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Research article

Pre-service teachers' technology acceptance of artificial intelligence (AI) applications in education

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Abstract: We verified a pre-service teachers' Extended Technology Acceptance Model (ETAM) for AI application use in education. Partial least squares structural equation modeling (PLS-SEM) examined data from 400 pre-service teachers in Central Visayas, Philippines. Perceived usefulness and attitudes, usefulness and attitudes, ease of use and attitudes, and intention to use AI apps were significantly correlated. However, subjective norms, experience, and voluntariness did not affect how valuable AI was viewed or intended to be used. Attitudes toward AI mediated specific correlations use. These findings improve the ETAM model and highlight the significance of user-friendly AI interfaces, educational activities highlighting AI's benefits, and institutional support to enhance pre-service teachers' adoption of AI applications in education. Despite its limitations, this study establishes the foundation for further research on AI adoption in educational settings.

Keywords: artificial intelligence, education, partial least squares structural equation modeling, pre-service teachers, technology acceptance

1. Introduction

Artificial intelligence (AI) applications have become more important in education because of their potential to revolutionize conventional approaches to teaching and learning [1–3]. These applications allow personalized learning experiences, adaptive training, automated assessment, and data-driven decision-making processes [4–6]. Teachers can more effectively identify learning gaps, customize training to each student's needs, and provide timely feedback using AI technology [7–9]. Additionally, AI-powered solutions can foster collaborative learning settings and help create interesting instructional content [10,11]. Given these possible advantages, it is essential to investigate pre-service teachers' adoption of AI applications to determine whether or not they are prepared to use these tools in the classroom.

However, integrating AI into education also brings up some issues and difficulties that must be carefully considered [12,13]. The major concerns surrounding adopting AI technologies in educational settings are privacy and security issues related to collecting and using student data, ethical implications of algorithmic decision-making, and the potential for bias reinforcement [14–16]. Furthermore, there are apprehensions about AI's impact on teachers' roles, including fears of job displacement and the erosion of human-centered teaching practices [17,18]. Addressing these challenges requires a nuanced understanding of the factors influencing teachers' acceptance and adoption of AI applications.

Many theoretical frameworks that provide distinct insights into the adoption process have been put forth to explain why people accept technology [19–21]. To comprehend consumers' attitudes and behaviors about technology adoption, Davis [19] developed the Technology Acceptance Model (TAM), which has been widely used since [19–21]. According to TAM, consumers' intentions to utilize technology are determined mainly by its perceived usefulness and ease of use. Enhancing upon the TAM, the Extended TAM (ETAM) integrates extraneous elements, including subjective norms, attitudes toward technology, and behavioral intention, offering a more all-encompassing understanding of technology adoption behavior [22].

The ETAM, among other theoretical frameworks, provides a robust framework for analyzing the adoption of AI applications in education [19–21]. According to Davis [19], perceived usefulness is the extent to which people think technology will improve their productivity or effectiveness at work. The degree to which people believe technology is simple to use and understand is reflected in its perceived ease of use. People's opinions and sentiments on using a specific technology are included in their attitudes. According to Ajzen [21], subjective norms consider how social influences, including peer pressure or organizational expectations, affect people's intentions to utilize technology. As a crucial predictor of actual usage behavior, intention to use reflects people's readiness and willingness to adopt a technology [19].

However, the possible moderating impacts of people's technological experiences and their willingness to adopt AI apps have yet to be explored well in research that employs the ETAM paradigm [19,22]. People's opinions and attitudes about adopting AI can be influenced by their technological experiences, mainly if they have previously used AI tools or comparable educational technologies. Similarly, voluntariness represents people's independence and decision to accept or reject a technology, which may impact their acceptance behavior. Not considering these moderating factors could reduce the ETAM framework's capacity for explanation and cause significant subtleties in technology acceptance behavior to go unnoticed [19].

These deficiencies in the ETAM framework must be addressed to understand better pre-service teachers' adoption of AI applications in education. A significant gap exists in integrating pedagogical connections, purpose, rationality, and support in designing and implementing AI in education contexts, as highlighted by Díaz and Nussbaum [23] and Rahm and Rahm-Skågeby [24]. Researchers can better understand the intricate relationship between individual traits and accepting behavior by considering the moderating effects of experiences and voluntariness. Using the extended TAM framework, we examined pre-service teachers' adoption of AI applications, paying particular attention to their experiences and willingness to serve as moderators. By looking at these factors, the researchers hoped to offer information to help develop and apply AI technologies in educational environments, eventually improving teaching and learning outcomes.

1.1. Research questions

We investigated the technology acceptance by preservice teachers regarding AI applications in education. Specifically, we answered the following questions:

1. How valid is the technology acceptance model of AI application use in education among preservice teachers?
2. Do significant relationships occur in the structural model of the technology acceptance of AI application use in education?
3. Do experience and voluntariness significantly moderate pertinent relationships in the structural model?
4. Do perceived usefulness and attitudes mediate relevant relationships in the structural model?

1.2. Construct definitions

Within the framework of the ETAM, perceived usefulness, ease of use, attitudes toward technology, and intention to use are critical to understanding people's adoption of technology [25,26]. This model acknowledges the significance of moderators like voluntariness and experience, which affect how these variables and users' acceptance behavior relate [27]. Research on people's acceptance of AI in education has shed important light on the different elements impacting people's willingness to use AI-driven solutions. These researchers identified numerous vital aspects influencing people's acceptance behaviors, including perceived usefulness, ease of use, attitudes toward technology, intention to use, experience, and voluntariness, as presented in Figure 1.

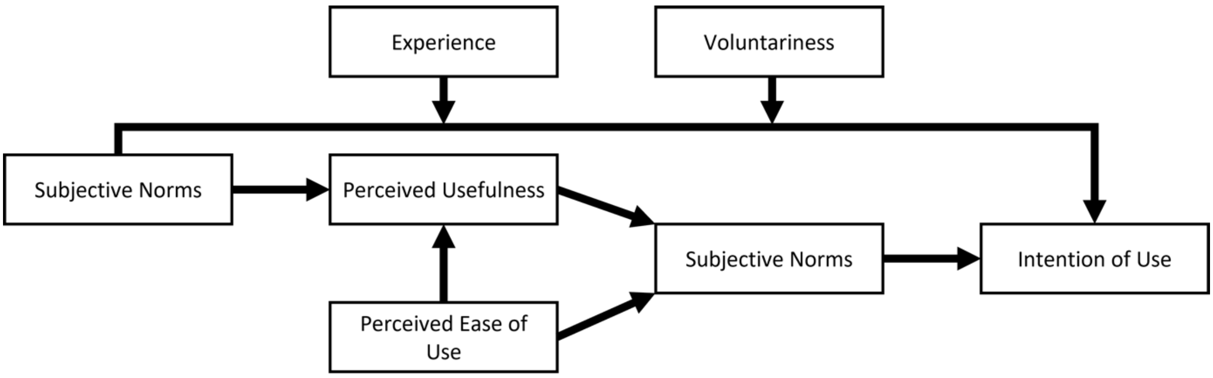

Figure 1. Constructs in the ETAM.

Perceived Usefulness. The degree to which a person feels that utilizing a given technology would improve their overall efficacy in reaching particular goals, productivity, or job performance is known as perceived usefulness [19]. It expresses how the user views the advantages and uses that technology offers. According to studies by Zhang et al. [28] and Ofosu-Ampong et al. [29], perceived usefulness is the term used to describe people's opinions of the advantages and benefits of AI applications in education. People are more inclined to accept AI technologies as essential teaching methods when they believe they can improve teaching and learning results. Suppose an AI-powered learning management system assists in more accurately identifying students' learning gaps, enabling individualized instruction and enhancing overall learning outcomes. In that case, a teacher may view it as beneficial in an educational context [30].

Perceived Ease of Use: Perceived ease of use refers to the degree to which a person believes a technology is simple to operate and comprehend [19]. It includes system complexity, user interface design, and the learning curve related to technology use. According to research by Al Darayseh [31] and Esiyok et al. [32], perceived ease of use refers to how accessible and user-friendly people believe AI-driven educational platforms and applications to be. People are more likely to integrate these technologies into their teaching or learning routines when they are user-friendly, with simple interfaces and functionalities. If users find technology easy to use, intuitive, and manageable, they are more likely to accept it. If AI-powered educational technologies are easy to use, do not require much training, and fit in well with current teaching methods, teachers might be more likely to embrace them [33].

Attitudes toward Technology: People's opinions and sentiments on using a particular technology are reflected in their attitudes [19]. Subjective assessments of the technology's perceived advantages, challenges, and general desirability are included. Users who have positive attitudes toward technology are more likely to be willing to accept it. In contrast, those with negative attitudes are more likely to oppose or be reluctant to do so [34]. Research by Al Darayseh [31] and Saqr et al. [35] examines attitudes toward technology, which include people's general thoughts, sentiments, and opinions regarding artificial intelligence in the classroom. Negative attitudes may hamper adoption attempts, but based on views of utility and simplicity of use, positive attitudes contribute to increased acceptance and readiness to interact with AI-driven applications. For example, teachers with positive attitudes regarding AI in education might see it as a way to improve student learning results. In contrast, teachers with negative attitudes might see it as a danger to their independence or job security.

Intention to Use: According to Davis [19], intention to use describes a person's preparedness and willingness to integrate technology into their daily activities or place of employment. It is a significant indicator of the actual usage behavior and is impacted by views about technology, perceived utility, and ease of use. While low intention to use denotes potential barriers or difficulties to acceptance, high intention to use indicates a substantial possibility of adoption [36]. As Zhang et al. [28] and Esiyok et al. [32] examined, intention to use reflects individuals' plans and readiness to integrate AI tools into their educational practices. Strong intentions to use AI, driven by perceived usefulness and ease of use, indicate a higher likelihood of adoption and implementation in academic settings. A teacher's intention to employ AI apps in the classroom may be influenced by how they believe these tools enhance their instructional strategies and help students learn more effectively.

Experience: According to Venkatesh [26], experience with technology refers to a person's past exposure to, knowledge of, and skill with related tools or similar technologies. Their attitudes, opinions, and comfort levels when embracing new technologies are shaped by it. According to research by Nja et al. [37] and Wu et al. [38], experience is a significant factor in determining how people accept things. People's opinions and comfort levels about AI technology and related educational tools might be influenced by their past experiences with them, which can eventually impact their readiness to accept AI in academic settings.

Voluntariness: The degree to which people are willing to employ technology reflects their autonomy and decision-making [27]. It considers how much users feel forced or obliged to utilize technology, whether due to internal (like personal interest or curiosity) or external reasons (such as organizational demands). When users feel that adopting a technology is a choice rather than an obligation, they are more inclined to accept and embrace it [26]. Although it is implied in research, voluntariness emphasizes how important it is for people to have agency and autonomy over whether or not to use AI-driven tools in the classroom. People are more committed to incorporating these technologies into their teaching or learning contexts and feel more empowered to decide how AI is used. In contrast to those who believe AI adoption is required or coerced, teachers who feel empowered to investigate and experiment with AI technologies at their discretion are more likely to display positive acceptance behaviors [30].

ETAM offers a thorough framework for comprehending users' adoption of technology. This framework considers perceived usefulness, ease of use, attitudes toward technology, and intention to use. The correlations between these categories may be influenced by moderators like voluntariness and experience, which provide essential insights into the nuances of technology adoption behavior in various situations, including education.

1.3. Statement of hypotheses

We examined the pre-service teachers' technology acceptance of AI applications in education. To answer the study's purpose, the following hypotheses were formulated:

- H_1: Subjective norms significantly influence the perceived usefulness of AI applications in education.
- H_2: Perceived ease of use significantly influences the perceived usefulness of AI applications in education.
- H_3: Perceived usefulness significantly influences the attitudes toward AI applications in education.
- H_4: Perceived ease of use significantly influences attitudes toward AI applications in education.
- H_5: Perceived usefulness significantly influences the pre-service teachers' intention to use AI applications in education.
- H_6: Attitudes toward AI applications significantly influence the pre-service teachers' intention to use them in education.
- H_7: Subjective norms significantly influence the pre-service teachers' intention to use AI applications in education.
- H_8: Experience significantly moderates the influence of subjective norms on the perceived usefulness of AI applications in education.
- H_9: Experience significantly moderates the influence of subjective norms on the intention to use AI applications in education.

H_{10}: Voluntariness significantly moderates the influence of subjective norms on the intention to use AI applications in education.

H_{11}: Voluntariness significantly moderates the influence of perceived usefulness on the intention to use AI applications in education.

H_{12}: Perceived usefulness significantly mediates between subjective norms and intention to use AI applications in education.

H_{13}: Perceived usefulness significantly mediates between perceived ease of use and intention to use AI applications in education.

H_{14}: Attitudes toward AI applications significantly mediate between perceived ease of use and intention to use them in education.

H_{15}: Attitudes toward AI applications significantly mediate between perceived usefulness and intention to use them in education.

H_{16}: Perceived usefulness and attitudes toward AI applications significantly mediate between subjective norms and intention to use them in education.

1.4. Proposed model of the study

The study proposed the model of the study as reflected in Figure 2.

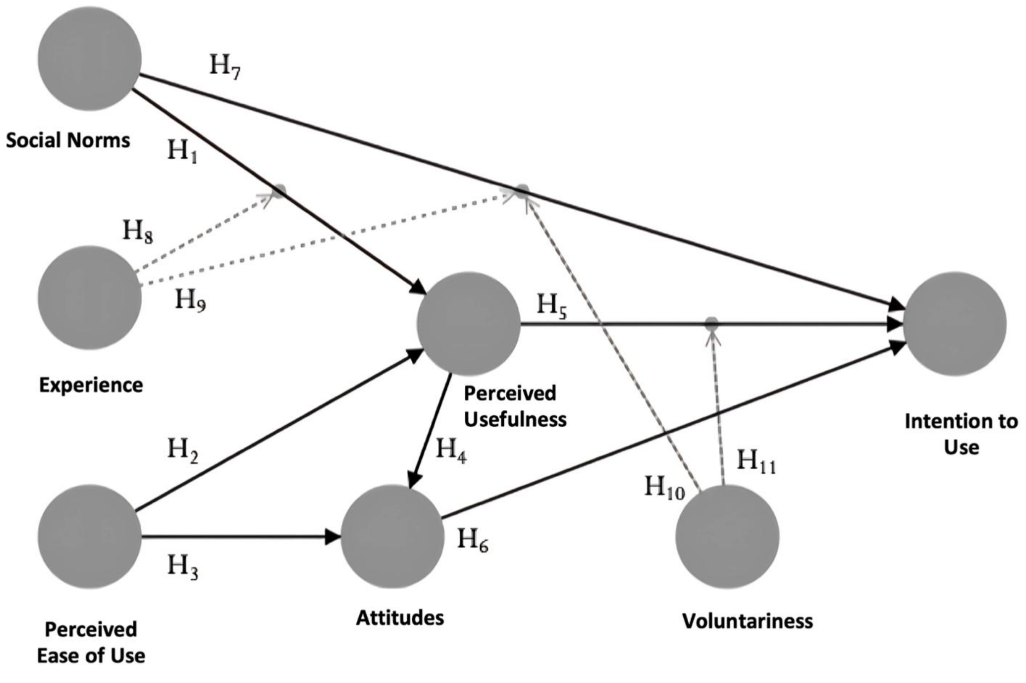

Figure 2. Proposed model of the study.

The proposed model for pre-service teachers' acceptance of AI applications in education incorporated subjective norms impacting perceived usefulness and ease of use, influencing perceived usefulness and attitudes toward AI applications. It proposed that attitudes, perceived usefulness, and subjective norms influence the intention to use AI applications in education. Furthermore, voluntariness and experience both moderate the effects of subjective norms on intention to use and perceived usefulness on intention to use. Subjective norms also impact intention to use, although voluntariness moderates the effects of subjective norms on intention to use.

2. Methodology

2.1. Research context

The study was conducted in state universities in Central Visayas, Philippines. These government-run universities house centers of development and excellence in teacher education, offering teacher preparation programs such as early childhood, special needs, elementary, secondary (English, Filipino, Mathematics, Science, Social Studies, and Values Education), physical, cultural and arts, and technology livelihood education, among others. In these programs, the preservice teachers are exposed to outcomes-based and technology-integrated courses, facilitating them to be prepared and ready for their in-service in their future careers as licensed professional teachers. With technology integration, these preservice teachers have used tools such as Microsoft Office, Google Suite, web-based applications, and AI applications to create academic outputs like images, videos, audio, presentations, and documents. These AI applications include Microsoft Designer, Canva, CapCut, Smallppt, and Remove.bg, AdobePodcaster, Vidnoz, NoteGPT, ElevenLabs.io, Quillbot, Grammarly, ChatGPT, and Gemini, among others, have aided them in their professional education courses, specialization subjects, and even online teaching internships. As in the education hub of the country, these preservice teachers are exposed to a uniform curriculum for teacher-training programs, guaranteeing that they have comparable experience regarding the use of technology in their studies, including the abovementioned AI-aided tools. With this, all the participants have sufficient exposure to these technologies throughout their training, ensuring the research outcomes are valid and consistent.

2.2. Participants

Pre-service teachers from state universities in Central Visayas, Philippines, participated in the study. They were selected through purposive sampling and met specific inclusion criteria: They must be pre-service teachers enrolled in state universities in the said region and have prior experience using AI applications in education during the last semesters. With these criteria, the results obtained from the participants were meaningful, as the data aligned with the study's focus. Five hundred ninety-seven preservice teachers were sent the online questionnaire, and 423 teachers responded via Google Forms. Data were cleaned by removing incomplete responses with missing critical values, excluding outliers, and eliminating cases with inconsistent data, eliminating 23 participants from the dataset. After this thorough data cleaning, only four hundred pre-service teachers remained and became part of the study. This sample is significantly more than the minimum size of 223, calculated with 0.80 statistical power, seven latent variables, and 20 observed variables using an apriori sample size calculator for structural equation models by Free Statistics Calculators, version 4.0 [41]. The sample size adheres to the recommended sample size in partial least squares structural equation modeling (PLS-SEM) [39]. The demographic profile of the study participants is presented in Table 1.

Based on Table 1, most participants were over 20, with the largest age group comprising those 22 years old (41%), female pre-service teachers making up 82% of the participants, making up the majority. The distribution of the year level was pretty even over the four years, with the highest representation occurring in the second year (32%). Participants' socioeconomic status varied, but most (62%) stated that their family income was below Php 10,957. Last, the school profile revealed that a slight majority of participants were from urban locales (65%).

Table 1. Demographic profile of the participants.

Profile	Category	Frequency	Percentage
Age	Below 20 years old	40	10.00%
	20 years old	116	29.00%
	21 years old	56	14.00%
	22 years old	164	41.00%
	Above 22 years old	24	6.00%
Sex	Male	72	18.00%
	Female	328	82.00%
Year Level	First Year	44	11.00%
	Second Year	128	32.00%
	Third Year	124	31.00%
	Fourth Year	104	26.00%
Socio-economic Status	Below Php 10,957	248	62.00%
	Php 10,957-Php 21,914	100	25.00%
	Above Php 21,914	52	13.00%
School Locale	Rural	140	35.00%
	Urban	260	65.00%

2.3. Instrument

The researchers employed a 20-item five-point Likert scale questionnaire to assess the pre-service teacher participants' technology acceptance of AI applications in education. The items were derived from various studies related to ETAM, comprising six sections. These sections include subjective norms (SN), perceived usefulness (PU), perceived ease of use (PEU), attitudes toward technology (ATT), intention to use (IU), experience (E), and voluntariness (V). These are presented in Table 2.

With Smart PLS software, version 4.0.9.8, the study used Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the data obtained using the research tool. This method works exceptionally well for investigating intricate interactions between variables, which makes it a good fit for research like technology acceptance. The researchers used this to evaluate the significance of proposed associations and acquire reliable estimates of path coefficients, offering a more detailed understanding of the underlying concepts of the ETAM variables.

The researchers first evaluated the measurement model by examining the validity and reliability of the constructs in the research tool using the PLS-SEM algorithm. Measures like outer loadings, Cronbach's alpha, composite reliability, AVE, discriminant validity, and model fit indices were assessed closely to determine the quality and robustness of the proposed model. Afterward, the structural model was tested using PLS-SEM bootstrapping, with 5,000 subsamples, a 0.05 significance level, and a path weighting scheme [42]. The results of this bootstrapping process enabled the examination of the hypotheses. Direct and indirect effects among variables and moderating and mediating effects were uncovered, shedding light on the underlying explanations driving the pre-service teachers' acceptance of AI applications in education. All tests were conducted at a 95% confidence level, and all p-values of less than .05 were considered significant.

Table 2. Likert scale items of the study.

Code	Item	5	4	3	2	1
SN1	1. My peers advise that AI can complement traditional teaching methods effectively.					
SN2	2. People around me see the potential benefits of AI adoption outweighing any potential challenges.					
SN3	3. I perceive that there is a consensus among teachers that AI can play a significant role in shaping the future of education.					
PU1	4. I believe that the integration of AI can positively impact the quality of education.					
PU2	5. I see the potential benefits of AI in education and support its widespread implementation.					
PU3	6. I consider AI as a helpful tool that can assist in my academic success.					
PEU1	7. I feel comfortable using AI applications as part of my academic coursework.					
PEU2	8. I am willing to invest time and effort to learn and adapt to AI-based educational tools.					
PEU3	9. I am open to experimenting with new AI technologies to improve my learning experience.					
ATT1	10. I have a positive attitude towards the inclusion of AI in various aspects of my education.					
ATT2	11. I am optimistic about the positive impact AI can have on the learning experience.					
ATT3	12. Overall, I am accepting of the use of AI technologies in educational settings.					
IU1	13. I am enthusiastic about exploring and adopting AI tools to enhance my learning.					
IU2	14. I actively seek opportunities to integrate AI into my educational activities.					
IU3	15. I am open to incorporating AI into my study routine to enhance productivity.					
E1	16. The use of AI in education enhances my overall academic experience.					
E2	17. I perceive AI as a learning aid that can contribute to my academic achievements.					
E3	18. My past encounters with AI have shown it to be a valuable resource for personalized learning and skill development.					
V1	19. I am open to the idea of incorporating AI into my educational experience.					
V2	20. I am willing to adapt to changes in my educational environment brought about by AI.					

3. Results

The tool was validated using the partial least square confirmatory factor analysis (CFA) in the Smart PLS software, version 4.0.9.8. Figure 3 presents the outer loadings in the measurement model.

As presented in Figure 3, the outer loadings of the observed variables ranged from 0.753 to 0.933, indicating a well-constructed and reliable measurement model. These results imply that the observed variables highly represent their underlying constructs. Therefore, the scale items effectively capture the latent construct, strengthening the validity and quality of the collected data.

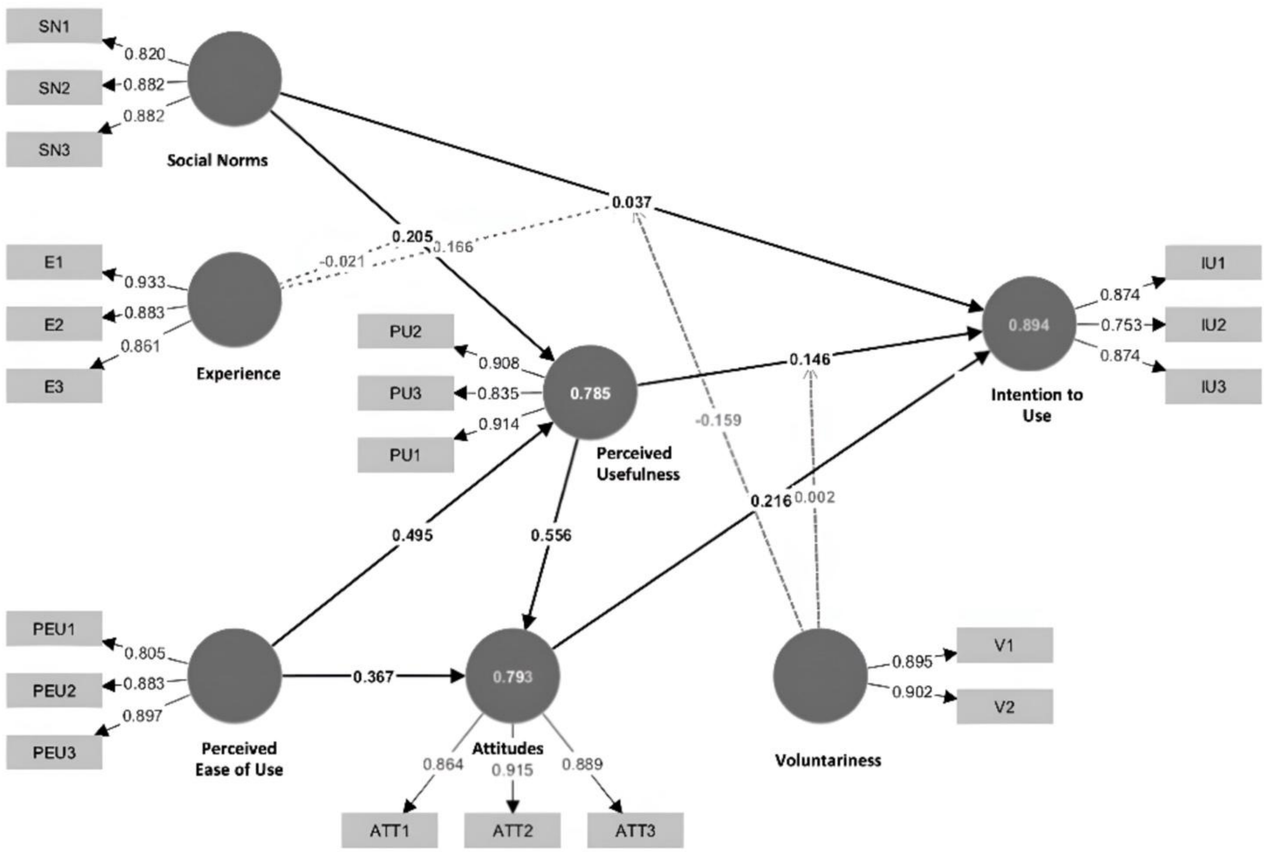

Figure 3. Outer loadings in the measurement model.

Testing the validity and reliability of the constructs yielded four acceptable values in Table 3.

Table 3. Validity and reliability of the constructs.

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
ATT	0.868	0.871	0.919	0.791
E	0.872	0.876	0.922	0.797
IU	0.782	0.794	0.873	0.608
PEU	0.827	0.831	0.897	0.744
PU	0.863	0.865	0.917	0.786
SN	0.827	0.832	0.896	0.743
V	0.762	0.762	0.894	0.808

As indicated in Table 3, the seven constructs have strong validity and reliability, showing high levels of internal consistency based on Cronbach's alpha coefficients (0.762 to 0.872). With composite reliability coefficients higher than 0.70, the variables in each construct consistently measure the same latent variables. Furthermore, the AVE values are beyond the threshold of 0.50, suggesting that the constructs accounted for significant variance in their observed variables.

Aside from these tests, discriminant validity was also assessed through the Fornell-Larcker criterion, gleaned in Table 4.

Table 4. Discriminant validity of the constructs.

Construct	ATT	E	IU	PEU	PU	SN	V
ATT	0.890						
E	0.756	0.893					
IU	0.862	0.868	0.835				
PEU	0.843	0.821	0.801	0.862			
PU	0.870	0.814	0.833	0.857	0.886		
SN	0.801	0.786	0.809	0.783	0.785	0.862	
V	0.822	0.792	0.825	0.815	0.870	0.810	0.899

As gleaned in Table 4, the inter-construct correlations provide satisfactory discriminant validity of the constructs. With correlations less than 0.90 and less than the square roots of their AVEs, the constructs are unique, and their variance can be explained more on their own than the variances shared between the constructs. Hence, the results demonstrate that the constructs measure distinct underlying concepts in the ETAM. Furthermore, the PLS-CFA assessed the model fit, as highlighted in Table 5.

Table 5. Model fit indices of the study.

Fit indices	Saturated Model	Estimated Model
Standardized root mean square residual (SRMR)	0.074	0.078
Unweighted least squares fit function (d_ULS)	1.282	1.163
Goodness of fit index (d_G)	1.562	1.458
Chi-square	741.339	712.542
Normal fit index (NFI)	0.683	0.670

According to Table 5, the SRMR values of the saturated and estimated models were lower than 0.080, indicating an acceptable fit. Although the d_ULS and d_G values were slightly higher than 1.000, the values are within the acceptable range. Moreover, the chi-square values for both models were significantly higher than 1.000; these values are common in large samples. The lower chi-square value for the estimated model than the saturated model suggests an improvement in the fit. Last, the NFI values are relatively lower than 1.000, indicating a reasonable fit. Overall, the proposed model offers a sensible and adequate explanation of the relationships between constructs, albeit with some room for improvement in future studies.

A structural model analysis was conducted using the Smart PLS software, version 4.0.9.8, to examine the hypothetical relationships. The structural model in Figure 4 visualizes the path coefficients and p-values of the overall model.

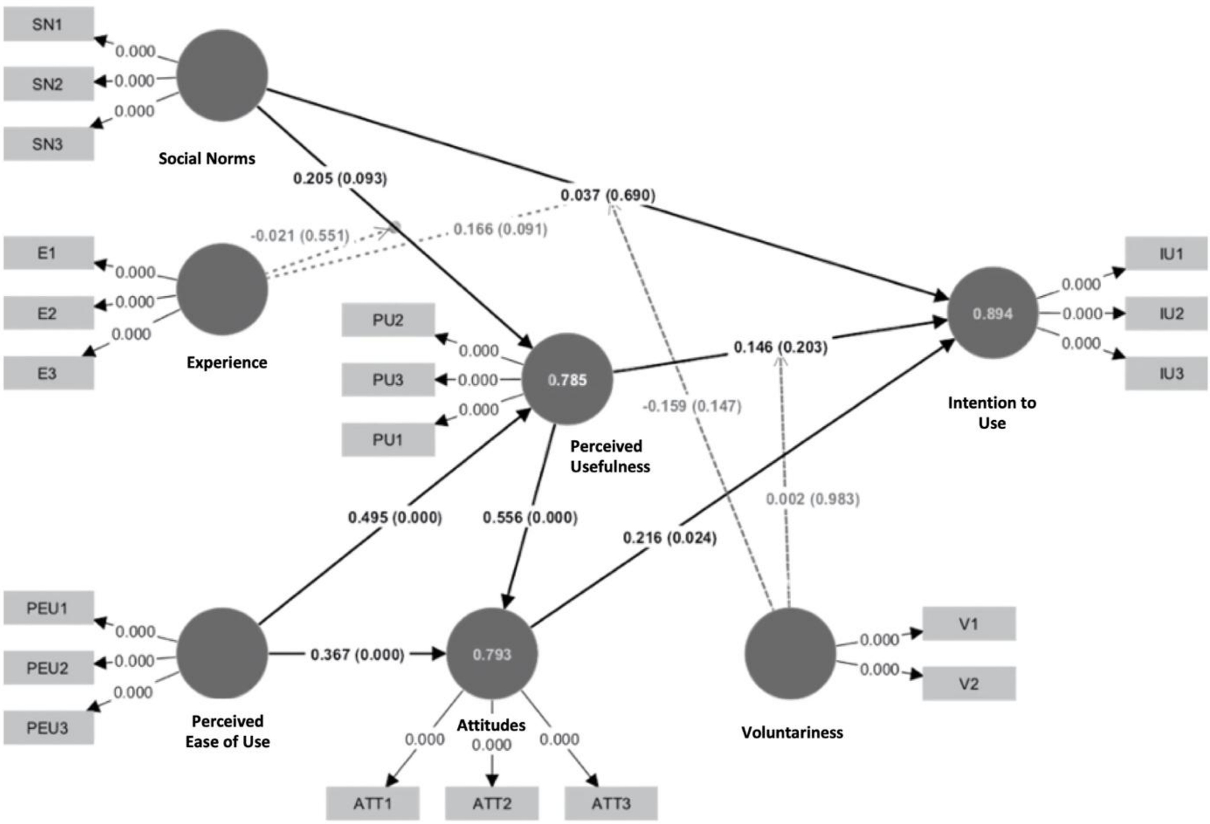

Figure 4. Path coefficients and p-values of the structural model.

The coefficient of determination, R^2, is crucial in the structural model analysis because this value offers insights into the explanatory power of the independent variables in predicting the dependent constructs. Table 6 reflects the R^2 values of the dependent constructs in the model.

Table 6. R-square values of the dependent constructs.

Construct	R-square	R-square adjusted	Strength
ATT	0.793	0.788	High
IU	0.894	0.884	Very High
PU	0.785	0.776	High

As reflected in Table 6, the corresponding independent variables can explain approximately 79.30% of the variances in ATT. Similarly, their independent variables explain roughly 89.40% of the variances in IU and 78.50% of the variances in PU. These R^2 values suggest the model can effectively capture and explain variances in pre-service teachers' ATT, IU, and PU of AI applications in education.

Moreover, the structural model provided insights regarding the hypothetical relationships among technology acceptance variables. Table 7 showcases the path coefficients among the said variables.

The empirical data provided by the pre-service teachers in education supported four hypotheses in Table 7. With p-values less than .05, H_2, H_3, H_4, and H_6 showed significant associations between two ETAM variables. In the present study, perceived ease of use significantly influenced the usefulness of AI applications in education. Aside from the path coefficients between variables, the structural model also analyzed the effect of moderators in the relationship of some variables. However, the empirical data did not support the present study's hypothetical relationships. These are H_1, H_5, and H_7, stressing the insignificant influence of subjective norms on perceived usefulness and the negligible impact of the former and latter variables on intention to use AI applications.

Table 7. Path coefficients of the overall model.

Path	Original Sample (O)	Sample Mean (O)	t-value	p-value	Results
SN→PU	0.205	0.217	1.697	.093	Not supported
PEU→PU	0.495	0.487	4.262	.000	Supported
PU→ATT	0.146	0.167	4.841	.000	Supported
PEU→ATT	0.367	0.368	3.826	.000	Supported
PU→IU	0.146	0.167	1.274	.203	Not supported
ATT→IU	0.216	0.194	2.257	.024	Supported
SN→IU	0.037	0.051	0.399	.690	Not supported

The results of the moderator analysis are shown in Table 8.

Table 8. Path coefficients of the moderators.

Moderator	Path	Original Sample (O)	Sample Mean (O)	t-value	p-value	Results
Experience	SN→PU	-0.021	-0.022	0.596	.551	Not supported
	SN→IU	0.166	0.139	1.691	.091	Not supported
Voluntariness	SN→PU	-0.159	-0.131	1.450	.147	Not supported
	PU→IU	0.002	-0.004	0.022	.983	Not supported

According to Table 8, H_8 and H_9 were not supported by the model's findings. These results mean that experience is not a significant moderator between subjective norms and the pre-service teachers' perception and intention to use AI applications in the classroom. This indicates that prior experience may not affect the influence of subjective societal standards on the teachers' AI use.

Finally, the structural model also looked into the mediation analysis of some variables in the model. The results are presented in Table 9.

Table 9. Path coefficients of the mediation analysis.

Mediator	Path	Original Sample (O)	Sample Mean (O)	t-value	p-value	Results
PU	SN→IU	0.003	0.036	0.869	.385	Not supported
	PEU→IU	0.072	0.083	1.143	.253	Not supported
ATT	PEU→IU	0.079	0.071	0.039	.041	Supported
	PU→IU	0.120	0.108	1.978	.048	Supported
PU, ATT	SN→IU	0.025	0.023	1.281	.200	Not supported

In Table 9, H_{14} and H_{15} have been supported by the present study. These results indicate that attitudes toward AI constitute a significant mediator between perceived ease of use and perceived usefulness with the pre-service teachers' intention to use AI. On the other hand, H_{12} and H_{13} were not supported by the study. This lack of support means that perceived usefulness does not influence pre-service teachers' intentions to use AI applications in the classroom. Perceived usefulness and attitudes had no significant mediating roles between subjective norms and intention to use. We found that future teachers' intentions to use AI applications in the classroom are not influenced by how useful they think the AI is or their attitudes toward it. This suggests that their intentions are not affected by their perceptions of the utility of AI or their attitudes towards it.

4. Discussion

Pre-service teachers are more likely to view AI applications as helpful tools for improving teaching methods if they find them user-friendly. Studies like Zhang et al. [28], Al Darayseh [31], and Ofosu-Ampong et al. [29] provide evidence of the substantial influence of perceived simplicity of use on the perceived usefulness of AI applications in education. This association can be explained by Davis [19], which shows that people are more likely to view technology as applicable when it is simple to use, as demonstrated by the findings of Esiyok et al. [32] and Saqr et al. [35]. These apps must have user-friendly interfaces and functionality to successfully deploy and integrate AI applications into educational settings and improve teaching and learning results.

Perceived usefulness significantly influenced the pre-service teachers’ attitudes toward AI applications in education. This finding confirms how perceived usefulness impacts people’s attitudes toward new technology. It is consistent with the principle that people who believe technology will benefit them are more likely to accept it and have favorable attitudes toward it [19]. This is corroborated by studies by Zhang et al. [28] and Ofosu-Ampong et al. [29], which show that attitudes and acceptance of AI in education are significantly influenced by perceived usefulness. Positive views on using AI applications are more likely to emerge when people believe these tools can enhance teaching and learning results. Thus, stressing AI's practical advantages and benefits in education might encourage more positive attitudes in teachers and students, making it easier to incorporate AI technologies into teaching and learning successfully.

Moreover, H_4 was also supported by the model’s result. Perceived ease of use of AI applications can significantly influence pre-service teachers’ attitudes toward them in education. This finding highlights the significance of the tool’s ease of use in shaping people’s attitudes on using AI in education, positing that people who believe technology is easy to use are more likely to accept it and have positive attitudes toward it [19]. This is corroborated by studies by Esiyok et al. [32] and Al Darayseh [31], which show that perceptions of ease of use significantly influence views on adopting AI in education. Positive views regarding integrating AI applications into teaching and learning activities are more likely to emerge among teachers and learners when they believe these apps to be easily navigable and accessible. As a result, giving user-friendliness top priority when designing AI technologies can help to promote more positive attitudes and make it easier for AI to be successfully implemented in educational settings.

Additionally, pre-service teachers’ attitudes significantly influence their intention to use AI applications in school. This result highlights the importance of attitudes in realizing the intention to use AI, suggesting that the former dramatically impacts people’s intention to do certain behaviors [21]. Saqr et al. [35] and Al Darayseh [31] support this, which shows a favorable relationship between views toward AI and plans to adopt AI-driven educational tools. Pre-service teachers are more likely to state that they want to use AI applications in their lesson plans when they have a positive attitude toward these tools. Thus, pre-service teachers' willingness to accept and use AI tools in education can be increased by cultivating positive attitudes through effective communication, training, and demonstrating AI's potential benefits. This will help integrate AI successfully into teaching and learning processes.

Subjective norms may not play an essential role in shaping valid perceptions or behavioral intentions toward AI application use, deviating from the tenets of the Theory of Reasoned Action [40], contending that people’s attitudes and behavioral intentions are influenced by subjective standards reflecting perceived societal pressures. However, the lack of evidence to support these theories can suggest that other factors, such as individual experiences, perceptions of ease of use, or institutional support, more significantly influence pre-service teachers' attitudes and intentions toward adopting AI in educational settings. Perceived social pressures may influence their views and intentions toward adopting AI, but not necessarily because of their level of technological competence. Pre-service teachers' perceptions and intentions about the use of AI in education may be more influenced by other factors, such as personal beliefs, institutional support, or perceived benefits. Socio-cultural factors also influenced acceptance and attitudes towards AI [43].

Similarly, voluntariness was not a significant moderator in the relationships between subjective norms and perceived usefulness, as well as between perceived usefulness and intention to use AI applications in education. These findings suggest that the teachers’ intention to use AI is not significantly impacted by their perception of voluntarily adopting these applications. Possible explanations could involve the strong influence of social norms and perceived benefits, according to Wu and Yu [44], which may overshadow the perceived voluntariness of adopting AI applications. Furthermore, the moderating effect of voluntariness may be lowered by perceived societal or institutional expectations, which may place more substantial pressure on people's intentions to use AI in education, as stated by Chin et al. [45].

Pre-service teachers are more likely to have positive attitudes toward AI applications and intend to employ them in educational settings when they believe these programs are helpful or easy to use [47]. Because these criteria directly influence people's intentions to embrace and use AI apps in education, the mediation effect highlights how important it is to shape positive attitudes toward these applications through perceived utility and simplicity of use. According to Stein et al. [46], by encouraging favorable attitudes among pre-service teachers, initiatives to improve usability and demonstrate the benefits of AI apps can indirectly increase their adoption.

The lack of mediating effect of perceived usefulness on pre-service teachers' intentions to use AI applications in the classroom suggests that pre-service teachers' intentions to utilize AI apps in educational settings may be directly influenced by subjective norms and perceived ease of use rather than needing perceived usefulness to operate as a mediating factor. Thus, pre-service teachers' intent to utilize AI applications may be shaped by variables other than perceived usefulness [44].

Pre-service teachers' subjective norms and intention to use AI applications in the classroom are not mediated by either perceived usefulness or attitudes toward AI applications, suggesting that attitudes toward and perceptions of the utility of AI apps do not sequentially mediate the influence of subjective norms on intention to employ them in educational settings [48]. Rather than going through the consecutive mediation pathway, which includes attitudes and perceived usefulness, pre-service teachers' decisions to utilize AI applications may be directly impacted by subjective norms [49]. This result emphasizes the need to reevaluate the consecutive mediation theory, underscoring the complexity of the decision-making process and the diversity of factors influencing the acceptability of technology in education.

5. Conclusions and recommendations

Our results verified an Extended Technology Acceptance Model for pre-service teachers' AI application use in education, revealing significant relationships. These included attitudes and intention to use AI apps, perceived utility and ease of use, usefulness and attitudes, and ease of use and attitudes. However, subjective norms, experience, and voluntariness did not significantly influence the perceived utility or intention to use AI. The association between subjective norms and intention to use was not mediated by attitudes, even though they did mediate several other correlations, such as those involving ease of use and intention to use. These results improved the suggested ETAM model by illuminating the variables influencing pre-service teachers' acceptance of AI applications.

The findings emphasize the importance of creating AI apps with approachable user interfaces to increase pre-service teachers' acceptance. To cultivate good impressions, teachers and legislators should prioritize projects that illustrate AI's usefulness in education. It is essential to offer thorough, practical training programs beyond raising pre-service teachers' AI awareness and literacy to give them firsthand experience with AI tools. This includes chances to use AI in actual classroom environments and see successful case studies, which can decrease worries and boost self-assurance in applying AI wisely. Improved institutional support is also essential; this includes mentorship from seasoned teachers who have effectively incorporated AI into their teaching techniques, access to resources, and continual professional development. Together, these actions help address pre-service teachers' apprehensions and provide them with the tools they need to use AI to enhance student learning.

Even with the robust methodology, there are limitations to the study. The fact that the sample was limited to pre-service teachers from Central Visayas state colleges limits the findings' generalizability. Future studies ought to use a more varied sample to improve external validity. Additionally, longitudinal research should examine how people's attitudes and views of AI applications change. These studies can offer important insights into how AI will be used and accepted in education in the long run. In addition to quantitative investigations, qualitative studies can provide a more profound knowledge of the primary factors impacting pre-service teachers' acceptance of artificial intelligence in the classroom. Moreover, addressing pre-service teachers' concerns over the adoption of AI requires investigating institutional support mechanisms, such as extensive training programs and resource availability. Acceptance among teachers will be further enhanced by emphasizing the creation of user-friendly interfaces in AI systems. One should use caution when extrapolating results from this specific sample to other regions. To further understand the dynamics driving AI acceptance, more research into the mediation effects of perceived utility and attitudes is necessary.

Author contributions

All authors conceptualized and conducted the study. G. Sumalinog and J. Mananay wrote the Introduction while C. Goles and C. Fernandez crafted the Methodology. I. M. Alejandro and J. M. Sanchez curated, analyzed, visualized, and interpreted the data. C. Goles and C. Fernadez contributed to discussing the results, while G. Sumalinog and J. Mananay wrote the conclusions and recommendations. All authors contributed to the writing of the first draft, and J. M. Sanchez and I. M. Alejandro finalized this draft.

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Conflict of interest

The authors declare no conflict of interest in this paper.

Ethics declaration

The study was conducted according to local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

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