UNDERSTANDING ACTUAL E-LEARNING ADOPTION: A COMPREHENSIVE TAM-BASED INVESTIGATION OF PRE-SERVICE MATHEMATICS TEACHERS

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ABSTRACT

This study investigates the determinants of e-learning adoption among pre-service mathematics teachers through an extended Technology Acceptance Model (TAM) framework. Using structural equation modeling with data collected from 508 pre-service mathematics teachers in Indonesia, we examined thirteen hypothesized relationships between system accessibility, enjoyment, perceived ease of use, perceived usefulness, attitude toward using, behavioral intention, and actual system usage. Results revealed that system accessibility ($\beta = 0.535$) and enjoyment ($\beta = 0.319$) significantly predicted perceived ease of use, explaining 58.9% of its variance. Perceived usefulness was primarily influenced by enjoyment ($\beta = 0.468$), perceived ease of use ($\beta = 0.323$), and system accessibility ($\beta = 0.165$). Attitude toward using was significantly affected by perceived usefulness ($\beta = 0.489$) and perceived ease of use ($\beta = 0.265$), while behavioral intention was predominantly determined by perceived usefulness ($\beta = 0.469$), attitude toward using ($\beta = 0.277$), and perceived ease of use ($\beta = 0.106$). Notably, the relationship between behavioral intention and actual system usage was borderline significant ($\beta = 0.082$, $p = 0.050$), supporting critique of TAM's limited ability to predict actual use. These findings highlight the importance of developing accessible, enjoyable mathematics e-learning systems while acknowledging the complex relationship between intention and actual usage behavior.

Keywords: Technology acceptance model, e-learning, actual system usage, enjoyment, system accessibility.

INTRODUCTION

The integration of e-learning has become essential in contemporary teacher education, responding to evolving technological demands. Digital tools in teacher preparation programs are increasingly vital, equipping future educators with necessary competencies for modern classrooms. Pre-service mathematics teachers must leverage these technologies to enhance instruction, foster interactive learning, and accommodate diverse student needs. However, the transition from intended adoption to effective implementation of e-learning tools remains problematic, characterized by inconsistent utilization patterns despite recognized potential benefits.

The integration of technology into educational frameworks has fundamentally reshaped learning paradigms, creating unprecedented opportunities for educators and students alike. Within Indonesia's higher education landscape, e-learning has emerged as a cornerstone element, driven by escalating demands for learning environments characterized by flexibility and accessibility (Luschei, Dimyati, & Padmo, 2008; Sarnato, Sari, Rahmawati, Hidayat, & Patry, 2024; Sewandono, Thoyib, Hadiwidjojo, & Rofiq, 2023; Ulanday, Centeno, Bayla, & Callanta, 2021). These technological advancements have substantially enhanced the accessibility, interactivity, and personalization dimensions of educational experiences (Benkhalfallah, Laouar, Benkhalfallah, Liu, & Yu, 2024; Liu & Yu, 2023).

The convergence of expanding digital technology adoption and increasing internet penetration rates has catalyzed the implementation of e-learning platforms across universities throughout Indonesia. This digital transformation extends beyond mere instructional delivery, supporting comprehensive institutional evolution across teaching methodologies, learning approaches, administrative systems, experimental protocols, professional development initiatives (Falqueto, Hoffmann, Gomes, & Onoyama Mori, 2020), and physical infrastructure enhancements (Kenno, Lau, Sainty, & Boles, 2021). Consequently, these developments have fostered innovative pedagogical approaches through the strategic deployment of ubiquitous computing and cutting-edge technological solutions (Madni et al., 2022).

Mathematics e-learning, however, presents unique challenges. Mathematics demands enhanced online learning systems for favorable recognition particularly given its reliance on formulas and concepts requiring robust explanation (Borba et al., 2016; Moreno-Guerrero, Aznar-Diaz, Caceres-Reche, & Alonso-Garcia, 2020; Waquar, Kareem, Yasmeen, & Hussain, 2025). Empirical studies suggests that effective mathematics e-learning platforms must incorporate interactive problem-solving, facilitate the visualization of complex concepts, and provide guided, step-by-step procedural learning (Akugizibwe & Ahn, 2020; Borba et al., 2016; Liu & Yu, 2023; Shurygin, Berestova, Litvinova, Kolpak, & Nureyeva, 2021).). Studies shows that robust digital mathematics environments improve concept comprehension, boost student engagement, and enable personalized learning pathways (Abrahamson et al., 2020; Engelbrecht & Oates, 2022; Utterberg Moden, 2021).

For pre-service mathematics teachers, e-learning serves a dual purpose. It not only facilitates their own mathematical learning but also models effective technology integration, which they can subsequently implement in their future teaching practices. As highlighted in the Technological Pedagogical Content Knowledge (TPACK) framework, teachers require a sophisticated, integrated understanding of content, pedagogy, and technology to effectively harness digital tools in the classroom (Haleem, Javaid, Qadri, & Suman, 2022; Peter, 2023). This integration is particularly critical in mathematics education, where technological advancements have the potential to fundamentally transform both the content being taught and the methods through which students learn (Bonfield, Salter, Longmuir, Benson, & Adachi, 2020; Schmidt & Tang, 2020).

The Technology Acceptance Model (TAM), pioneered by Davis, offers a theoretical framework for analyzing technology adoption determinants (Davis, 1989). This model proposes that Perceived Usefulness (PU) and Perceived Ease of Use (PEU) shape attitudes toward technology utilization, subsequently influencing Behavioral Intention (BI) and Actual Usage. TAM has been widely implemented in e-learning research, demonstrating consistent validity across diverse educational settings (Abdullah, Ward, & Ahmed, 2016; Alassafi, 2022; Scherer, Siddiq, & Tondeur, 2019). These meta-analytical evidences confirm TAM's robustness in explaining teacher technology acceptance, establishing it as a foundational paradigm for investigating educational technology adoption processes.

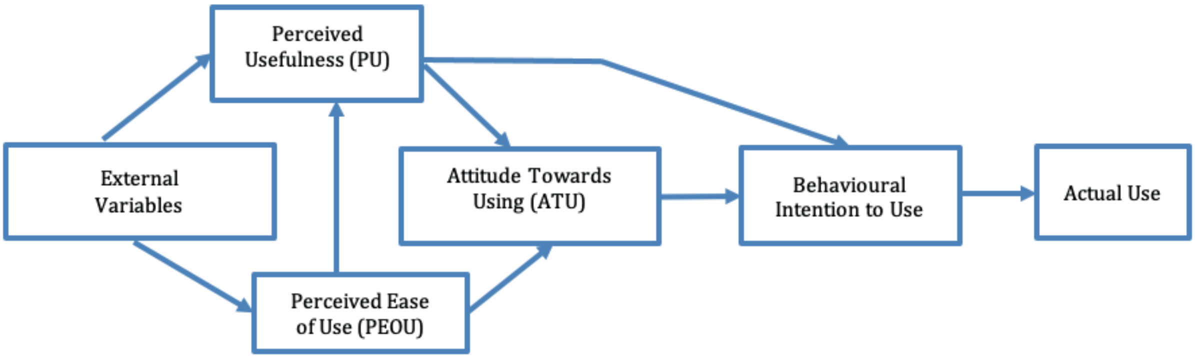

Figure 1. Extended TAM Model (Davis, 1985, 1989)

The Technology Acceptance Model posits that actual system usage is determined by an individual's behavioral intention, which is itself influenced by two critical factors: perceived usefulness and attitude toward the system (Davis, 1985, 1989). Pre-service teacher actual system usage refers to the measurable engagement of pre-service teachers with digital learning platforms. It encompasses the frequency, duration, and depth of their interactions with system features and functionalities in authentic, real-world educational contexts. Perceived ease of use is closely associated with intention, influencing it both directly and indirectly by enhancing perceived usefulness (Venkatesh; Viaswanath & Davis; Fred D., 2000) and by shaping the attitude toward using the system (Davis, 1985; Venkatesh & Davis, 1996). Pre-service teacher Behavioural Intention (BI) is defined as their subjective probability, willingness, decision, conflict, and commitment to using web-based video conferencing in mathematics learning. This behavioral intention was used to predict the pre-service teacher's actual use of web-based video conferencing as supported by a systematic literature review that proposed BI likely correlated to the actual system (Turner, Kitchenham, Brereton, Charters, & Budgen, 2010).

While the original TAM provides valuable insights, researchers have recognized the need to extend the model to better capture the complexities of e-learning environments. This study incorporates two additional constructs: Enjoyment and System Accessibility. Enjoyment, defined as the intrinsic pleasure derived from system use, has been identified as a significant predictor of technology adoption (FakhrHosseini et al., 2024; Pereira & Tam, 2021). In educational contexts, enjoyment enhances motivation, engagement, and persistence in learning activities (Hejazi & Sadoughi, 2023). For mathematics learning, where student anxiety and negative attitudes are common barriers, enjoyment becomes particularly crucial for sustained engagement (Barnes, 2021). Additionally, System Accessibility encompasses the availability, reliability, and ease of access to e-learning platforms (Duggal, 2022; Timbi-Sisalima, Sanchez-Gordon, Hilera-Gonzalez, & Oton-Tortosa, 2022). Research has demonstrated that accessibility significantly influences users' perceptions and adoption behaviors (Kumar, Bervell, Annamalai, & Osman, 2020; Ma et al., 2025; Yan, Siddik, Akter, & Dong, 2021). In developing countries, where technological infrastructure may be limited or inconsistent, system accessibility represents a critical factor in e-learning adoption (Almaiah, Al-Khasawneh, & Althunibat, 2020).

A comprehensive review of the literature reveals several critical limitations in our understanding of e-learning adoption, particularly in specialized educational contexts. The first significant constraint concerns the predominant focus on behavioral intention rather than actual usage in TAM-based studies. Systematic reviews of TAM research highlighted that while behavioral intention has been extensively studied, the actual usage behavior, remains comparatively underexplored (Al-Qaysi, Mohamad-Nordin, & Al-Emran, 2020; Alsharida, Hammood, & Al-Emran, 2021; Granic, 2022; Granic & Marangunic, 2019; Mustafa & Garcia, 2021; Rosli, Saleh, Md. Ali, Abu Bakar, & Mohd Tahir, 2022; Scherer et al., 2019). This focus on intention generates what can be described as an "intention-behavior discrepancy," wherein favorable dispositions toward technology do not consistently manifest in ongoing usage behaviors. This discrepancy is particularly problematic in educational settings, where the effective implementation of technology directly impacts learning outcomes. The factors that influence pre-service teachers' intentions to use technology may differ significantly from those that determine their actual usage in classroom settings.

The second major limitation concerns the insufficient research examining e-learning adoption among pre-service mathematics teachers, especially in developing countries. Mathematics education presents unique challenges for e-learning implementation due to its abstract nature, symbolic representation requirements, and procedural learning aspects (Borba et al., 2016). These discipline-specific characteristics necessitate specialized approaches to technology integration that may not be captured in general e-learning adoption studies.

Furthermore, the context of developing countries introduces additional complexities. Studies have highlighted how technological infrastructure limitations, cultural factors, and institutional support systems in developing nations create distinct environments for technology adoption (AlBar & Hoque, 2019; Darko & Chan, 2018). In Indonesia specifically, studies have indicated that factors such as technological readiness, digital literacy levels, and access to reliable internet connections significantly influence technology adoption in educational settings (Yetti, 2024; Yusuf, Rahman, & Subiyakto, 2024).

The intersection of these two limitations, the focus on intention rather than usage and the insufficient research on pre-service mathematics teachers in developing countries, creates a significant blind spot in our understanding of e-learning adoption. This blind spot is particularly concerning given the increasing emphasis on technology integration in teacher education programs globally and the unique role that mathematics teachers play in developing students' technological and analytical skills.

PURPOSE OF THE STUDY

This study aims to examine the determinants of actual e-learning usage among pre-service mathematics teachers through an extended Technology Acceptance Model (TAM). This investigation explores the relationships between traditional TAM constructs, Perceived Usefulness (PU) and Perceived Ease of Use (PEU), and supplementary factors, namely System Accessibility and Enjoyment, in influencing authentic e-learning adoption behaviors and usage.

The research addresses three central questions; (1) What factors influence actual e-learning system usage among pre-service mathematics teachers? (2) How do PU, PEU, System Accessibility, and Enjoyment contribute, both independently and collectively, to the adoption process? (3) Which construct exerts the most significant influence on actual usage behavior?

Through systematic investigation of these questions, this study seeks to provide sophisticated insights into the interplay between affective and pragmatic dimensions of technology acceptance in educational contexts. The findings are expected to enhance theoretical understanding of technology adoption in mathematics education while offering evidence-based strategies for improving technology integration in teacher preparation programs.

METHOD

This study employed a quantitative approach to investigate the determinants of actual e-learning usage among Pre-service mathematics teachers using Structural Equation Modeling (SEM). A cross-sectional survey design was utilized to collect quantitative data. The research model is an extended Technology Acceptance Model (TAM), incorporating traditional constructs; Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Using (ATU), Behavioral Intention (BI), and Actual System Usage (ASU) along with the additional constructs of Enjoyment (E) and System Accessibility (SA). Each construct is operationalized as follows:

- Enjoyment (E). For pre-service Mathematics teachers, Enjoyment represents the intrinsic pleasure and satisfaction experienced during the use of e-learning systems. This construct reflects the affective response that motivates ongoing engagement with digital learning tools designed for mathematical content. It asks respondents to rate the extent to which they find the e-learning environment enjoyable and stimulating.

- System Accessibility (SA). System Accessibility refers to the ease with which pre-service Mathematics teachers can access and interact with the e-learning platform. This includes the availability of reliable technological infrastructure, user-friendly interfaces, and the consistency of system performance. Survey items gauge teachers' perceptions of the ease of obtaining access to the system, navigating its features, and receiving timely support when needed.
- Perceived Ease of Use (PEOU). For pre-service Mathematics teachers, Perceived Ease of Use measures the degree to which they believe that operating the e-learning system requires minimal effort. It captures users' assessments of the system's usability, including the simplicity of navigating its digital environment and learning features relevant to mathematics instruction. This is evaluated through items that rate the perceived ease and clarity of the system's functionalities.
- Perceived Usefulness (PU). Perceived Usefulness is defined as the extent to which pre-service Mathematics teachers believe that the e-learning system will enhance their learning and instructional effectiveness. This includes improved access to mathematical content, better organization of learning resources, and facilitation of understanding complex mathematical concepts. It is operationalized through items measuring perceived improvements in performance and overall learning outcomes attributed to the e-learning platform.
- Attitude Toward Using (ATU). Attitude Toward Using reflects the overall affective evaluation of e-learning systems by pre-service Mathematics teachers. It captures whether teachers have a favorable or unfavorable disposition towards using the e-learning technology in their academic preparation and future teaching. This construct is measured through survey items assessing the degree of positive or negative sentiment associated with using the system.
- Behavioral Intention (BI). Behavioral Intention measures the willingness of pre-service Mathematics teachers to use the e-learning system in the future. It serves as an indicator of their commitment to integrate digital learning tools into their teaching practice. The construct is operationalized through items that capture the likelihood and readiness of teachers to continue engaging with the e-learning platform.
- Actual System Usage (ASU). Actual System Usage quantifies the real engagement of pre-service Mathematics teachers with the e-learning system. It is assessed using self-reported measures of frequency, duration, and intensity of system use in their academic activities. This construct represents the ultimate outcome of the extended TAM framework, indicating how effectively the e-learning system is being integrated into their training and preparation for future teaching roles.

The research model used on this study illustrated on Figure 2.

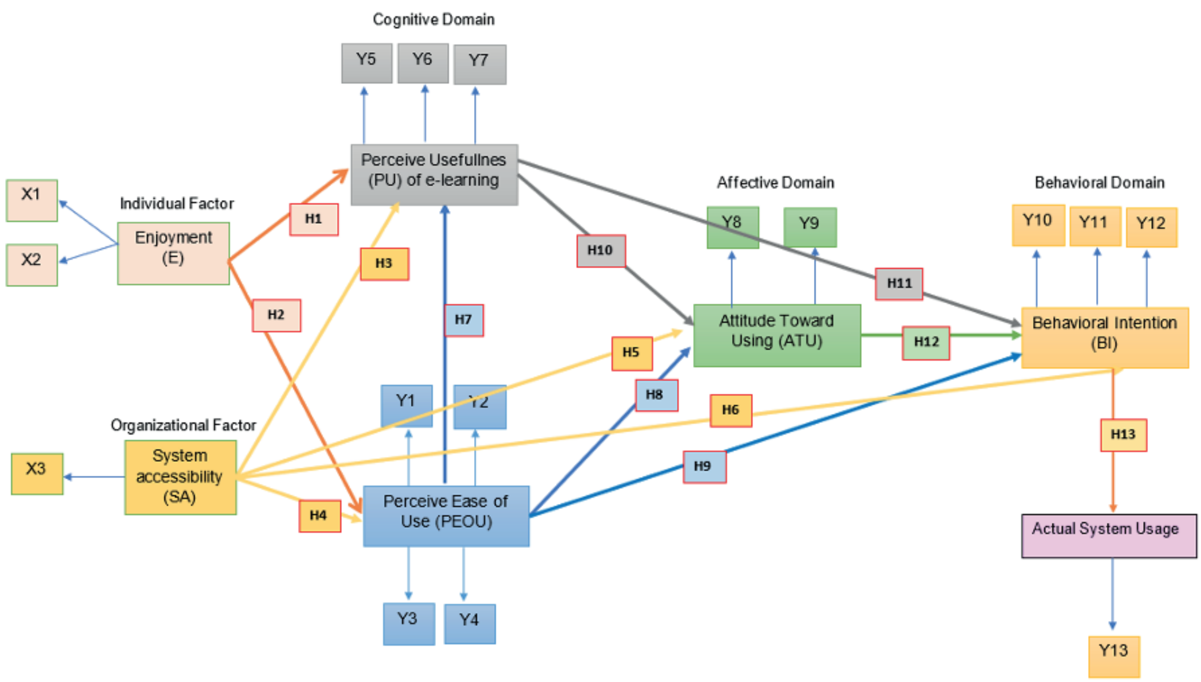

Figure 2. The Model of Research

Thirteen hypotheses were developed to evaluate the relationships between these constructs:

H1: Enjoyment (E) has a positive effect on Perceived Usefulness (PU).

H2: Enjoyment (E) has a positive effect on Perceived Ease of Use (PEOU).

H3: System Accessibility (SA) has a positive effect on Perceived Usefulness (PU).

H4: System Accessibility (SA) has a positive effect on Perceived Ease of Use (PEOU).

H5: System Accessibility (SA) has a positive effect on Attitude Toward Using (ATU).

H6: System Accessibility (SA) has a positive effect on Behavioral Intention (BI).

H7: Perceived Ease of Use (PEOU) has a positive effect on Perceived Usefulness (PU).

H8: Perceived Ease of Use (PEOU) has a positive effect on Attitude Toward Using (ATU).

H9: Perceived Ease of Use (PEOU) has a positive effect on Behavioral Intention (BI).

H10: Perceived Usefulness (PU) has a positive effect on Attitude Toward Using (ATU).

H11: Perceived Usefulness (PU) has a positive effect on Behavioral Intention (BI).

H12: Attitude Toward Using (ATU) has a positive effect on Behavioral Intention (BI).

H13: Behavioral Intention (BI) has a positive effect on Actual System Usage (ASU).

Participants

A total of 508 pre-service mathematics teachers from 15 universities participated in the study. Participants were selected using a stratified random sampling technique to ensure representation across different universities and academic years, enhancing the generalizability of the findings.

Table 1. Demographics of Participants

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	187	36,8
	Female	321	63,2
Academic Year	First year	96	18,9
	Second year	112	22
	Third year	143	28,1
	Fourth year	157	30,9
University	Univ A	48	9,4
	Univ B	42	8,3
	Univ C	39	7,7
	Univ D	36	7,1
	Univ E	35	6,9
	Univ F	34	6,7
	Univ G	33	6,5
	Univ H	32	6,3
	Univ I	31	6,1
	Univ J	30	5,9
	Univ K	29	5,7
	Univ L	31	6,1
	Univ M	30	5,9
	Univ N	29	5,7
	Univ O	29	5,7

Prior E-learning Experience	Less than 6 months	87	17,1
	6-12 months	163	32,1
	1-2 years	178	35
	More than 2 years	80	15,7
Device Used for E-learning	Smartphone	289	56,9
	Laptop/Desktop	198	39
	Tablet	21	4,1
Internet Access Quality	Poor	67	13,2
	Fair	183	36
	Good	196	38,6
	Excellent	62	12,2

Data Collection and Analysis

Data were collected via an online survey, which was distributed using validated Likert-scale items sourced from previous TAM studies. These items were designed to measure each of the constructs reliably and accurately. Prior to data collection, the study received ethical approval, and informed consent was obtained from all participants, ensuring adherence to ethical standards in research. Table 2 presented items used to measure students actual e-learning usage. The constructs were adopted from preliminary researchs. The items were measured in a five-point Likert-type scale questionaire, where 1 represented as "Strongly Disagree" to 5 represented as "Strongly agree". For items on Actual System Usage, the answer is converted to five-point Likert-type scale. Table 2 show the items use in survey.

Table 2. Items Used in Survey

Construct	Variables	Items	Measure
Enjoyment	X_1	E1	I enjoy using the e-learning application
		E2	The features provided in e-learning are exciting
	X_2	E3	The e-learning application makes me passionate about learning
System Accessibility	X_3	SA1	E-learning applications are user-friendly
		SA2	E-learning applications are easy to use in online learning processes (online)
Perceive Ease of Use	Y_1	PEOU1	I am familiar with the features contained in e-learning
	Y_2	PEOU2	The registration system on the e-learning application is easy to understand and run
		PEOU3	The e-learning application makes it easier for me to upload/upload assignments given by the lecturer
		PEOU4	E-learning applications make it easier to find the information needed
		PEOU5	The e-learning application makes it easier for me to communicate with other students by using one of the features
		PEOU6	The e-learning application facilitates communication between lecturers and students by using one of the features
	Y_3	PEOU7	The e-learning application can display comments and answers given by other students
		PEOU8	The e-learning application makes it easier for me to reply to comments from other students
	Y_4	PEOU9	Operation of e-learning makes it easier for me to adapt to the features contained in e-learning

Perceived Usefullness	Y_5	PU1	My study productivity increases when I study using e-learning
		PU2	The e-learning application makes it easier for me to find the material needed
		PU3	The e-learning application helps me master the material provided independently
		PU4	Learning using e-learning helps improve my skills in operating a computer/laptop
	Y_6	PU5	The e-learning application that is used when studying does not consume a lot of internet quota
		PU6	The e-learning application used when studying is very efficient
		PU7	The e-learning application helps me optimize my study time
	Y_7	PU8	The e-learning application makes it easier for me to access grades
		PU9	The features of the e-learning application that I currently use is more straightforward compared to other e-learning applications
Attitude Toward Using	Y_8	ATU1	The e-learning application provides features for discussions with lecturers
		ATU2	The e-learning application provides features for discussing with other students
		ATU3	The e-learning application makes me comfortable when interacting with other students
		ATU4	The e-learning application makes me comfortable when interacting with lecturers
	Y_9	ATU5	The e-learning application made me explore further the features contained in e-learning
Behavioral Intention to Use	Y_{10}	BI1	The features contained in e-learning help me to study online
		BI2	The module features in the e-learning application make it easier for me to understand the learning material
		BI3	The discussion feature in the e-learning application makes it easier for me to interact with lecturers and classmates
		BI4	The assignment and quiz features in e-learning make it easier for me to do the assignments given by the lecturer
		BI5	The grades feature in e-learning makes it easier for me to access grades
		BI6	The attendance feature makes it easier for me to see the percentage of online lecture attendance
		BI7	I can download files provided by the lecturer when using this e-learning
	Y_{11}	BI8	I am interested in trying the features presented in this e-learning
	Y_{12}	BI9	I will use this e-learning application in the following semester
Actual System Usage	Y_{13}	ASU1	I access this e-learning within a period: (5) every day, (4) every 2 days, (3) once a week, (2) once every 2 weeks, (1) once a month
		ASU2	The effective time that I use when studying with lecturers using e-learning applications: (1) less than 2 hours per week, (2) 2 to 4 hours per week, (3) 4 to 6 hours per week, (4) 6 to 8 hours per week, (5) 8 to 10 hours per week
		ASU3	The adequate time that I use when studying independently using e-learning applications: (1) Less than 2 hours per week, (2) 2 to 4 hours per week, (3) 4 to 6 hours per week, (4)6 to 8 hours per week, 8 to 10 hours per week

Data analysis was conducted in two distinct phases to rigorously assess both the measurement and structural models. Phase 1 is the measurement model assessment. In this initial phase, the focus was on establishing the reliability and validity of the survey instruments. The following steps were conducted.

- Reliability of the measures was evaluated using Cronbach's Alpha. A Cronbach's Alpha value above 0.70 was considered acceptable, indicating internal consistency among the items measuring each construct.
- Convergent validity was assessed via the Average Variance Extracted (AVE). An AVE value of 0.50 or higher for each construct signified that, on average, more than 50% of the variance was explained by the indicators.
- Composite Reliability values were also computed for each construct, with thresholds set at 0.70 or higher. This provided additional assurance that the items reliably represent the underlying constructs.
- The loadings of each survey item on its respective construct were examined. Items with loadings below 0.70 were reviewed for potential removal or re-specification, to enhance the robustness of the measurement model.

Phase 2 is the structural model evaluation. After confirming the adequacy of the measurement model, the next step was to assess the structural relationships among the constructs. Structural Equation Modeling (SEM) was performed using SmartPLS 3.2.9. This software facilitated the estimation of complex relationships and provided robust assessments of model fit. A structural model was evaluated by testing the 13 formulated hypotheses. Bootstrapping techniques were employed to determine the statistical significance of the hypothesized paths. This approach provided confidence intervals and p-values for the path coefficients. In addition to path significance, various model fit indices and the coefficient of determination (R^2) were examined to assess the explanatory power of the model. These indices indicated the extent to which the independent variables collectively explained the variance in the dependent variables. Variance Inflation Factor (VIF) values were computed to check for multicollinearity among the independent variables. A VIF value below the threshold of 5 confirmed that multicollinearity was not an issue in the model.

The Scale

Reliability and validity of the measurement items were assessed using Cronbach's Alpha, Average Variance Extracted (AVE), and Composite Reliability (CR) to ensure internal consistency and construct validity. Hulland proposed that factor loadings of measured variables should be more than 0.7 and stated that a low factor loading indicates a low explanatory power of the model (Hulland, 1999). Seven constructs were identified for examining factor analysis: E, SA, PEU, PU, ATU, BI, and AU shown in Figure 3. The fact that the factor loadings in the latent variables varied from 0.71 to 1.00 indicates that the measured variables in the study had an overall convergent validity (Hair et al., 2017), as shown in Table 3. The two important indicators used to assess convergent validity are composite reliability (CR) and average variance extracted (AVE) (Lee, Cheung, & Chen, 2007). Composite reliability (CR) should be larger than 0.7 (Fornell & Larcker, 1981; Werts, Linn, & Joreskog, 1974), showing high internal consistency reliability for latent variables. Each latent variable in Table 3 has a good internal consistency, ranging from 0.79 to 1.00. An average variance extracted (AVE) should have a value greater than 0.5 (Fornell & Larcker, 1981). As can be seen in Table 3, each latent variable had an average extracted variance that ranged from 0.65 to 1.00.

Table 3. Convergent Validity and Composite Reliability Construct

Construct	Measured Variable	Loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)
ASU	AS1	1.000	0.791	0.657
ATU	AT1	0.707	1.000	1.000
	AT2	0.902		
BI	BI1	0.853	0.891	0.731
	BI2	0.897		
	BI3	0.813		
PEU	PEU2	0.873	0.893	0.736
	PEU3	0.828		
	PEU4	0.872		
PU	PU1	0.884	0.910	0.771
	PU2	0.866		
	PU3	0.884		
E	X1	0.925	0.923	0.857
	X2	0.926		
SA	X3	1.000	1.000	1.000

The measurement model demonstrated satisfactory reliability and convergent validity across all constructs. Specifically, Actual System Usage (ASU), measured by a single indicator (AS1), yielded a composite reliability (CR) of 0.791 and an average variance extracted (AVE) of 0.657, thus meeting the recommended thresholds. The Attitude Toward Using (ATU) construct, assessed via two indicators (AT1 and AT2) with loadings of 0.707 and 0.902 respectively, achieved a CR of 1.000 and an AVE of 1.000, indicating excellent internal consistency and convergent validity. Behavioral Intention (BI), represented by three items with loadings ranging from 0.813 to 0.897, obtained a CR of 0.891 and an AVE of 0.731, further supporting the robustness of the construct. Perceived Ease of Use (PEU) and Perceived Usefulness (PU) constructs also displayed high reliability, with CR values of 0.893 and 0.910 and AVEs of 0.736 and 0.771, respectively. Similarly, the Enjoyment (E) construct, measured by two indicators with loadings exceeding 0.925, recorded a CR of 0.923 and an AVE of 0.857. Finally, the System Accessibility (SA) construct, reflected by a single indicator, achieved perfect scores (CR = 1.000, AVE = 1.000). Overall, these findings confirm that the constructs are measured with a high degree of internal consistency and convergent validity, providing a robust foundation for subsequent structural analysis.

The measurement model demonstrated strong internal consistency and convergent validity across all constructs. Actual System Usage (ASU), measured by one indicator (AS1), yielded a Composite Reliability (CR) of 0.791 and an Average Variance Extracted (AVE) of 0.657, surpassing the minimum recommended thresholds. Attitude Toward Using (ATU) was assessed with two indicators (AT1 and AT2) showing loadings of 0.707 and 0.902, respectively, and achieved perfect reliability and validity scores (CR = 1.000, AVE = 1.000). Behavioral Intention (BI), represented by three items with loadings ranging from 0.813 to 0.897, recorded a CR of 0.891 and an AVE of 0.731, confirming the robustness of the construct. Perceived Ease of Use (PEU) and Perceived Usefulness (PU) constructs exhibited high reliability with CR values of 0.893 and 0.910 and AVE values of 0.736 and 0.771, respectively. The Enjoyment (E) construct, measured with two indicators having loadings above 0.925, demonstrated excellent reliability (CR = 0.923, AVE = 0.857). Lastly, the System Accessibility (SA) construct, measured with a single indicator, attained perfect scores (CR = 1.000, AVE = 1.000). These results underscore the soundness of the measurement model, ensuring a robust basis for further structural analysis.

Table 4. Discriminant Validity (Fornell-Larcker Criterion)

	ATU	AU	BI	E	PEOU	PU	SA
ATU	**0.811**						
AU	-0.005	**1.000**					
BI	0.705	0.085	**0.855**				
E	0.762	-0.008	0.735	**0.925**			
PEOU	0.636	0.097	0.678	0.639	**0.858**		
PU	0.694	0.076	0.786	0.775	0.740	**0.878**	
SA	0.536	0.087	0.610	0.599	0.723	0.678	**1.000**

Additionally, Fornell and Larcker proposed that the square root of the AVE in each latent variable can be utilized to prove discriminant validity; as a result, this value must be greater than the correlation between constructs to reveal discriminant validity between constructs (Fornell & Larcker, 1981). Table 4 displays the discriminant validity matrix (Fornell-Lacker criterion). The measurement's discriminant validity is acceptable because the value is higher than other correlation values between latent variables (Estriegana, Medina-merodio, & Barchino, 2019). According to Table 4, all constructs for ATU (0.811), AU (1.000), BI (0.855), E (0.925), PEOU (0.858), PU (0.878) and SA (1.000) have achieved the required level of discriminant validity.

FINDINGS

The PLS program can obtain t-statistics for significance testing of both the inner and outer model, using the technique known as bootstrapping (Chin, 1998). In this process, 508 samples are obtained from the original sample with replacement to provide bootstrap standard errors, which in turn provide approximately T-values for the structural path significance test. Furthermore, the discussion for the lateral collinearity problem uses the Variance Inflation Factor (VIF). VIF values must be higher than 0.2 and lower than 5.0 (Hair et al., 2017).

Table 5. Lateral Collinearity Assessment and Hypothesis Testing

Hypothesis	Relationship	VIF	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	R2	F2
H1	E→PU	1.810	0.468	0.042	11.303	0.000	0.714	0.430
H3	SA→PU	2.246	0.165	0.044	3.672	0.000		0.042
H7	PEU→PU	2.430	0.323	0.049	6.571	0.000		0.148
H6	SA→BI	2.314	0.067	0.043	1.511	0.066	0.677	0.006
H9	PEU→BI	2.911	0.106	0.046	2.348	0.014		0.012
H11	PU→BI	2.937	0.469	0.044	10.674	0.000		0.234
H12	ATU→BI	2.060	0.277	0.044	6.193	0.000		0.113
H2	E→PEU	1.561	0.319	0.041	7.732	0.000	0.589	0.160
H4	SA→PEU	1.561	0.535	0.040	13.249	0.000		0.439
H5	SA→ATU	2.314	0.017	0.054	0.238	0.406	0.515	0.000
H8	PEU→ATU	2.766	0.264	0.058	4.536	0.000		0.052
H10	PU→ATU	2.445	0.484	0.050	9.723	0.000		0.201
H13	BI→ASU	1.000	0.082	0.051	1.650	0.050	0.007	0.007

*Note. *p<.05, **p<.01*

According to Table 5, it was determined that 11 out of 13 relationships had a t-value > 1.645, so that they are significant at the 0.05 level of significance (Hair et al., 2017). The Variance Inflation Factor (VIF) values ranged between 1.000 and 2.937, indicating that multicollinearity among the model constructs was within acceptable limits.

The results indicate that the predictors of PU are statistically significant. Enjoyment (E→PU) yielded a coefficient of 0.468 with a robust t statistic of 11.303 and a corresponding p-value of less than 0.001. Additionally, Perceived Ease of Use (PEU→PU) demonstrated a significant positive relationship with a coefficient of 0.323 ($t = 6.571$, $p < 0.001$). Although System Accessibility (SA→PU) displayed a smaller coefficient of 0.165 ($t = 3.672$, $p < 0.001$), it remained statistically significant. Overall, the model explains 71.4% of the variance in PU with a moderate-to-large effect size for the experience construct ($f^2 = 0.430$).

For BI, the strongest predictor was PU ($\beta = 0.469$, $t = 10.674$, $p < 0.001$). Attitude Toward Use (ATU→BI) also showed a significant influence ($\beta = 0.277$, $t = 6.193$, $p < 0.001$) alongside a lesser contribution from PEU ($\beta = 0.106$, $t = 2.348$, $p = 0.014$). Conversely, System Accessibility (SA→BI) approached but did not reach conventional significance ($\beta = 0.067$, $t = 1.511$, $p = 0.066$). This component of the model accounted for 67.7% of the variance in BI.

The influence of System Accessibility on PEU was highly significant, with SA→PEU yielding the strongest relationship observed in the study ($\beta = 0.535$, $t = 13.249$, $p < 0.001$). Enjoyment (E→PEU) also contributed significantly ($\beta = 0.319$, $t = 7.732$, $p < 0.001$) to explaining variance in PEU, where the model explains 58.9% of the observed variance.

While PU ($\beta = 0.484$, $t = 9.723$, $p < 0.001$) and PEU ($\beta = 0.264$, $t = 4.536$, $p < 0.001$) both emerged as significant predictors of ATU, the path from System Accessibility to ATU (SA→ATU) was not statistically supported ($\beta = 0.017$, $t = 0.238$, $p = 0.406$). The explained variance for ATU was 51.5%.

The direct effect of Behavioral Intention on Actual System Use (BI→ASU) was marginally significant ($\beta = 0.082$, $t = 1.650$, $p = 0.050$), suggesting that the translation from intention to actual usage may be underpinned by additional mediating factors. The model accounted for only 0.7% of the variance in ASU, indicating that other factors not included in the model may be influential.

Table 6. Summary of Hypotheses Testing

Hypothesis	Relationships	Direction	Path Coefficient	Conclusion
H1	E→PU	Positive	.472	Supported
H2	E→PEU	Positive	.321	Supported
H3	SA→PU	Positive	.163	Supported
H4	SA→PEU	Positive	.531	Supported
H5	SA→ATU	Positive	.013	Not Supported
H6	SA→BI	Positive	.065	Not Supported
H7	PEU→PU	Positive	.321	Supported
H8	PEU→ATU	Positive	.265	Supported
H9	PEU→BI	Positive	.108	Supported
H10	PU→ATU	Positive	.489	Supported
H11	PU→BI	Positive	.471	Supported
H12	ATU→BI	Positive	.275	Supported
H13	BI→ASU	Positive	.085	Supported

Table 5 and 6 revealed several significant relationships among the constructs. The hypothesis testing results are presented below.

Enjoyment demonstrated strong positive effects on both Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). The relationship between Enjoyment and PU (H1) was supported with a substantial path coefficient of 0.472, indicating that pre-service mathematics teachers who find e-learning systems enjoyable are more likely to perceive them as useful. Similarly, the hypothesis linking Enjoyment to PEOU (H2) was confirmed with a path coefficient of 0.321, suggesting that enjoyable e-learning experiences contribute to perceptions of system usability.

System Accessibility (SA) exhibited varying degrees of influence across different constructs. Its effect on Perceived Usefulness (H3) was supported, albeit with a relatively modest path coefficient of 0.163. More notably, System Accessibility strongly influenced Perceived Ease of Use (H4), as evidenced by the robust path coefficient of 0.531, the highest among all tested relationships. This finding underscores the critical importance of reliable system access in shaping usability perceptions.

However, the hypothesized direct effects of System Accessibility on Attitude Toward Using (H5) and Behavioral Intention (H6) were not supported, with negligible path coefficients of 0.013 and 0.065, respectively. This suggests that System Accessibility primarily influences attitudes and intentions indirectly through its effects on perceived usefulness and ease of use.

The traditional TAM relationships were largely confirmed in this study. Perceived Ease of Use positively influenced Perceived Usefulness (H7) with a path coefficient of 0.321, supporting the notion that usability enhances perceptions of utility. PEOU also demonstrated positive effects on Attitude Toward Using (H8) and Behavioral Intention (H9), with path coefficients of 0.265 and 0.108, respectively.

Perceived Usefulness emerged as a strong predictor of both Attitude Toward Using (H10) and Behavioral Intention (H11), with substantial path coefficients of 0.489 and 0.471, respectively. These findings reinforce the central role of perceived benefits in shaping attitudes and intentions toward e-learning adoption.

The attitudinal-behavioral pathway was confirmed, with Attitude Toward Using positively influencing Behavioral Intention (H12) as indicated by a path coefficient of 0.275. Finally, the critical link between Behavioral Intention and Actual System Usage (H13) was supported, though with a relatively weak path coefficient of 0.085, suggesting that while intentions do translate into behavior, this relationship may be moderated by additional factors not captured in the current model.Finaly, twelve of the thirteen hypothesized relationships were supported by the data, with System Accessibility's direct effects on Attitude Toward Using and Behavioral Intention being the only exceptions. The findings highlight the importance of both utilitarian factors (usefulness, ease of use, accessibility) and hedonic elements (enjoyment) in understanding pre-service mathematics teachers' adoption of e-learning systems.

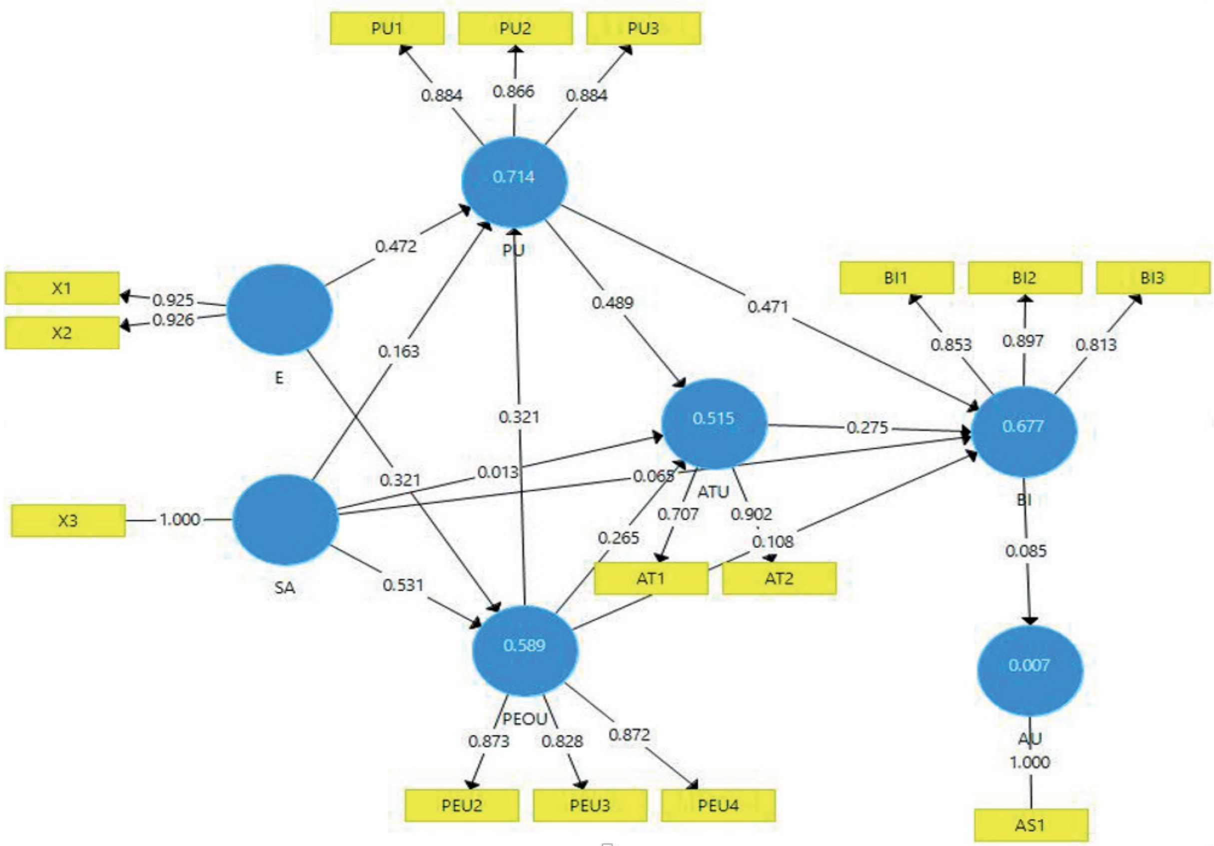

Figure 3. PLS Test of Proposed Model

The result revealed that Enjoyment is the strongest predictor of Perceived Usefulness, demonstrating a large effect size ($\beta = 0.468$, $p < .001$, $f^2 = 0.430$). Perceived Ease of Use also has a significant impact with a medium effect size ($\beta = 0.323$, $p < .001$, $f^2 = 0.148$), while System Accessibility contributes with a small effect size ($\beta = 0.165$, $p < .001$, $f^2 = 0.042$), together explaining 71.4% of the variance in Perceived Usefulness. Confirming H1, enjoyment had a significant effect on perceived usefulness (β=0.472, t-value = 11.303, $p < 0.001$). This relationship emerges as one of the most robust in the model. The finding indicates that pre-service mathematics teachers who experience enjoyment while interacting with e-learning systems are significantly more likely to perceive these systems as useful for their educational purposes. This strong association underscores the importance of affective factors in shaping utilitarian perceptions of technology, suggesting that the hedonic aspects of e-learning experiences substantially influence how pre-service teachers evaluate the practical benefits of these systems. The magnitude of this effect highlights enjoyment as a critical determinant in the technology acceptance process for mathematics education contexts. Furthermore, system accessibility had a significant effect on perceived usefulness (β=0.163, t-value = 3.672, $p < 0.001$), H3 were supported. This finding indicates that while reliable access to e-learning systems does contribute to pre-service mathematics teachers' perceptions of system utility, the effect is less pronounced compared to other relationships in the model. Supporting H7, perceive ease of use had a significant effect on perceived usefulness (β=0.321, t-value = 6.571, $p < 0.001$). This finding suggests that when pre-service mathematics teachers find an e-learning system easy to use, they are more likely to perceive it as useful, underscoring the integral role of system usability in enhancing its overall perceived value.

The strongest predictors of Behavioral Intention ($R^2 = 0.677$) are Perceived Usefulness ($\beta = 0.469$, $p < .001$, $f^2 = 0.234$) with a medium effect, followed by Attitude Toward Using ($\beta = 0.277$, $p < .001$, $f^2 = 0.113$) and Perceived Ease of Use ($\beta = 0.106$, $p = .014$, $f^2 = 0.012$), both with small effect sizes. These findings emphasize that while all three constructs contribute to Behavioral Intention, Perceived Usefulness holds the most significant influence. Supporting H11, perceived usefulness had a significant effect on behavioral intention (β=0.471, t-value = 10.674, $p < 0.001$). This finding, representing one of the most robust relationships in the model, demonstrates that pre-service mathematics teachers' perceptions of e-learning system utility are a primary driver of their intentions to use these systems. Perceive ease of use had a significant effect on behavioral intention (β=0.108, t-value = 2.348, $p < 0.05$), therefore, H9 were supported. This finding indicates that while pre-service mathematics teachers' perceptions of system usability do contribute to their intentions to use e-learning systems, the relationship is relatively modest compared to other predictors of behavioral intention in the model. Additionally, supporting H12, attitude toward using had a significant effect on behavioral intention (β=0.275, t-value = 6.193, $p < 0.001$). The results for H12 indicate that Attitude Toward Using exerts a positive influence on Behavioral Intention, underscoring its supportive role in shaping intentions to adopt e-learning systems among pre-service mathematics teachers.

The strongest predictors of Perceived Ease of Use ($R^2 = 0.589$) are System Accessibility, which exhibits a large effect ($\beta = 0.535$, $p < .001$, $f^2 = 0.439$), and Enjoyment, which shows a medium effect ($\beta = 0.319$, $p < .001$, $f^2 = 0.160$). These results highlight that both reliable system access and engaging e-learning experiences significantly drive usability perceptions among pre-service mathematics teachers. Supporting H2, enjoyment had a significant effect on perceive ease of use (β=0.321, t-value = 7.732, $p < 0.001$). This finding emphasizes that pre-service mathematics teachers who experience enjoyment with e-learning systems are more inclined to perceive them as user-friendly. Furthermore, supporting H4, system accessibility had a significant effect on perceive ease of use (β=0.531, t-value = 13.249, $p < 0.001$). This statistically significant relationship emphasizes that as pre-service mathematics teachers perceive greater accessibility in the e-learning system, they are more likely to view it as easier to use. The robust effect suggests that system accessibility critically shapes usability perceptions, thereby potentially enhancing overall acceptance and subsequent adoption of the e-learning platform.

The effect size of PEU and PU on ATU, f2 for PEU ($f^2 = 0{,}052$) is considered as a small effect size, while f2 for PU ($f^2 = 0{,}201$) is considered as medium effect size. Perceive ease of use had a significant effect on attitude toward using (β=0.265, t-value = 4.536, $p < 0.001$), therefore, H8 were supported. This finding suggests that pre-service mathematics teachers tend to develop more favorable attitudes toward e-learning systems when they perceive these systems as easy to use. Supporting H10, perceived usefulness had a significant effect on attitude toward using (β=0.489, t-value = 9.723, $p < 0.001$). This result underscores the critical role of utility perceptions in fostering favorable attitudes toward e-learning systems among pre-service mathematics teachers.

The analysis indicates that System Accessibility has no significant effect on Attitude Toward Using (β = 0.017, p = .406, f^2 = 0.000) and only a marginally significant, very small effect on Behavioral Intention (β = 0.067, p = .066, f^2 = 0.006). Inconsistent with H5, system accessibility had no significant effect on attitude toward using (β=0.013, t-value = 0.238, p > 0.001, p > 0.05). This extremely low coefficient indicates a negligible direct relationship between these constructs. Consequently, H5 was not supported by the empirical data. This finding suggests that the mere accessibility of an e-learning system does not directly influence pre-service mathematics teachers' attitudes toward using it. While System Accessibility may be a necessary condition for e-learning engagement, it appears insufficient to independently generate positive attitudinal responses. Instead, the data implies that System Accessibility likely influences attitudes indirectly through other mediating variables, such as Perceived Usefulness and Perceived Ease of Use, which demonstrated stronger relationships with Attitude Toward Using. Inconsistent with H6, system accessibility had no significant effect on behavioral intention (β=0.065, t-value = 1.511, p > 0.001, p > 0.05). This result was not statistically significant, suggesting that SA does not have a robust direct impact on pre-service mathematics teachers' intention to use e-learning systems. Instead, any potential effects of SA on BI may be mediated through other constructs, such as Perceived Usefulness or Perceived Ease of Use.

The relationship between Behavioral Intention and Actual System Usage is borderline significant (β = 0.082, p = .050) with a very small effect size (f^2 = 0.007), explaining only 0.7% of the variance in actual usage behavior. The findings for H13 indicate that Behavioral Intention has a positive effect on Actual System Usage (β=0.085, t-value = 1.650, p > 0.001). This result, though statistically significant, represents a relatively weak relationship. It suggests that while pre-service teachers' intentions to use e-learning systems do lead to actual usage, other factors beyond intention may also play important roles in determining the extent and quality of system use in practice.

DISCUSSIONS AND CONCLUSION

The findings regarding the predictors of Perceived Usefulness (PU) underscore the importance of enjoyment, system accessibility, and perceived ease of use in shaping pre-service mathematics teachers' perceptions of e-learning platforms. In particular, the robust effect of enjoyment (H1; β = 0.468, p < .001) aligns with prior research indicating that intrinsic pleasure derived from system interaction can drive technology adoption (Abdullah et al., 2016; FakhrHosseini et al., 2024; Pereira & Tam, 2021; Yi & Hwang, 2003). In educational settings, this affective component not only enhances motivation and engagement (Hejazi & Sadoughi, 2023) but may also counterbalance typical negative attitudes toward challenging subjects like mathematics (Barnes, 2021), thereby significantly elevating perceptions of the utility of e-learning systems.

Furthermore, the positive impact of system accessibility (H3; β = 0.165, p < .001) on PU reinforces previous studies that highlight the role of reliable and effortless access in fostering positive user attitudes (Duggal, 2022; Timbi-Sisalima et al., 2022). The modest yet significant effect of system accessibility corroborates research suggesting that in environments with potentially inconsistent technological infrastructure, often observed in developing countries, the availability and ease of access to e-learning platforms are crucial determinants of users' adoption behaviors (Almaiah et al., 2020; Kumar et al., 2020; Ma et al., 2025; Yan et al., 2021). For example, Park indicated that system accessibility had no effect on perceived usefulness (Park, 2009). This is because Korea has a strong IT infrastructure and approximately 95% of the study sample has high-speed internet access at home, therefore it is immaterial whether or not colleges give students easy accessibility (Park, 2009). Meanwhile, internet speed in Indonesia, both for mobile and fixed broadband networks, is still a concern. For mobile internet, Indonesia is ranked 97th out of 143 countries in the world and for fixed broadband, Indonesia is ranked 126th out of 143 countries in the world (Speedtest Global Index, 2023).

Additionally, the influence of perceived ease of use on perceived usefulness (H7; β = 0.323, p < .001) reinforces the central tenets of the TAM, wherein usability is a core antecedent of perceived benefits. This relationship is consistent with the established literature that posits that when an e-learning system is easy to navigate and interact with, users are more likely to evaluate it as beneficial for their educational needs. Moreover, previous research supports the correlation between perceived ease of use and perceived usefulness that was identified (Abdullah et al., 2016; Alharbi & Drew, 2014; Chang, Yan, & Tseng, 2012; Mailizar, Almanthari, & Maulina, 2021; Park, Nam, & Cha, 2011; Saade´ & Bahli, 2005; Salloum, Qasim

Mohammad Alhamad, Al-Emran, Abdel Monem, & Shaalan, 2019). Collectively, these findings not only align with the theoretical foundation of technology adoption models but also illuminate the synergistic effects of affective and pragmatic factors in determining the perceived usefulness of e-learning initiatives.

The analysis identifies Perceived Usefulness as a primary determinant of Behavioral Intention, with H11 indicating a substantial relationship ($\beta = 0.469$, $p < .001$) and a medium effect size. This finding is consistent with prior research, which argues that when teachers perceive digital tools as beneficial and effective, their intention to adopt such tools increases (Venkatesh; Viaswanath & Davis; Fred D., 2000). This relationship is particularly relevant in mathematics education where perceived usefulness of technology can lead to significant transformations in both instructional strategies and student learning outcomes (Bonfield et al., 2020; Schmidt & Tang, 2020).

Attitude Toward Using also contributes positively to Behavioral Intention, as evidenced by H12 ($\beta = 0.277$, $p < .001$), although with a smaller effect size. This supports the claim that a favorable attitude towards digital tools can enhance teachers' intentions to integrate these systems into their pedagogical practice, aligning with the Technological Pedagogical Content Knowledge (TPACK) framework which emphasizes the integration of content, pedagogy, and technology for effective teaching (Haleem et al., 2022; Peter, 2023).

In contrast, the effect of Perceived Ease of Use on Behavioral Intention (H9; $\beta = 0.106$, $p = .014$) is statistically significant yet relatively modest. This suggests that while usability plays a role in shaping behavioral intent, its influence may be indirect, primarily by enhancing perceptions of usefulness and shaping overall attitudes towards technology (Davis, 1985; Venkatesh & Davis, 1996). The comprehensive impact of these predictors underscores the multifaceted nature of technology adoption, intimating that while ease of use is important, it is the perceived benefits and the resulting favorable attitudes that ultimately drive Behavioral Intention in the context of e-learning adoption among pre-service mathematics teachers.

Collectively, these findings not only align with systematic reviews of TAM research (Al-Qaysi et al., 2020; Alsharida et al., 2021; Granic, 2022; Granic & Marangunic, 2019; Mustafa & Garcia, 2021; Rosli et al., 2022; Scherer et al., 2019) but also emphasize the need for a nuanced approach in further exploring how these constructs interact to inform actual technology use in educational settings.

The findings reveal a clear hierarchy of influence on Behavioral Intention, with Perceived Usefulness emerging as the dominant predictor, followed by Attitude Toward Using and Perceived Ease of Use. This pattern suggests that pre-service mathematics teachers prioritize the practical benefits of e-learning systems when forming usage intentions, with attitudinal factors and usability considerations playing supporting roles.

The analysis of factors influencing Perceived Ease of Use (PEU) reveals a significant impact of both System Accessibility (H4; $\beta = 0.535$, $p < .001$) and Enjoyment (H2; $\beta = 0.319$, $p < .001$), with these variables collectively explaining 58.9% of the variance in PEU. The substantial effect size of System Accessibility ($f^2 = 0.439$) underscores its primacy in shaping pre-service mathematics teachers' perceptions of e-learning usability, while Enjoyment demonstrates a moderate but meaningful contribution ($f^2 = 0.160$).

The dominant influence of System Accessibility on Perceived Ease of Use aligns with previous research highlighting the critical role of reliable technological infrastructure in e-learning adoption (Kumar et al., 2020; Ma et al., 2025). This finding is particularly relevant in the Indonesian context, where digital infrastructure varies considerably across regions (Almaiah et al., 2020; Sarnato et al., 2024). The strong relationship between accessibility and perceived usability suggests that consistent, dependable access to e-learning platforms constitutes a fundamental prerequisite for positive user experiences, especially in mathematics education where complex formulas and concepts require robust digital representation (Borba et al., 2016; Moreno-Guerrero et al., 2020; Waquar et al., 2025).

The significant contribution of Enjoyment to Perceived Ease of Use corroborates previous studies identifying affective factors as important determinants of technology adoption (Abdullah et al., 2016; Al-Aulamie, Mansour, Daly, & Adjei, 2012; Chen, Mou-Te Chang, Chen, Huang, & Chen, 2012; FakhrHosseini et al., 2024; Luschei et al., 2008; Pereira & Tam, 2021; Shyu & Huang, 2011; Zare & Yazdanparast, 2013). This relationship is especially pertinent in mathematics education, where anxiety and negative attitudes often present substantial barriers to engagement (Barnes, 2021). The findings suggest that when pre-service teachers experience pleasure and satisfaction while using e-learning systems, they perceive these systems as more intuitive and manageable. This aligns with research demonstrating that enjoyable digital mathematics environments enhance concept comprehension and student engagement (Abrahamson et al., 2020; Engelbrecht & Oates, 2022; Utterberg Moden, 2021).

These results emphasize the dual importance of both technical and affective dimensions in shaping usability perceptions. For mathematics e-learning platforms to be perceived as easy to use, they must not only provide reliable, consistent access but also deliver engaging, enjoyable experiences that mitigate the inherent challenges of the subject matter. This dual requirement supports empirical studies suggesting that effective mathematics e-learning must incorporate interactive problem-solving, visualization of complex concepts, and guided procedural learning (Liu & Yu, 2023; Shurygin et al., 2021). As Indonesian higher education continues its digital transformation (Mailizar, Almanthari, et al., 2021; Sewandono et al., 2023; Yetti, 2024), these findings provide valuable insights for developing mathematics e-learning systems that balance technical accessibility with engaging user experiences.

The analysis of factors influencing Perceived Ease of Use (PEU) reveals that System Accessibility (H4) and Enjoyment (H2) are the strongest predictors, collectively explaining a substantial portion of the variance in PEU ($R^2 = 0.589$). The impact of System Accessibility ($\beta = 0.535$, $p < .001$, $f^2 = 0.439$) is particularly robust, underscoring that reliable, accessible e-learning platforms are crucial for fostering user-friendly experiences. This finding is in line with prior research emphasizing that dependable access is a key facilitator of technology adoption (Amin, Masita, Jalil, & Man, 2016; Park, 2009; Park et al., 2011), particularly in contexts where infrastructural constraints may otherwise hinder seamless interaction with digital learning environments (Benkhalfallah et al., 2024; Falqueto et al., 2020; Kenno et al., 2021).

Similarly, the predictive role of Enjoyment ($\beta = 0.319$, $p < .001$, $f^2 = 0.160$) supports the view that intrinsic pleasure derived from system use significantly enhances usability perceptions. This aligns with earlier studies which have documented the role of enjoyment in promoting technology acceptance and engagement, especially within mathematics education where overcoming anxiety and fostering positivity are essential (Barnes, 2021). Together, these findings highlight the necessity for mathematics e-learning platforms to integrate both technical robustness in accessibility and engaging, enjoyable user experiences to effectively support learning.

The findings demonstrate that Perceived Usefulness (H10; $\beta \approx 0.489$, $p < .001$) is a robust predictor of Attitude Toward Use (ATU), underscoring the importance of teachers recognizing the practical benefits of e-learning systems. This result corroborates the foundational principles of the TAM and aligns with the TPACK framework, which argues that effective integration of digital tools in educational settings, particularly in mathematics, requires a nuanced synthesis of content, pedagogy, and technology (Haleem et al., 2022; Park, 2009; Peter, 2023). As teachers perceive these systems to be instrumental in enhancing learning outcomes, their favorable attitudes toward using the technology are bolstered, an observation that is consistent with previous studies emphasizing the transformational potential of digital tools in mathematics education (Akugizibwe & Ahn, 2020; Borba et al., 2016).

In addition, Perceived Ease of Use (H8; $\beta \approx 0.265$, $p < .001$) is also shown to significantly influence ATU, albeit to a slightly lesser extent compared to Perceived Usefulness. This finding aligns with the broader TAM literature, which highlights that when technology is perceived as user-friendly, it not only enhances perceived usefulness but also shapes positive attitudes toward its integration (Bagozzi et al., 2001; Mailizar, Burg, & Maulina, 2021; Nagy, 2018). The significant role of ease of use reinforces the notion that intuitive system design and minimal learning barriers are critical to fostering favorable attitudes, aligning with research from diverse fields including ICT adoption in education (Amoroso et al., 2022). Together, these determinants highlight that both the practical utility and the user-friendly nature of e-learning platforms are essential for cultivating positive attitudes among pre-service mathematics teachers.

The analysis revealed two non-significant relationships within the extended Technology Acceptance Model: System Accessibility did not directly influence either Attitude Toward Using (H5; $\beta = 0.017$, $p = .406$, $f^2 = 0.000$) or Behavioral Intention (H6; $\beta = 0.067$, $p = .066$, $f^2 = 0.006$). These findings suggest that while System Accessibility strongly predicts Perceived Ease of Use and moderately affects Perceived Usefulness, it does not exert direct effects on attitudinal or intentional outcomes among pre-service mathematics teachers.

The absence of a significant direct relationship between System Accessibility and Attitude Toward Using contradicts some previous research. For instance, a study found that system accessibility directly influenced students' attitudes toward e-learning in higher education contexts (Salloum et al., 2019). Similarly, Almaiah et al. identified accessibility as a critical factor directly affecting attitudes toward mobile learning systems (Almaiah et al., 2020). However, the current findings align with research, who demonstrated that technical factors like accessibility primarily influence attitudes through mediating variables rather than directly (Teo, 2010). This suggests that for pre-service mathematics teachers, the impact of system accessibility on attitudes is fully mediated by perceptions of usefulness and ease of use.

Similarly, the non-significant direct effect of System Accessibility on Behavioral Intention, though marginally approaching significance ($p = .066$), contradicts studies by Revythi and Tselios, who found direct relationships between accessibility and intention to use e-learning systems (Revythi & Tselios, 2019). However, the current results are consistent with research by Park (2009) and (Al-Maroof, Salloum, Hassanien, & Shaalan, 2023), who demonstrated that system accessibility influences behavioral intention primarily through indirect pathways mediated by perceived usefulness and perceived ease of use (Al-Maroof et al., 2023; Park, 2009). This pattern suggests that while reliable access to e-learning systems is necessary, it is not sufficient to directly drive usage intentions without first enhancing perceptions of system utility and usability.

These findings have important theoretical implications, suggesting that the relationship between technical infrastructure factors and adoption outcomes may be more complex than often assumed in technology acceptance models. Rather than directly influencing attitudes and intentions, system accessibility appears to operate through cognitive perceptions of system characteristics. This aligns with the cognitive mediation perspective proposed by Venkatesh and Davis, which posits that external variables primarily influence behavioral outcomes through their effects on key perceptual constructs (Venkatesh; Viaswanath & Davis; Fred D., 2000). For mathematics education specifically, these results suggest that while ensuring reliable system access is crucial, developers and institutions must focus on how this accessibility translates into enhanced perceptions of usefulness and ease of use to ultimately drive positive attitudes and adoption intentions.

The analysis of the relationship between Behavioral Intention and Actual System Usage (H13) reveals a borderline significant effect ($\beta = 0.082$, $p = .050$) with a very small effect size ($f^2 = 0.007$). This marginal significance suggests that while intention to use an e-learning system may subtly influence actual usage behaviors among pre-service mathematics teachers. This finding aligns with the critical perspectives offered by Turner et al., who argued that although the Technology Acceptance Model (TAM) is robust in predicting user intentions, its capability to forecast actual technology use is substantially limited (Turner et al., 2010). Additonally, some research indicates that while intention-to-use can significantly predict actual use behavior, the direct impact of perceived usefulness and ease of use, which influence behavioral intention, may not always translate into actual usage in real-world settings (Tao, 2009). The borderline significance observed in H13 underscores the contextual nuances and methodological challenges inherent in linking intentions to behaviors, as TAM's predictive power for actual system usage may vary according to the study's context, sample, and type of technology implemented. These results therefore contribute to the ongoing discourse regarding the gap between intention and use, and they highlight the importance of incorporating additional contextual factors and mediating variables in future research to better capture the dynamics influencing actual usage patterns.

While the extended Technology Acceptance Model (TAM) employed in this research has provided valuable insights into the determinants of actual e-learning usage among pre-service mathematics teachers, several practical implications emerge. Educational institutions should prioritize developing accessible and engaging mathematics e-learning platforms incorporating interactive problem-solving, gamification, and adaptive feedback mechanisms. Additionally, targeted training programs should be implemented to improve pre-service teachers' digital competence and enhance their perceived usefulness and ease of use of such systems, thereby translating intention into sustained e-learning engagement.

To advance theoretical understanding and practical applications, future investigations should examine additional variables that could enrich the model's explanatory power. These include digital self-efficacy, which could inform scaffolded training program design; teaching presence, which has direct implications for faculty development initiatives; and institutional support mechanisms, which could guide administrative decision-making regarding resource allocation. These factors are particularly relevant in teacher education settings where pedagogical practices and institutional environments intersect with individual learner behaviors.

Furthermore, adopting longitudinal research designs would capture the dynamic nature of technology adoption, revealing how behavioral intentions develop into consistent usage behaviors and how external events affect adoption trajectories. This approach would be particularly valuable in diverse educational contexts, including developing countries where access and institutional readiness vary widely. Expanding inquiry in these directions will strengthen theoretical contributions while providing practical guidance for designing responsive and sustainable e-learning systems in teacher education.

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