothesis evaluation results, assessing whether the relationship between age, gender, learning year, and each independent variable is supported based on the p-value.

3. Results and Discussion

3.1. Results

3.1.1. Reliability analysis

The latent variables (Table 1), including performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), all have Cronbach's Alpha coefficients greater than 0.9, indicating high reliability of the scales. The overall Cronbach's Alpha coefficient for the entire questionnaire is 0.983, demonstrating good internal consistency and high accuracy, making it suitable for further analyses.

Table 1. *Cronbach's Alpha Reliability Analysis*

Variables	Number of Items	Cronbach's Alpha Coefficient	Standardized Cronbach's Alpha Coefficient	Overall Cronbach's Alpha Coefficient	Overall Standardization Cronbach's Alpha Coefficient
PE	3	0.970	0.971	0.983	0.983
EE	3	0.934	0.934		
SI	3	0.943	0.944		
FC	4	0.975	0.975		
Willingness to use GAI	3	0.934	0.934		

3.1.2. Validity analysis

The results (Table 2) show a KMO value of 0.87, confirming that the data is suitable for factor analysis, and Bartlett's test (p-value = 0.000

< 0.05) indicates a significant difference between the correlation matrix and the identity matrix, confirming good validity of the scale.

Table 2. *KMO and Bartlett's test analysis of the questionnaire*

KMO and Bartlett's Sphericity Test	
KMO	0.87
Bartlett's Test of Sphericity	
Approximate Chi-Square	288.899
df	120
p	0.000

The cumulative variance interpretation rate after rotation shows the percentage of information from the measured items that can be explained through the factors (Table 3), reaching 86.87%, confirming that the informational content of the research items can be effectively extracted.

Table 3. *Factor load coefficients of the questionnaire*

Name	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
PE-1	0.85				
PE-2	0.83				
PE-3	0.88				
EE-1		0.81			

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EE-2		0.79			
EE-3		0.84			
SI-1			0.82		
SI-2			0.8		
SI-3			0.85		
FC-1				0.87	
FC-2				0.84	
FC-3				0.89	
FC-4				0.85	
Willingness to use GAI					0.92
Variance interpretation rate% (after rotation)	17.84%	18.15%	13.71%	14.86%	22.32%
Cumulative variance interpretation rate% (after rotation)	17.84%	35.99%	48.69%	64.55%	86.87%

3.1.3. Descriptive statistics

Data from 115 surveyed students show an average age of 19.43, with a standard deviation of 2.48, and ages ranging from 16 to 34. The measured variables (Table 4) have mean values ranging from 3.339 to 3.649, with the highest score belonging to Performance Expectancy (PE) (3.649) and the lowest to Social Influence (SI) (3.339). The standard deviations of the variables range from 1.31 to 1.47, indicating that the scores are relatively tightly distributed around the mean.

Table 4. *The descriptive statistical analysis of the model variables*

Variable	Mean	Standard Deviation
PE	3.649	1.649
EE	3.583	1.402
SI	3.339	1.340
FC	3.626	1.330
Willingness to use GAI	3.435	1.313

3.1.4. Structural equation model (SEM)

The analysis results (Table 5) show that the model has a good fit, with indices such as $\chi^2/df = 2.41$, GFI = 0.87, CFI = 0.95, NFI = 0.93, TLI = 0.95, and RMSEA = 0.07. This indicates that the analysis model is acceptable.

Specifically, factors such as performance expectancy (PE), social influence (SI), and facilitating conditions (FC) all have a positive and significant impact on students' willingness to use GAI. The path coefficients (Table 6) are $\beta = -0.057$ for PE, $\beta = 0.159$ for SI, and $\beta = 0.528$ for FC. All these coefficients are statistically significant, indicating the influence of these factors on students' willingness to use GAI. However, the impact of effort expectancy (EE) on the willingness to use GAI has a coefficient of $\beta = 0.188$ but lacks clear statistical significance.

Table 5. *Model Fit*

Common Indicators	Evaluation Criterion (Acceptable)	Evaluation Criterion (Good)	Model Fit Value	Adaptation Judgment
χ^2/df	<5	<2	2.41	Accept

GFI	[0.7–0.9]	>0.9	0.87	Accept
CFI	[0.7–0.9]	>0.9	0.95	Accept
NFI	[0.7–0.9]	>0.9	0.93	Accept
TLI	[0.7–0.9]	>0.9	0.95	Accept
RMSEA	<0.08	<0.05	0.07	Accept

Table 6. *Hypothesis Test Results in the Model*

Hypothesis	Route	Normalised Path Coefficient	SE	C.R. Coefficient	P Value	Hypothetical Judgement
H1	PE → Willingness to use GAI	-0.057	0.077	2.933	0.003	Supported
H2	EE → Willingness to use GAI	0.188	0.057	-1.773	0.076	Not supported
H3	SI → Willingness to use GAI	0.159	0.076	4.827	0.0	Supported
H4	FC → Willingness to use GAI	0.528	0.065	2.916	0.004	Supported

3.1.5. Adjustment effect test

Based on the analyses conducted on the correlation between factors such as Age, Gender, and Learning Year with the willingness to use GAI, some preliminary conclusions are as follows:

Age (H5):

Table 7. *Interaction between Age and Independent Variables*

Interaction	Age 16-18 (t)	Age 16-18 (p)	Age 19-21 (t)	Age 19-21 (p)	Age > 21 (t)	Age >21 (p)	Hypothetical Judgement
PE	N/A	N/A	0.448	0.655	- 1.442	0.152	Not supported
EE	N/A	N/A	0.649	0.518	-1.560	0.122	Not supported
SI	N/A	N/A	1.574	0.118	0.143	0.887	Not supported
FC	N/A	N/A	1.090	0.278	0.831	0.408	Not supported

The relationship between age and the independent factors (PE, EE, SI, FC) (Table 7) shows that none of the factors reach statistical significance. This indicates that age does not have a significant impact on the willingness to use GAI.

Gender (H6):

Table 8. *Interaction between Gender and Independent Variables*

Interaction	Gender Male (t)	Gender Male (p)	Gender Female (t)	Gender Female (p)	Hypothetical Judgement
PE	N/A	N/A	-0.98	0.329	Not supported
EE	N/A	N/A	-1.56	0.122	Not supported
SI	N/A	N/A	-1.15	0.252	Not supported
FC	N/A	N/A	-2.00	0.048	Supported for females

The results (Table 8) show that gender moderates the influence of Facilitating Conditions on the willingness to use GAI, with female students demonstrating a stronger reliance on support and resources. This finding may suggest to educators and administrators that more targeted support should be provided to female students to encourage their adoption of GAI. For both genders, Performance Expectancy, Effort Expectancy, and Social Influence are not significant predictors, indicating that these factors do not have a major impact on the decision to use GAI in this context.

Learning Year (H7):

Table 9. *Interaction between Learning Year and Independent Variables*

Interaction	Year 2 (t)	Year 2 (p)	Year 3 (t)	Year 3 (p)	Hypothetical Judgement
PE	N/A	N/A	0.81	0.421	Not supported
EE	N/A	N/A	-0.24	0.808	Not supported
SI	N/A	N/A	-0.08	0.936	Not supported
FC	N/A	N/A	-0.54	0.593	Not supported

The results (Table 9) show that learning year does not play an important moderating role in the relationship between factors (PE, EE, SI, FC) and students' willingness to use GAI. This means that students in different learning years have a similar level of willingness to use GAI, regardless of their expectations regarding performance, effort, social influence, or available support.

3.2. Discussion

The survey results show that hypotheses H1, H3, and H4 were confirmed, indicating that performance expectancy (PE), social influence (SI), and facilitating conditions (FC) all have a positive and significant impact on IT students' willingness to use Generative Artificial Intelligence (GAI) in learning. This implies that students believe GAI can enhance their learning effectiveness and better support their professional skill development. These factors also affirm the important role of GAI in helping students access advanced technologies, thereby improving their programming skills and IT knowledge. Conversely, hypothesis H2 (effort expectancy) was not confirmed, suggesting that effort expectancy does not have a significant impact on the willingness to use GAI. This may be explained by the fact that students are already familiar with using technological tools, so they do not encounter many difficulties when approaching GAI. The average score for effort expectancy (EE) was also the lowest in the descriptive statistics, indicating that students expect GAI to be easy to use and not require too much effort to learn and apply. Hypotheses H5, H6, and H7 (related to age, gender, and learning year) were also not confirmed, except that female students showed a stronger reliance on support and resources. This indicates no significant differences among student groups in terms of age, gender, or learning year regarding the willingness to use GAI. However, educators and administrators should provide more targeted support for female students to encourage their adoption of GAI.

4. Conclusions

With the rapid development of Artificial Intelligence and related technologies, integrating GAI into education is an inevitable trend. Although the sample size was limited, especially the number of female students (9 participants), the research results emphasize that students' willingness to use GAI primarily depends on performance expectancy, social influence, and facilitating conditions. The willingness to use GAI not only helps improve students' learning outcomes but also plays a crucial role in the successful adoption of this technology in education. Educational institutions should continue investing in training programs, supporting students in accessing new technological tools, and encouraging innovation in teaching methods. This will create a supportive learning environment that enables students to access technology and provides the best conditions for students to develop and enhance their technical skills.

Conflict of Interest

The authors declare no conflict of interest

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