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Research Article

ChatGPT in Vietnamese math classrooms: What are the influencing factors behind teachers' adoption?

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In the context of the widespread integration of artificial intelligence (AI) technology into education, this study aims to understand the factors influencing Vietnamese mathematics teachers' adoption of ChatGPT in secondary school teaching. Based on the Unified Theory of Acceptance and Use of Technology model, the study uses a quantitative approach with data collected from 490 teachers. It applied the Partial Least Squares Structural Equation Modeling to examine factors influencing this adoption. The results indicate that Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Perceived Trust (PT) significantly affect teachers' Behavioral Intention (BI) to incorporate ChatGPT into their instruction. The study also examines the influence of moderator variables, such as geographic location and gender. While PE, SI, and PT significantly impact BI, no statistically significant differences were found between urban and rural teachers. In contrast, gender differences emerged: PE had a more substantial effect on females, SI influenced males and females differently, PT was significant only for males, and EE impacted only females. Most of these results align with existing research on AI adoption in education. To implement ChatGPT effectively, the study introduces a structured training program aimed at helping teachers integrate ChatGPT into their classrooms. Despite its theoretical and practical contributions, this study has certain limitations and suggests directions for future research. Further studies could incorporate qualitative methods to gain deeper insights, employ random sampling techniques with more extensive and diverse samples to enhance generalizability and explore additional constructs within the theoretical model to provide a more comprehensive understanding of AI adoption in education.

Keywords: Artificial Intelligence; Behavioral intention; ChatGPT; Generative AI; Mathematics teacher; Theory of acceptance

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1. Introduction

Digital transformation in education is taking place firmly worldwide, including in Vietnam. Among the many emerging technologies introduced into education, AI has attracted significant attention from education leaders, lecturers, and scholars. In particular, ChatGPT, introduced in November 2022, has promoted a wave of research and application of generative AI in teaching and learning. Generative AI is a subset of artificial intelligence technology that automatically generates content based on requests written in natural language (UNESCO, 2023). This technology predicts and creates data sequences based on user input, allowing for various creative and language-related tasks (Chan & Hu, 2023; Walczak & Cellary, 2023). Instead of simply scraping information from

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existing websites, generative AI creates new content in various formats (text, images, video, audio, and code). ChatGPT, a popular application of generative AI, has quickly become a vital resource, especially in education, due to its ability to customize learning experiences and assist teachers with routine tasks (Javaid et al., 2023).

Furthermore, ChatGPT can be a useful tool for teachers by helping with student assessments and offering personalized feedback. For this, it is a time-saving tool that lets teachers focus on improving their efficacy (Chaudhry & Kazim, 2022). ChatGPT can be used to develop intelligent tutoring systems, apply adaptive learning methodologies, and reduce teachers' workloads (Kabudi et al., 2021). Teachers can use ChatGPT to create customized learning activities for each student, provide thorough insights into their academic performance, and encourage growth in students' creativity and critical thinking (Anderson, 2023).

Despite its vast potential, AI—particularly ChatGPT—also brings significant challenges and concerns to the field of education. One major issue is the risk of AI misuse, which can impact academic integrity. Students may become overly reliant on AI tools to complete assignments, reducing analytical and creative thinking skills (Chaudhry et al., 2023). Additionally, AI's ability to generate misinformation raises questions about the reliability of the content students access for learning (Lo, 2023). The use of AI in education also introduces ethical and legal challenges. Privacy and data security concerns arise when AI collects and analyzes students' personal information. Legally, the lack of clear regulations surrounding AI has made its implementation complex and, at times, unsafe (Lozano & Fontao, 2023). Furthermore, AI may exacerbate educational inequalities if not deployed carefully, especially when certain groups of students lack access to this technology.

Teachers' attitudes play a crucial role in determining the effectiveness of AI applications in education. According to Siegle (2023), educators must establish clear guidelines and policies to ensure students use AI safely and responsibly. Simultaneously, teachers should monitor and guide students' use of ChatGPT, encouraging the development of critical thinking skills to help students assess AI-generated information. This underscores the need to study teachers' attitudes toward AI, particularly ChatGPT. Akgun and Greenhow (2022) note that many educators still lack adequate skills for integrating AI into their teaching practices, which can result in ineffective or harmful student applications. This gap can widen the digital skills divide between teachers and students, negatively impacting technology adoption in education (Kohnke et al., 2023). Teachers need appropriate digital skills to effectively deploy AI in the classroom to address these challenges, including designing AI-based learning tasks, personalizing lesson plans, and enhancing assessment methods. Additionally, teachers should adopt a positive attitude toward AI, recognizing it as a supportive tool rather than a threat to their roles. Qian et al. (2022) indicate that fostering positive attitudes among teachers can alleviate concerns about AI diminishing their value, thus encouraging them to embrace and leverage the potential of this technology in their teaching practices.

For these reasons, identifying the factors influencing teachers' behavioral intention to use ChatGPT is essential for improving their attitudes toward this technology. Behavioral intention has been a focal point in numerous prior studies, but few current studies have addressed this topic in teachers. Through exploring these factors, our study contributes essential insights for educational policymakers and stakeholders to develop support strategies and training programs that facilitate effective AI adoption and address teachers' concerns regarding ChatGPT's reliability and potential educational benefits. This paper aims to determine the factors influencing the behavioral intention to use ChatGPT among mathematics teachers in Vietnamese secondary schools.

2. Theoretical Framework: An Adapted Version of the UTAUT Model for the AI-driven Vietnamese Educational Context

According to the systematic review study by Kelly et al. (2023), three theoretical models commonly used to study the factors contributing to the acceptance of AI are the Technology acceptance model

[TAM], the Unified theory of acceptance and use of technology [UTAUT] and the AI device use acceptance model [AIDUA]. Among these three models, we choose the UTAUT model developed by Venkatesh et al. (2003) because it synthesized eight other popular theoretical models of acceptance of technology, including TAM, and has proven its value through many studies on this topic over a long period. Specifically in the case of ChatGPT (or, more broadly, chatbots), this model has been used in the study of Menon and Shilpa (2023) on Indian ChatGPT users, Rahim et al. (2022) on Malaysian postgraduate students.

In the traditional UTAUT model (Venkatesh et al., 2003), Behavioral Intention [BI] is influenced by four constructs: Performance Expectancy [PE], Effort Expectancy [EE], Social Influence [SI], and Facilitating Conditions [FC]. In this study, the constructs related to the technology chosen, specifically ChatGPT, and the subject of mathematics teachers are understood as follows.

BI refers to the degree to which an individual has formulated conscious plans to engage in a specific behavior—in this case, ChatGPT is used in teaching mathematics. Within the context of this study, BI captures Vietnamese mathematics teachers' willingness and readiness to adopt ChatGPT as an instructional tool. For instance, a teacher who incorporates ChatGPT into lesson plans or expresses clear intentions to utilize ChatGPT in future classes demonstrates a high level of BI. This construct is critical because it indicates potential actual usage, providing insight into how likely it is that teachers will integrate ChatGPT into their everyday teaching practices.

PE refers to the degree to which an individual believes using a particular technology will enhance their job performance. In the context of this study, PE reflects Vietnamese mathematics teachers' beliefs that integrating ChatGPT into their teaching practices will improve instructional effectiveness and student outcomes. This includes the perception that ChatGPT can assist in generating diverse mathematical problems, providing step-by-step solutions, and offering personalized learning support. For instance, a teacher who believes that ChatGPT can quickly produce tailored exercises for students with varying skill levels or automate the grading process is likelier to adopt the technology.

EE refers to the degree of ease associated with using a specific system. In this study, EE reflects the perceptions of Vietnamese mathematics teachers regarding the ease or intuitiveness of using ChatGPT for instructional purposes. This construct is particularly significant because teachers are more likely to adopt new technologies if they believe the system is user-friendly and requires minimal effort to learn and operate. For instance, a mathematics teacher who finds ChatGPT easy to navigate—such as entering problems in natural language and receiving clear, step-by-step solutions—may be more inclined to incorporate it into lesson planning and classroom activities. Additionally, accessing ChatGPT through familiar digital platforms, such as web browsers or mobile applications, further reduces the perceived burden complexity.

SI refers to the degree to which an individual believes that important others—such as colleagues, school administrators, or the wider educational community—think they should use a specific technology. In this study, SI reflects the impact of the surrounding social environment on Vietnamese mathematics teachers' decisions to adopt ChatGPT in their teaching practices. This influence can arise from professional networks, peer support, or institutional policies encouraging AI adoption in education. For example, when a mathematics teacher notices that colleagues successfully utilize ChatGPT to create personalized learning materials or that school leaders actively promote its use during professional development workshops, the teacher may feel more inclined to integrate the tool into their instruction.

FC represents the level of belief that an individual (in this case, a mathematics teacher) holds regarding the availability of organizational and technical infrastructure that supports the use of the system (ChatGPT). However, in this study, we have decided to exclude FC as a construct. This decision is based on the nature of ChatGPT, which is accessible through common web browsers and mobile devices and does not require specialized or extensive technical infrastructure for effective use in Vietnamese mathematics classrooms

Instead, we will include another construct mentioned in the systematic review by Kelly et al. (2023) regarding the factors influencing AI adoption, which is Perceived Trust [PT]. PT refers to teachers' perceptions of the reliability and integrity of ChatGPT. It encompasses their views on the overall dependability of ChatGPT as a tool for educational purposes (Walczak & Cellary, 2023). In this study, PT reflects the extent to which Vietnamese mathematics teachers believe that ChatGPT delivers accurate, unbiased, and ethically sound content that can be trusted for instructional support. For instance, a teacher may evaluate ChatGPT based on its capability to generate mathematically correct solutions and its alignment with established pedagogical practices. This evaluation impacts their willingness to use the tool and shapes their broader acceptance of AI-driven educational innovations. Incorporating PT into the theoretical model is essential because trust is a crucial factor influencing AI adoption. As concerns about reliability and ethical use continue to pose challenges for ChatGPT, integrating PT allows the model to better account for the unique aspects of AI technology in education, offering a more nuanced understanding of teachers' behavioral intentions. This construct highlights an important distinction in researching ChatGPT, as the reliability and integrity of the technology remain ongoing challenges

Drawing on an adapted version of the UTAUT model for the Vietnamese educational context, this study formulates four hypotheses to identify the determinants of mathematics teachers' BI to adopt ChatGPT. These hypotheses effectively convert the study's aim into a coherent framework that explores the diverse factors influencing the adoption of ChatGPT among Vietnamese mathematics teachers.

H1: PE positively influences BI.
H2: EE positively influences BI.
H3: SI positively influences BI.
H4: PT positively influences BI.

3. Method

This study used a quantitative approach to determine the factors influencing BI using the above theoretical model to test the proposed hypotheses.

3.1. Sample

3.3.1. Sampling method

According to Hair et al. (2022), determining the minimum sample size for PLS-SEM analysis can be guided by the 10-times rule, which recommends using a sample size at least ten times the largest number of structural paths leading to any latent variable in the model. In this study, the latent variable with the most structural paths has four incoming paths, requiring a minimum sample size of $10 \times 4 = 40$. However, to ensure robustness and account for potential data issues (e.g., missing data), we collected a sample size exceeding the minimum requirement to improve the reliability and validity of the results.

Since our study focused on in-service mathematics teachers working across multiple provinces, accessing a broad and diverse group of participants proved challenging. To tackle this, we employed a convenience sampling method, surveying secondary school mathematics teachers who participated in Artificial Intelligence training courses that we organized. Despite this approach, the sample retains a relatively high level of representativeness, as participants were drawn from 24 southern provinces of Vietnam. Additionally, the gender distribution and the urban/non-urban work environment ratios were approximately balanced (Table 1), further supporting the generalizability of our findings. On the other hand, due to the methodological requirements of a study examining factors influencing Behavioral Intention (BI), the surveyed issue must be a real social phenomenon. Therefore, we only selected teachers with prior experience using ChatGPT to ensure they understood the items in the questionnaire. Including teachers with no prior exposure to ChatGPT could have resulted in unreliable responses, as they might not have had a sufficient understanding of the tool's capabilities and limitations. A total of 490 valid teacher responses (average teaching experience: 16.1±0.4 years; SD: 8.8) were used for data processing and analysis.

Table 1
The demographics of the participants

Characteristic	*Frequency*	*Percentage (%)*
Gender		
Female	194	39.6
Male	296	60.4
Location		
Urban	239	48.8
Rural	200	40.8
Mountainous	39	8
Island	12	2.4
ChatGPT Usage Frequency		
Occasional	436	89
Frequent	54	11
Total	490	100

3.2. Data Collection

A 5-point Likert scale was used in the questionnaire design, providing a range of response options that facilitate categorization (Miller, 1956) and are consistent with methods for assessing behavioral psychology (Montano & Kasprzyk, 2015). Using this 5-point Likert scale, mathematics teachers were asked to rate from 1 to 5, indicating their level of agreement or perception regarding the factors affecting their behavior of ChatGPT usage, as explored in the survey.

The questionnaire consists of two main parts. Part 1 collects demographic information of participants, including Gender, Location of affiliation, and ChatGPT usage frequency. Part 2 includes a total of 24 items, including BI (4 items), PE (4 items), EE (5 items), SI (7 items) and PT (4 items). These items are taken from the questionnaire of Rahim et al. (2022). A researcher proficient in English and specialized in mathematics education adapted and translated items in the questionnaire. This initial adaptation was then thoroughly discussed in meetings with two other education experts to ensure the appropriateness and clarity of the items in the Vietnamese educational context. To validate the questionnaire further, we conducted a pilot test with 14 secondary school mathematics teachers. After the pilot, we interviewed these teachers for feedback on any items they found unclear or difficult to understand. Using their insights, we made the necessary revisions to improve the questionnaire's clarity and cultural relevance for Vietnamese teachers.

Participants' data were collected through an online survey supported by Google Forms from August 2023 to September 2024. All participating teachers will have prior experience interacting with ChatGPT. Moreover, all data in the survey had to be complete, with no missing values.

3.3. Data Analysis

3.3.1. Evaluation of the measurement model

This procedure aims to assess the reliability of the measurement scale using the Partial Least Squares [PLS] algorithm in SmartPLS software, focusing on three critical criteria: reliability, convergent validity, and discriminant validity (Henseler & Chin, 2010).

Model fit evaluation. The model's fit with the research data is assessed using the SRMR (standardized root mean square residual) index. According to Henseler et al. (2016), the SRMR measures the difference between the observed data and the predicted model, helping to prevent bias in parameter estimates. A model is considered a good fit if the SRMR value is below 0.08 (Hu & Bentler, 1998).

Reliability evaluation. The scale's internal consistency is evaluated through two main indicators: Cronbach's alpha [CRA] and composite reliability [CR]. Higher CRA values indicate greater internal consistency (DeVellis & Thorpe, 2022). Composite reliability ranges from 0 to 1, with acceptable values above 0.7 (Nunnally & Bernstein, 1994); however, in exploratory studies, values between 0.6 and 0.7 are also considered acceptable (Hair et al., 2022). The reliability of each observed indicator is assessed by its outer loading on the corresponding factor, with a minimum acceptable value of .7. Indicators with loadings between .4 and .7 may be considered for removal if doing so improves CR and the average variance extracted [AVE] (Hair et al., 2022).

Convergent validity evaluation. Convergent validity checks the extent to which indicators that measure the same construct are closely related (Kline, 2016). AVE should be at least 0.5 to confirm convergent validity (Fornell & Larcker, 1981).

Discriminant validity evaluation. Discriminant validity ensures that indicators for different constructs are not overly correlated. The PLS-SEM approach employs the HTMT (Heterotrait-Monotrait ratio) to assess discriminant validity. The HTMT ratio, calculated as the ratio of correlations between constructs to the internal correlation, should be less than 0.85 to confirm discriminant validity (Kline, 2016).

Multicollinearity detection. Multicollinearity is detected using the variance inflation factor [VIF]. A VIF value exceeding 10 indicates potential multicollinearity issues (Henseler et al., 2009).

3.3.2. Evaluation of the structural model

The structural model is evaluated to assess the relationships between the constructs and determine the impact and strength of independent variables on the dependent variable, including the role of any mediating variables. The evaluation criteria are as follows:

Coefficient of determination (R^2). The R^2 value measures the model's goodness of fit by indicating the proportion of variance in the dependent variable explained by the independent variables. Henseler et al. (2009) classify R^2 values as follows: 0.67 (strong), 0.33 (moderate), and 0.19 (weak). Meanwhile, Hair et al. (2022) suggest that an R^2 value of .25 reflects a weak endogenous construct, .5 is moderate, and .75 is high. In addition, the Q^2 statistic is used to assess the predictive relevance of the model for dependent variables, as Chin (2010) proposed. Hair et al. (2022) further classify predictive relevance based on Q^2 values: $Q^2 > 0$ indicates good predictive relevance; $Q^2 \approx 0.02$ shows weak predictive relevance; $Q^2 \approx 0.15$ indicates moderate predictive relevance; and $Q^2 \approx 0.35$ reflects predictive solid relevance. The f^2 statistic is used to evaluate the effect size of an independent variable on a dependent variable when adding or removing a specific variable. The effect size based on f^2 is categorized as follows: $f^2 \approx 0.02$ (small effect), $f^2 \approx 0.15$ (medium effect), and $f^2 \approx 0.35$ (significant effect).

Path coefficient. The path coefficient indicates the strength of the relationships between constructs, akin to the standardized beta coefficient in regression analysis. It offers empirical evidence of the theoretical relationships between latent variables. The coefficient sign represents the impact's direction: a positive (+) value indicates a direct positive effect, while a negative (-) value indicates an inverse effect.

***t*-value.** A *t*-value greater than 1.96 indicates that the relationship is statistically significant at the 5% level.

3.3.3. Bootstrap estimation test

The non-parametric bootstrap method is utilized in PLS path modeling to produce confidence intervals for all parameter estimates, thereby facilitating statistical inference (Henseler et al., 2009). This approach generates a bootstrap sample by randomly selecting cases with replacements from the original dataset. Each bootstrap sample undergoes PLS analysis, after which the resulting path coefficients are compiled into a bootstrap distribution, effectively approximating the sampling distribution of these estimates.

3.3.4. Distribution of the data

Although PLS-SEM is a non-parametric method that does not require the assumption of normal distribution (Hair et al., 2022), checking skewness and kurtosis values remains important to ensure data quality. According to Dash and Paul (2021), extreme skewness and kurtosis values can affect the reliability of bootstrap standard errors and path coefficient stability.

In this study, skewness and kurtosis values were assessed to confirm that the dataset does not exhibit extreme deviations from normality. Both the skewness and kurtosis values were within the acceptable range (below 2), indicating that the data distribution is sufficiently balanced to ensure robust bootstrapping results (Table 2).

Table 2
Distribution test for the research sample

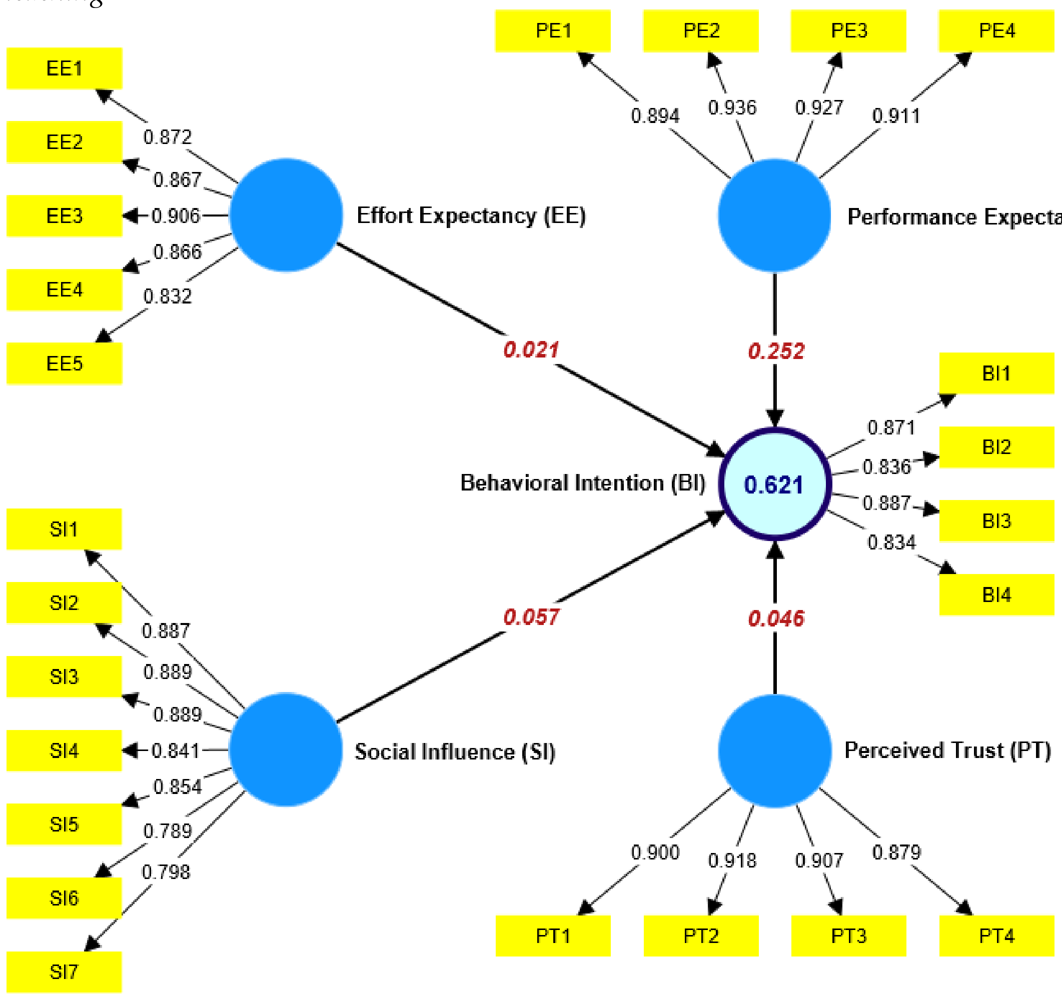
Scale	*Mean*	*Median*	*Standard Deviation*	*Skewness*	*Kurtosis*
BI1	3.778	4.000	0.870	0.960	−0.822
BI2	3.624	4.000	0.946	0.160	−0.608
BI3	3.873	4.000	0.910	1.076	−0.935
BI4	3.827	4.000	0.926	1.194	−1.010
EE1	3.869	4.000	0.864	0.998	−0.850
EE2	3.904	4.000	0.811	1.346	−0.881
EE3	3.957	4.000	0.823	1.908	−1.021
EE4	3.688	4.000	0.925	0.472	−0.692
EE5	3.751	4.000	0.903	0.635	−0.806
PE1	3.931	4.000	0.869	1.687	−1.065
PE2	3.896	4.000	0.885	1.250	−0.983
PE3	3.827	4.000	0.922	0.494	−0.732
PE4	3.957	4.000	0.852	1.533	−0.989
PT1	3.933	4.000	0.789	1.302	−0.807
PT2	4.008	4.000	0.767	1.963	−0.914
PT3	4.049	4.000	0.743	1.683	−0.826
PT4	4.041	4.000	0.744	1.888	−0.841
SI1	3.663	4.000	0.871	0.380	−0.500
SI2	3.686	4.000	0.859	0.456	−0.568
SI3	3.684	4.000	0.871	0.671	−0.621
SI4	3.747	4.000	0.881	0.760	−0.703
SI5	3.512	4.000	1.002	0.240	−0.698
SI6	3.590	4.000	0.982	0.157	−0.648
SI7	3.731	4.000	0.922	0.902	−0.898

4. Results

4.1. Estimation Model Evaluation

The reliability, convergent validity, and discriminant validity of the measurement model are assessed in the study. Figure 1 presents a structural equation modeling analysis of the measurement model, assessing the relationships between Effort Expectancy, Performance Expectancy, Social Influence, Perceived Trust, and Behavioral Intention. The model examines how these constructs influence BI, with factor loadings and path coefficients providing insights into the model's validity and reliability. The findings summarized in Figure 1 can be extended in the tables below. Table 3 presents the reliability and convergent validity of the scales.

Figure 1
PLS-SEM model of secondary school teachers' behavioral intention to use ChatGPT in Mathematics teaching



Note. R^2 values (in blue, bold); f^2 values (in red, italic); outer loadings (black, regular font)

Table 3
Reliability and convergent validity of the measurement scales

Scale	*Outer loading*	*CA*	*CR*	*AVE*
BI1	0.871	0.879	0.917	0.735
BI2	0.836			
BI3	0.887			
BI4	0.834			
EE1	0.872	0.919	0.939	0.755
EE2	0.867			
EE3	0.906			
EE4	0.866			
EE5	0.832			
PE1	0.894	0.923	0.945	0.812
PE2	0.936			
PE3	0.927			
PE4	0.911			
PT1	0.900	0.937	0.955	0.841
PT2	0.918			
PT3	0.907			
PT4	0.879			

Table 3 continued

Scale	*Outer loading*	*CA*	*CR*	*AVE*
SI1	0.887			
SI2	0.889			
SI3	0.889			
SI4	0.841	0.936	0.948	0.723
SI5	0.854			
SI6	0.789			
SI7	0.798			

The results of the tests presented in Table 3 indicate that all measurement scales demonstrate internal consistency. The outer loadings of the indicators are all greater than 0.7, with Cronbach's Alpha values for the factors ranging from .879 to .937 and Composite Reliability values ranging from .917 to .955, all exceeding the threshold of 0.7. The Average Variance Extracted values for the scales range from .723 to .841, which are also above 0.5, confirming that the constructs meet the requirements for convergent validity (see Table 4).

Table 4

Discriminant validity assessment using Fornell-Larcker criteria

Scale	*BI*	*EE*	*PT*	*PE*	*SI*
BI	**0.857**				
EE	0.609	**0.869**			
PT	0.585	0.580	**0.901**		
PE	0.713	0.564	0.508	**0.917**	
SI	0.665	0.668	0.576	0.625	**0.851**

Note. The diagonal elements (in bold) represent the square root of the AVE. Off-diagonal elements represent the correlations between constructs.

The analysis of discriminant validity for the scales in this study, as shown in Table 4, indicates that all indices exceed the correlation coefficients among the relevant constructs, thus meeting the Fornell-Larcker criteria for discriminant validity. All these coefficients are more significant than 0.8, demonstrating a clear distinction between the constructs. Additionally, the correlation coefficients among the constructs are all below 0.85, further confirming the discriminant validity of the measurement scales. Moreover, the HTMT (Heterotrait-Monotrait Ratio) index was employed for supplementary testing, revealing that all pairs of constructs have HTMT values ranging from 0.547 to 0.784, from below to approaching the threshold value of 0.85 (see Table 5). Therefore, all measurement scales adequately meet the criteria for discriminant validity, ensuring both reliability and validity within the research model.

Table 5

Discriminant validity assessment using the Heterotrait-Monotrait ratio

Scale	*BI*	*EE*	*PT*	*PE*	*SI*
BI					
EE	0.673				
PT	0.649	0.630			
PE	0.784	0.602	0.547		
SI	0.729	0.708	0.618	0.662	

4.2. Structural Model Evaluation

4.2.1. Testing for multicollinearity violations

Multicollinearity among independent variables may threaten the validity of path coefficients. The Variance Inflation Factor analysis results, as shown in Table 6, indicate potential multicollinearity among predictor variables; however, all VIF values fall within the acceptable range (VIF = 1.802–

2.277, all < 5). Additionally, a model is generally considered a good fit for the data when the Standardised Root Mean Square Residual [SRMR] is below 0.08. In this study, the SRMR value of 0.052 meets this criterion, affirming the model's suitability within the context of the study conducted in Vietnam.

Table 6
Results of the variance inflation factor

Measure	*EE*	*PT*	*PE*	*SI*
BI	2.09	1.716	1.802	2.277

4.2.2. R^2 and Q^2 coefficients

In PLS-SEM analysis, the structural model's explanatory power is assessed by the dependent variable's structural paths and the R^2 coefficient. A non-parametric analysis using bootstrapping with 5,000 iterations was conducted. The R^2 value 0.25 indicates a weak endogenous structure, 0.5 suggests moderate explanatory power, and 0.75 signifies strong explanatory capability (Hair et al., 2022).

Table 7
R^2 and Q^2 results

Measure	*R^2*	*Explanatory level*	*Q^2*	*Predictive level*
BI	.621	High	0.449	Strong

With an R^2 coefficient of .621 for the dependent variable BI, the results indicate that the research model explains a substantial 62.1% of the variance in teachers' behavioral intentions. This finding suggests that EE, PT, PE, and SI significantly influence teachers' decisions to use ChatGPT in their teaching practices. The Blindfolding method was employed, revealing that the Q^2 values for the dependent variables in the study are all greater than 0, indicating predictive solid capabilities and a high level of relevance for the dependent constructs within the model (Table 7).

4.2.3. Hypothesis testing

To determine if the path coefficients differ significantly from zero, *t*-values were calculated using a *bootstrapping* technique. It is essential to note that the significance level was set at 5% ($p < .05$). The evaluation of the research results was conducted through non-parametric Bootstrap analysis. Resampling is an effective strategy for validating the model in practice. Bootstrapping involves sampling with replacement and is employed in Partial Least Squares to provide confidence intervals for all parameter estimates, thereby forming a basis for statistical inference. This study performed non-parametric bootstrapping with n = 490 observations, repeating the process 5,000 times to satisfy the requirements for testing the structural equation model (see Table 8).

Table 8
Bootstrapping results for the structural model with direct effects

Hypothesis	*Relationship*	*Path coefficient (β)*	*p-value*	*Result*	*f^2*	*Effect level*
H1	PE → BI	0.415	<.001***	Supported	0.252	Medium
H2	EE → BI	0.128	<.05*	Supported	0.021	Small
H3	SI → BI	0.221	<.001***	Supported	0.057	Small
H4	PT → BI	0.173	<.001**	Supported	0.046	Small

Note. ***, **, and * denote statistical significance levels of 0.001, 0.01, and 0.05, respectively.

Table 8 summarises the results from the hypothesis testing using the bootstrapping process with 5,000 samples. The findings indicate that all hypotheses were supported at the 5% significance level. The structural model estimation results confirm that all accepted relationships had positive path coefficients, demonstrating direct positive effects on Behavioural Intention.

Among the tested factors, PE exhibited the most significant path coefficient (β = 0.415, $p < .001$), suggesting that teachers are more likely to use ChatGPT if they perceive it will enhance their performance. SI also showed a significant effect (β = 0.221, $p < .001$), indicating that encouragement from colleagues, leaders, or the teaching community may motivate teachers to adopt this new technology in their practices.

The analysis of f^2 values – which measure the effect size of each independent variable on the dependent variable – reveals that PE has the most significant effect on BI ($f^2 = 0.252$), classified as a medium effect. Other factors, including SI, PT, and EE, show small effect sizes with f^2 values of 0.057, 0.046, and 0.021, respectively. This underscores the importance of PE as a key factor in influencing teachers' intentions to adopt new technology, while the remaining factors play more supplementary roles.

Furthermore, Table 9 demonstrates the variability in the impact of various factors on BI when moderated by variables such as Location and Gender. These findings indicate that the influence of these factors could be more consistent; it varies significantly according to the specific moderating variables considered.The multi-group analysis provides nuanced insights into the varying impacts of EE, PT, PE, and SI on BI across demographic subgroups, specifically gender and location (urban vs. non-urban). When examining location as a moderating variable, the influence of PE on BI is significantly high in both urban ($p < .001$) and non-urban groups ($p = .008$). However, the effect is more substantial in urban respondents, as indicated by a higher (β = 0.480) compared to the non-urban group (β = 0.323). This finding implies that urban participants may be more motivated by the anticipated benefits of technology adoption. Additionally, PT demonstrates a more substantial impact on BI in non-urban areas (β = 0.246, $p = .006$) than in urban areas (β = 0.138, $p = .050$), suggesting that trust in technology plays a more critical role in influencing the intentions of non-urban users. SI also exhibits a considerable effect in both groups, with a higher impact in non-urban settings ($p = .002$) than urban (p = .013), further reinforcing that social factors are more influential outside urban centers. Meanwhile, the effect of EE on BI appears weaker across both groups, with non-significant p-values, suggesting that ease of use is not a primary driver for technology adoption across locations. The Welch-Satterthwaite test further corroborates these results, showing no significant differences ($p > .05$) between rural and urban settings regarding the key factors influencing BI. This finding reflects the homogeneity of AI-technology adoption across different regions of Vietnam.

Gender as a moderating variable reveals distinctive patterns in the impact of these factors on BI. PE significantly affects BI for both males (p = .001, β = 0.318) and females ($p < .001$, β = 0.554), with a notably higher impact on females. This finding suggests that women's behavioral intentions toward technology adoption are more strongly influenced by the anticipated performance benefits than men's. In contrast, SI has a more pronounced effect on BI for males ($p < .001$, β = 0.288) than for females ($p = .044$, β = 0.137), indicating that men may be more susceptible to social cues and expectations in forming their intentions. PT also shows a significant impact on males ($p = .002$, β = 0.226), with a weaker, non-significant effect on females ($p = .192$), highlighting that trust may be a more critical factor for men when considering technology adoption. EE shows a slight impact on females ($p = .036$). However, it does not significantly affect males ($p = .241$), suggesting that ease of use is more relevant to females in shaping their behavioral intentions.

5. Discussion

Some previous studies have investigated the factors that lead to users' acceptance of AI in education. However, most relevant studies have focused on higher education and learners. Information on in-service teachers is still very limited. Moreover, these factors are influenced by the differences in educational context and culture in which users live (Kelly et al., 2023; Tran & Nguyen, 2021). This study aimed to identify factors influencing Vietnamese mathematics teachers' behavioral intention/adoption of ChatGPT in teaching. The study provides necessary information

Table 9

Influence of Moderating Variables

Location	*Urban (N=239)*				*Non-Urban (N=251)*				*Difference*	
	β	*p-value*	*CI 2.5%*	*CI 97.5%*	*β*	*p-value*	*CI 2.5%*	*CI 97.5%*	*β*	*p-value**
PE → BI	0.480	<.001	0.315	0.608	0.323	.008	0.110	0.568	0.157	.272
EE → BI	0.146	.052	−0.019	0.280	0.074	.489	-0.133	0.283	0.072	.583
SI → BI	0.168	.013	0.046	0.312	0.288	.002	0.095	0.467	−0.120	.298
PT → BI	0.138	.050	0.019	0.293	0.246	.006	0.083	0.434	−0.108	.345
Gender	*Male (N=296)*				*Female (N=194)*				*Difference*	
	β	*p-value*	*CI 2.5%*	*CI 97.5%*	*β*	*p-value*	*CI 2.5%*	*CI 97.5%*	*β*	*p-value**
PE → BI	0.318	.001	0.147	0.529	0.554	<.001	0.436	0.664	−0.236	.040
EE → BI	0.101	.241	−0.069	0.272	0.163	.036	0.001	0.302	−0.062	.593
SI → BI	0.288	<.001	0.127	0.438	0.137	.044	0.013	0.278	0.151	.149
PT → BI	0.226	.002	0.094	0.379	0.088	.192	-0.045	0.218	0.138	.168

*Note. *: Welch-Satterthwaite test*

for stakeholders to make decisions and policies to quickly bring the advantages and potential of AI tools into education through its key agents, the teaching staff.

In our study, PE was the most influential factor, indicating that teachers were willing to apply ChatGPT when they believed this tool would improve the effectiveness of mathematics teaching. This result is similar to the study of Acquah et al. (2024), which found that when pre-service teachers believed that an AI chatbot named T-bots would improve the effectiveness of lesson planning, they were more likely to use it for this purpose. However, the influence of PE on this BI may not be consistent. Indeed, in two studies on factors influencing the acceptance and use of ChatGPT in higher education learning in Indonesia, both using the UTAUT2 model and the same PLS-SEM analysis procedures, this influence was statistically significant in the study of Habibi et al. (2023), but not statistically significant in the study of Habibi et al. (2024).

SI also significantly impacted BI, emphasizing the importance of encouragement and influence from colleagues and the educational community in motivating teachers to use new technology. This finding aligns well with earlier studies on the adoption of ChatGPT, such as Acquah et al. (2024) on pre-service teachers, Habibi et al. (2023, 2024), Lai et al. (2024) on university students. However, other studies also report no significant impact of SI on BI of AI usage of postgraduate students (Rahim et al., 2022) or junior high school to college learners (Valle et al., 2024). This difference suggests that the impact of SI may depend on many other factors, such as differences in jobs, culture, ages, and types of AI technology. Although there may be potential for conflicting results, this study showed that ChatGPT's social media influence and peer influence in teaching Mathematics can significantly promote teachers' BI.

The positive correlation between EE and BI that we found in this study is aligned with the study by Acquah et al. (2024) of chatbots supporting lesson planning for pre-service teachers. Although the correlation is modest, it may be attributed to how Vietnamese mathematics teachers interact with ChatGPT. As ChatGPT operates through natural language input, Vietnamese mathematics teachers can utilize their native language (Vietnamese) to communicate with the chatbot without the necessity of proficiency in English—a skill that is frequently lacking among Vietnamese teachers. This ease of communication diminishes the challenge of utilizing ChatGPT, potentially diminishing the overall impact of EE on BI. Habibi et al. (2023) found that EE did not significantly affect BI using ChatGPT among Indonesian students. The differences between the study subjects may explain this. Specifically, younger generations (students) may be more comfortable using emerging technologies than older generations (teachers).

For the factor PT that we added to the traditional UTAUT model, the positive relationship between PT and BI can be considered a characteristic of AI technologies, and in this case, ChatGPT. Our results are similar to the studies of Rahim et al. (2022) and Lai et al. (2024) on undergraduates. However, the positive impact of PT on BI may need to be considered through mediating and contextual factors. For example, in some cases where the benefits of ChatGPT are so significant that they outweigh concerns about risks, PT may no longer be a decisive factor. The study of Lai et al. (2024) also included the Perceived Risk factor but only found the influence of this factor on undergraduates' BI, but did not find a relationship between PT and this factor. The limited effect size of PT on BI in our study may be attributed to the survey context. During the data collection period (2023–2024), ChatGPT was a new technology, and Vietnamese teachers were in the early stages of exploring its capabilities. Although they were willing to engage with the chatbot, their understanding of its accuracy and reliability in facilitating mathematics instruction remained limited. This context may explain why PT had a minimal impact on BI in our findings.

The results showed that PE, EE, SI, and PT significantly affected BI. The results of this research corroborate the influence factors identified in the systematic review conducted by Kelly et al. (2023). However, some studies in other contexts reported different results. This raises the need for more research with different methods (e.g., qualitative research) in more contexts (especially for the purpose of using ChatGPT) to better understand the effects of these factors on BI among teachers. On the other hand, the study utilized a convenience sampling method. While the sample covers 24 provinces, its generalizability remains limited. Future studies could employ random sampling techniques and more prominent, more diverse samples, including teachers from different subject areas, to enhance the representativeness of findings. Additionally, to ensure the quality of our research, given the sample size (490 in-service mathematics teachers) and the use of a rigorous statistical analysis approach (PLS-SEM), we needed to limit the number of factors included in the theoretical model (PE, EE, SI, PT). Future research might consider additional constructs, such as Facilitating Conditions from the original UTAUT model (Venkatesh et al., 2003) or Perceived Risk and Moral Obligation (Lai et al., 2024).

In examining the implications of geographic location, our research indicated that the effects of PE, SI, and PT on BI were statistically significant. However, no statistically significant differences were discerned between urban and rural educators. This observation underscores the uniformity of technology adoption across various regions in Vietnam, a phenomenon largely attributable to the extensive digital infrastructure that permeates the nation. As reported by the Vietnamese Ministry of Information and Communications (2023), 78.6% of the Vietnamese population had access to the Internet as of 2022, with 87.8% of households connected. This broad connectivity has played a critical role in bridging the digital divide, enabling rural and urban teachers to effectively utilize and investigate AI-enhanced educational resources such as ChatGPT. Moreover, government initiatives to foster digital transformation within the educational sector have been pivotal in mitigating regional disparities. Implementing policies that include substantial investments in digital infrastructure, comprehensive teacher training programs, and strategies to elevate digital literacy have collectively ensured that rural educational institutions are not marginalized in embracing educational technologies. By equipping educators in rural areas with training and necessary resources, these initiatives have empowered them to cultivate the requisite skills and confidence to integrate AI tools effectively, thus promoting equitable access to technological advancements across the educational landscape.

Regarding the moderating variable "gender," our findings highlight several key differences: the impact of PE on BI was more substantial for females, SI influenced both males and females differently, PT had a significant effect on BI only for males, and EE affected BI only for females. These results suggest different approaches to enhancing BI across genders. To strengthen BI among male teachers, strategies should build trust through transparent communication about ChatGPT's reliability and benefits while leveraging social endorsements and normative influences. For female teachers, efforts should simplify the user experience and emphasize ChatGPT's practical ease and effectiveness in addressing their specific instructional needs.

6. Practical Implication

Identifying factors that influence behavioral intention in this study provides researchers with the basis to propose structured training programs to support teachers in effectively integrating ChatGPT into the classroom. These programs should be structured around key constructs from our study—PE, SI, EE, and PT—ensuring that training efforts address the primary factors involving teacher adoption. We suggest a short-term training program consisting of three interconnected modules, each aligning with the study's results (see Table 10). After short-term training programs, teachers still need continuous professional support and community engagement to leverage SI and ensure long-term adoption. Some of the initiatives that could be implemented include (1) establishing teacher support forums (online and in-person) where educators can discuss AI applications, troubleshoot challenges, and refine their use of ChatGPT; (2) promoting mentorship programs that pair experienced AI-using teachers with newcomers to build confidence and sustain AI adoption; and (3) developing long-term AI professional development plans, ensuring that training evolves alongside advancements in AI technology.

Table 10
A proposed short-term training program to support teachers in effectively integrating ChatGPT into the classroom

Module	*Content*	*Factor related to BI*
1. Foundations of ChatGPT and AI Literacy	Introduce the fundamentals of AI and ChatGPT, helping teachers develop confidence in using the tool.	EE
	Provide hands-on practice with ChatGPT to demonstrate how it enhances teaching efficiency and student engagement.	PE
	Showcase real-world use cases in mathematics education, such as generating problem sets, step-by-step solutions, and lesson structuring.	PE
2. Trust, Risk Management, and Ethical AI Use	Address concerns about AI reliability and data privacy and ensure teachers critically evaluate ChatGPT outputs (aligning with UNESCO's (2023) recommendations on AI ethics).	PT
	Provide strategies for fact-checking AI-generated content, identifying biases, and avoiding misinformation.	PT
	Establish institutional guidelines for responsible AI use, including student data protection and academic integrity measures.	PT
3. Classroom Integration and Pedagogical Strategies	Train teachers on integrating ChatGPT into instructional design, such as lesson planning, assessment creation, and real-time student support.	PE
	Encourage peer collaboration and social learning by forming teacher discussion groups where experiences and best practices are shared.	SI
	Incorporate micro-teaching sessions, allowing teachers to experiment with ChatGPT in controlled settings before applying it in full classrooms.	PE

By organizing the short-term training program and long-term support in this manner, we ensure that the factors influencing BI are consistently present and upheld. Specifically, EE is enhanced by reducing barriers to technology use through structured, hands-on training. PE is strengthened by illustrating ChatGPT's advantages for lesson planning, assessments, and student interaction. SI is utilized to encourage peer support and collaborative AI integration strategies. Through critical evaluation strategies, PT is reinforced by addressing risk management, ethical concerns, and reliability.

7. Conclusion

Based on the UTAUT model, applying the PLS-SEM analysis procedure, this study sheds light on the factors affecting Vietnamese mathematics teachers' behavioral intention to integrate ChatGPT into their teaching. The findings confirm that teachers' recognition of ChatGPT's potential to enhance teaching effectiveness, the value of encouragement from peers and the educational community, the ease of use, and trust in ChatGPT's reliability are supported for adoption intentions. These insights provide the basis for impact policies on teachers to effectively integrate ChatGPT into math teaching and encourage further research to explore other influence factors.

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Data availability: Data generated or analyzed during this study are available from the authors on request.

Ethical declaration: The authors declare that this research adheres to ethical standards, including participant consent, confidentiality, and accurate reporting of findings without plagiarism or data manipulation.

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