Pre-service Teachers' Attitudes and Behavioral Intention Towards Generative Artificial Intelligence: A Structural Equation Modeling Investigation Based on TAM

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Abstract: *This study uses the Technology Acceptance Model (TAM) to explore factors influencing pre-service teachers' intention to adopt generative artificial intelligence (GenAI). A total of 715 pre-service teachers participated in a questionnaire survey. Structural equation modeling was used to analyze the relationships among perceived ease of use (PEU), perceived usefulness (PU), attitude (ATT), and behavioral intention (BI). The results show that PEU positively affects PU, PU positively affects ATT, and ATT positively affects BI. Additionally, three significant mediating effects are identified. The findings provide valuable insights into the complex relationship between pre-service teachers' attitudes toward GenAI and their intention to adopt it.*

Keywords: Pre-service teachers, generative artificial intelligence, technology acceptance model

1. Introduction

Generative Artificial Intelligence (GenAI), with its transformative capabilities, has emerged as a powerful tool in education, offering personalized learning, enhanced teaching resources, and innovative assessment methods (Jauhiainen & Guerra, 2023). For pre-service teachers, understanding and adopting such technologies is crucial to preparing for digitally driven classrooms. The Technology Acceptance Model (TAM) serves as a valuable framework for exploring the factors influencing technology adoption, such as perceived ease of use, perceived utility, and attitude (Davis, 1989). Prior study examined teachers' knowledge, attitudes, usage, and acceptance of GenAI, concluding that most teachers can actively adapt to and learn to use this technology (Zhai, 2024), but did not delve deeply into the underlying mechanisms and influence pathways. To address the gap, this study investigates the relationships among pre-service teachers' perceived ease of use, perceived utility, attitudes, and behavioral intention towards GenAI through a TAM-based structural equation modeling approach. The findings provide actionable insights to into enhancing pre-service teachers' AI literacy.

2. Literature review

2.1. Generative AI in Education

GenAI refers to a category of AI systems that leverage advancements in generative modeling and deep learning to create diverse forms of content using pre-existing media such as text, images, audio, and video (Alier et al., 2024; Fernández-Llorca et al., 2024). A prominent example is ChatGPT, an intelligent chatbot developed by OpenAI and built on large language models (Chiu, 2023; OpenAI, 2023). GenAI can respond effectively to questions and generate relatively accurate results quickly, leading to its growing popularity in education (Alier et al., 2024). For pre-service teachers, the adoption of GenAI necessitates not only technical proficiency but also a positive attitude toward its utility and ease of use (Wang et al., 2024). Understanding these factors is critical to ensuring that GenAI is effectively integrated into teacher education programs.

2.2. The Technology Acceptance Model

TAM provides a robust framework for understanding individuals' acceptance of new technologies (Davis, 1989). TAM posits that perceived ease of use (PEU) and perceived utility (PU) are the primary determinants of users' attitudes toward technology, which in turn influence behavioral intention and actual usage. Over the years, TAM has been extensively applied in educational contexts to examine the adoption of learning management systems, mobile applications, and digital tools (Al-Adwan et al., 2023; Strzelecki, 2024). In the context of GenAI, TAM offers valuable insights into how pre-service teachers perceive and adopt this technology, particularly in understanding its potential to enhance teaching effectiveness and reduce workload. By leveraging TAM, this study aims to identify key factors influencing attitudes and behavioral intentions toward GenAI in teacher education.

2.3. Hypothesis Development

Based on the study by Scherer et al. (2019) on the TAM, this study proposes three hypothesis, displayed by Figure 1. Additionally, we also examined the indirect effects of PEU on ATT through PU and on BI through PU and ATT, as well as the indirect effect of PU on BI through ATT.

Hypothesis 1: Pre-service teachers' PEU will positively influence their PU.

Hypothesis 2: Pre-service teachers' PEU and PU will positively influence ATT toward GenAI.

Hypothesis 3: Pre-service teachers' PU and ATT will positively influence their BI toward GenAI.

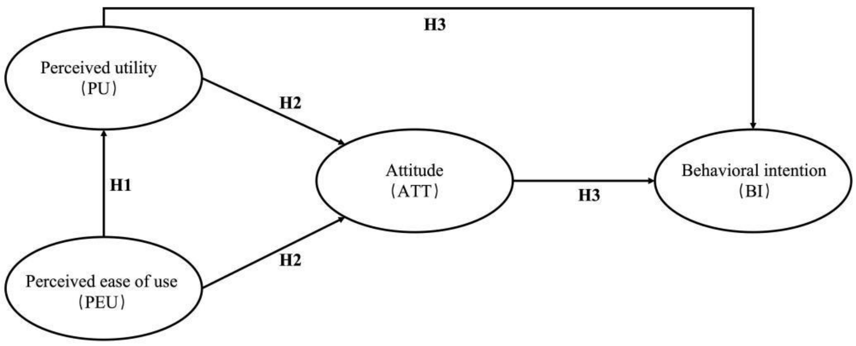

Fig.1 The hypothesized model of PU, PEU, ATT, and BI.

3. Methods

3.1. Participants and procedures

Between late September and early October 2023, this study surveyed pre-service teachers from six colleges and universities offering undergraduate teacher education programs in Guangdong Province, China. In this study, an electronic questionnaire was distributed to undergraduate teacher education students in these universities through social networks, and a total of 715 students voluntarily and anonymously participated in the survey. With "the sample must be teacher trainees" as the selection criterion, 616 valid samples were obtained. The samples cover a wide range of teacher education majors, including education, literature, history, political science, science, engineering, art, etc. The distribution of the samples is shown in Table 1.

Table 1. The gender, major, type of school, and year of study of the participants of the survey.

Variable	Values	n	%
Type of school	Double First-Class	432	70.10
	Other Universities	184	29.90
Gender	Male	103	16.70
	Female	513	83.30
Major	STEM	206	33.40
	Humanities and Social Sciences	410	66.60
Year of Study	Freshman	155	25.20
	Sophomore	175	28.40
	Junior	271	44.00
	Senior	15	2.40

3.2. Instruments

The questionnaire has five parts: the first part is demographic information, the experience of use, and university implementation, the second part is a perceived utility scale, the third part is a perceived ease of use scale, the fourth part is an attitude scale, and the fifth part is a behavioral intention scale. The second, third, fourth, and fifth parts are adapted from the scales related to teachers' acceptance and behavioral intention toward technology (Joo et al., 2018; Scherer & Siddiq, 2015). Perceived utility scale (3 items), perceived ease of use scale (4 items), and attitude scale (6 items) items were scored on a five-point Likert scale ranging from 1 (very non-conformant) to 5 (very conformant). The Cronbach's alpha coefficients were examined to account for the internal consistency of the instruments. The Behavioral Intention Scale (2 items) was scored using a yes/no question with yes and no options and corresponding scores of 1 and 0. Pearson correlation coefficients between the two questions were examined.

In this study, the alpha coefficients of the Perceived Ease of Use Scale (α = 0.84), Perceived Utility Scale (α = 0.87), and Attitude Scale (α = 0.95) were all higher than 0.70, and the Pearson's correlation coefficient for two questions of the Behavioral Intention Scale was 0.71. And the standardized factor loadings of all items were higher than 0.6, which supported the structural validity of the questionnaire. To measure convergent validity, the extracted average variance (AVE) and composite reliability (CR) values were tested against a minimum criterion of 0.5 and 0.7, respectively (Hair et al., 2010), and the AVE and CR values of all four factors exceeded these thresholds, and thus convergent validity was accepted. In addition, discriminant validity was assessed by comparing the square root of the AVE of the four factors with the inter-factor correlation coefficients.

3.3. Data analysis

The data analysis of this study consisted of three main stages. First, exploratory factor analysis (EFA) and validation factor analysis (CFA) were conducted to confirm the validity and reliability of the measurement scales. Second, descriptive statistical analyses, as well as analysis of variance (ANOVA), were conducted using SPSS to further understand the current status of GenAI knowledge, concepts, and behavioral intentions of the pre-service teacher population. For example, an independent samples t-test was used to examine the influence of factors such as gender, specialty, and experience of GenAI use, and one-way ANOVA was used to examine the influence of factors such as grade level, the status of GenAI-related learning activities carried out in the school, and the AI literacy-related requirements of the training program of their specialty. Finally, structural equation modeling was performed using the R language to examine the structural relationships among the variables in this study.

4. Results

4.1. Descriptive results

Perceived utility (M = 3.97, SD = 0.69) and attitude (M = 3.98, SD = 0.69) of pre-service teachers toward the educational application of GenAI were high, while perceived ease of use (M = 2.96, SD = 0.80) was low. In terms of behavioral intention, 77.30% of the pre-service teachers indicated that they would use GenAI for teacher education knowledge acquisition and 81.80% of the pre-service teachers indicated that they would use GenAI for teacher education skill enhancement.

The differences in PU, PEU, ATT, and BI of the pre-service teachers were analyzed in terms of gender, discipline, GenAI use, GenAI lectures offered by the school, and professional requirements. The results showed that there was a significant difference in pre-service teachers' PU in terms of GenAI use (p = 0.00), school offering GenAI lectures (p = 0.00), and professional requirements (p = 0.00), a significant difference in pre-service teachers' PEU in terms of GenAI use (p = 0.00), school offering GenAI lectures (p = 0.00), and professional requirements (p = 0.00), and a significant difference in pre-service teachers' ATT in terms of GenAI. Significant differences were found in pre-service teachers' ATT on GenAI use (p = 0.00), professional requirements (p = 0.02), and pre-service teachers' BI on GenAI use (p = 0.00), professional requirements (p = 0.00), and other than that, no other significant differences were found.

4.2. Structural model

Structural equation modeling (SEM) was utilized to examine the structural relationships among the variables. First, the model fit was examined. As shown in Table 2, this model has a still good fit with χ^2 = 1263.21, df = 360, χ^2/df = 3.51 < 5 (Kang & Ahn, 2021), root mean square error of approximation (RMSEA) = 0.06 < 0.08 (MacCallum et al., 1996), tucker-lewis index (TLI) = 0.92 > 0.9 (Hu & Bentler, 1999), comparative fit index (CFI) = 0.93 > 0.9 (Hu & Bentler, 1999).

Next, a path analysis was conducted. Figure 2 shows that pre-service teachers' PEU positively predicted PU; PU positively predicted ATT; PEU did not positively predict ATT; PU did not positively predict BI; and ATT positively predicted BI. Table 3 displays the results of the tests of the three hypothesis. Since PU had a positive effect on PEU (β = 0.36, p < 0.001), H1 was accepted. Since PU had a positive effect on ATT (β = 0.69, p < 0.001) and PEU did not predict ATT (β = -0.03, p > 0.05), H2 was partially accepted. Since ATT had a positive effect on BI (β = 0.35, p < 0.001), PU did not predict BI (β = 0.07, p > 0.05) and H3 was partially accepted. In total, the model explained 44.1% ATT variance and 19.5% BI variance.

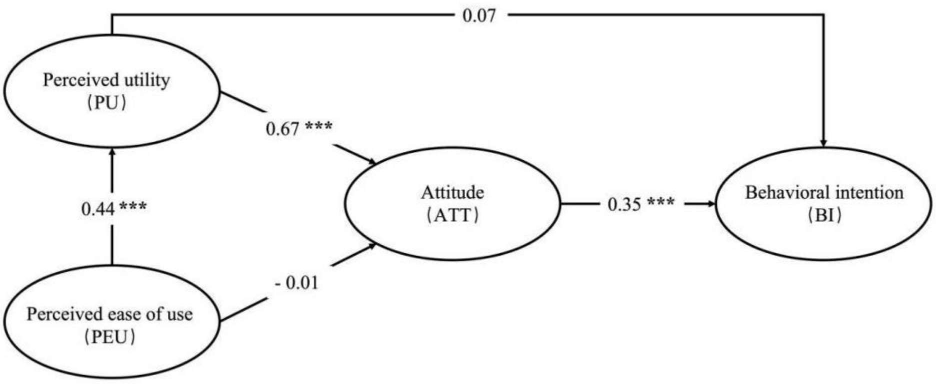

Fig.2 TAM of pre-service teachers' attitude towards GenAI.

Table 2. Model fitting analysis results.

Fitting index	χ^2	df	χ^2/df	RMSEA	TLI	CFI
Acceptable value	-	-	< 5	< 0.08	> 0.9	> 0.9
Results	491.55	144	3.41	0.06	0.94	0.95

Table 3. The results of hypothesis testing.

Hypothesis	Path	β	Supported?
H1	PEU → PU	0.44***	Yes
H2	PU → ATT	0.67***	Partially Supported
	PEU → ATT	-0.01	
H3	PU → BI	0.07	Partially Supported
	ATT → BI	0.35***	

Note. *p < 0.05, **p < 0.01, ***p < 0.001.

Table 4. The results of mediation effect test.

Path	Indirect effect	Lower bound	Upper bound
PEU → PU → ATT	0.29***	0.22	0.36
PU → ATT → BI	0.06***	0.04	0.09
PEU → ATT → BI	0.12***	0.08	0.16

Note. *p < 0.05, **p < 0.01, ***p < 0.001.

Finally, mediation effects were tested. Because the direct effects of PEU on ATT and PU on BI were not significant, the mediation effects involving these paths were not tested. Table 4 displays the mediation effect and 95% bootstrapped confidence intervals. PEU → PU → ATT indirect effect path is calculated as 0.29, and the lower limit and upper limit are 0.22 and 0.36 respectively. The statistical significance of this indirect effect is very robust ($P < 0.001$). The indirect effect path of PU → ATT → BI is calculated as 0.06, and the lower limit and upper limit are 0.04 and 0.09 respectively. The statistical significance of this indirect effect is very robust ($P < 0.001$). PEU → ATT → BI indirect effect path is calculated as 0.12, the lower limit and upper limit are 0.08 and 0.16 respectively. The statistical significance of this indirect effect is very robust ($P<0.001$).

5. Discussion and Conclusion

This study applied the Technology Acceptance Model (TAM) to explore pre-service teachers' views on generative AI (GenAI) and its potential impact on their behavioral intentions to adopt it. The results reveal important insights regarding the factors that influence pre-service teachers' attitudes and behavioral intentions toward GenAI.

First, the study found that PEU of GenAI positively influenced its PU. This is consistent with the findings of Joo et al. (2018), suggesting that when pre-service teachers find GenAI easy to use and intuitive, they are more likely to perceive it as useful in educational contexts. The improved ease of use helps reduce technology-related anxiety, allowing pre-service teachers to focus more on the educational benefits of the technology (Wang et al., 2024).

Second, PU of GenAI positively influenced pre-service teachers' ATT toward it. This implies that when pre-service teachers recognize the practical advantages GenAI offers in enhancing their teaching practices, they develop a more favorable attitude toward using it.

Third, the study also highlighted that the PU did not have a direct effect on BI. Instead, it influenced BI indirectly through ATT. This suggests that while pre-service teachers may acknowledge the usefulness of GenAI, their actual intention to adopt it is primarily shaped by their attitudes. The complexity and newness of GenAI might hinder pre-service teachers from fully realizing its potential, which in turn affects their motivation to adopt the technology (Lan et al., 2024). This emphasizes the importance of shaping positive attitudes toward GenAI, as attitudes serve as a key mediator between perceived usefulness and behavioral intention.

Additionally, the mediating effects of PEU, PU, and ATT on BI were explored. The analysis revealed significant indirect effects for the pathways PEU → PU → ATT, PEU → ATT → BI, and PU → ATT → BI. Among these, the indirect effect of PEU → PU → ATT was the strongest, suggesting that improving the ease of use of GenAI can significantly enhance pre-service teachers' perceptions of its usefulness and, consequently, their attitudes toward using it.

Moreover, the indirect effect of PU → ATT → BI, though smaller, was still statistically significant. This indicates that positive attitudes play a crucial role in translating the perceived usefulness of GenAI into actual behavioral intentions. These results contradict the findings of Ramnarain et al. (2024), who concluded that pre-service teachers' attention to GenAI has no significant effect on their intention to use it. On the contrary, the conclusion of this study proves that pre-service teacher training should pay attention to the introduction and promotion of new technology, so as to cultivate the identification and positive attitude towards technology, after all, attitude is the key intermediary for the adoption of new educational technology.

In conclusion, the findings suggest that integrating GenAI into teacher education programs requires not only focusing on its perceived ease of use and usefulness but also actively fostering positive attitudes among pre-service teachers. Educational institutions and teacher training programs should aim to reduce technology anxiety, offer hands-on experiences, and provide real-world examples of successful GenAI applications in educational contexts (Blonder et al., 2024). By addressing these aspects, pre-service teachers' behavioral intentions to adopt GenAI can be enhanced, ultimately enriching the teaching and learning experience.

6. Limitation

Despite the study's contributions, limitations must be acknowledged. First, the sample was limited to pre-service teachers, potentially constraining the generalizability of the findings to in-service teachers. Future studies could include diverse participant groups across different educational contexts to provide a more comprehensive perspective. Second, this study did not explore other potential factors, such as cognitive load or ethical concerns, that might influence attitudes and intentions toward GenAI. Future research could investigate these factors and their interplay with TAM constructs.

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