Contents lists available at https://ojs.unsulbar.ac.id/index.php/saqbe
Vol 2 No 2 September 2025, https://doi.org/10.31605/saqbe

Saqbe : Sains dan Pembelajarannya

Pre-Service Science Teacher Acceptance of and Satisfaction with Online Educational Classes through the Technology Acceptance Model (TAM)

Penerimaan dan Kepuasan Calon Guru Sains terhadap Pembelajaran Daring melalui Technology Acceptance Model *(TAM)*

Dita Puji Rahayu[1], Niken Yuni Astuti[2], Setia Rahmawan[3]

[1]Pendidikan IPA, Fakultas Matematika dan Ilmu Pendidikan, Universtas Negeri Yogyakarta
[2]Pendidikan Guru Sekolah Dasar, Fakultas Keguruan dan Ilmu Pendidikan, Universitas Lampung
[3]Pendidikan Kimia, Fakultas Ilmu Tarbiyah dan Keguruan, Universitas Islam Negeri Sunan Kalijaga, Yogyakarta

*Correspondence e-mail: ditapuji@uny.ac.id

Received: 1 August 2025
Revised: 1 September
Accepted : 15 September 2025
Published: 30 September 2025

Abstract

This study aims to examine pre-service science teachers' acceptance of and satisfaction with online educational classes using the Technology Acceptance Model (TAM). A quantitative cross-sectional survey design was employed, involving 193 pre-service science teachers selected through purposive sampling. Data were collected using a structured questionnaire measuring four latent constructs: Perceived Ease of Use (PEU), Perceived Usefulness (PU), Satisfaction (SAT), and Acceptance Intention (AI). The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate both measurement and structural models. The results indicate that all constructs meet the criteria for reliability and validity, including convergent and discriminant validity. Structurally, PEU significantly influences PU and SAT, while PU significantly affects SAT and AI. Satisfaction emerges as the strongest predictor of acceptance intention. However, PEU does not directly influence AI, although it shows significant indirect effects through PU and SAT. These findings highlight the importance of usability, perceived benefits, and satisfaction in shaping students' acceptance of online learning environments. The study provides insights for improving online educational practices in teacher education programs.

Keywords

Validation; Instructional Media; Educational Technology; Science Education; Motion and Force

Abstrak

Penelitian ini bertujuan untuk menganalisis penerimaan dan kepuasan calon guru sains terhadap pembelajaran daring dengan menggunakan Technology Acceptance Model (TAM). Penelitian ini menggunakan pendekatan kuantitatif dengan desain survei cross-sectional yang melibatkan 193 calon guru sains melalui teknik purposive sampling. Data dikumpulkan menggunakan kuesioner terstruktur yang mengukur empat konstruk laten, yaitu Perceived Ease of Use (PEU), Perceived Usefulness (PU), Satisfaction (SAT), dan Acceptance Intention (AI). Analisis data dilakukan dengan Partial Least Squares Structural Equation Modeling (PLS-SEM) untuk mengevaluasi model pengukuran dan model struktural. Hasil penelitian menunjukkan bahwa seluruh konstruk memenuhi kriteria validitas dan reliabilitas, termasuk validitas konvergen dan diskriminan. Secara struktural, PEU berpengaruh signifikan terhadap PU dan SAT, sementara PU berpengaruh terhadap

SAT dan AI. Kepuasan menjadi prediktor terkuat terhadap niat penerimaan. Namun, PEU tidak berpengaruh langsung terhadap AI, melainkan melalui pengaruh tidak langsung. Temuan ini menegaskan pentingnya kemudahan penggunaan, manfaat, dan kepuasan dalam meningkatkan penerimaan pembelajaran daring.
Kata Kunci
Validasi; Media Pembelajaran; Teknologi Pembelajaran; Pembelajaran IPA; Materi Gerak dan Gaya

INTRODUCTION

The rapid development of digital technologies has significantly transformed many aspects of modern education. Over the last decade, educational institutions around the world have increasingly integrated online learning platforms, learning management systems, and digital communication tools into teaching and learning processes. However, the global COVID-19 pandemic accelerated this transformation at an unprecedented rate (Cahyani, 2025; Ivanov, Radonjić, Stošić, Krčadinac, Đokić, & Đokić, 2025). When schools and universities were forced to close physical classrooms to prevent the spread of the virus, educational institutions quickly adopted online educational classes as an alternative method for continuing learning activities. As a result, online learning shifted from being a supplementary approach to becoming the primary mode of instruction in many educational settings (Hariyasasti, 2025).

During the pandemic, online educational classes enabled educational institutions to maintain learning continuity despite physical distancing restrictions. Various digital platforms such as Zoom, Google Classroom, Microsoft Teams, and other online learning environments were widely used to deliver lectures, facilitate discussions, distribute learning materials, and assess student performance. These technologies allowed teachers and students to interact remotely while ensuring that academic activities could continue without interruption. In addition, the rapid expansion of digital infrastructure and internet accessibility further supported the widespread adoption of online education. Consequently, both educators and students were required to adapt quickly to new forms of technology-mediated learning (Nieto-Taborda, & Luppicini, 2025; Okunlola, & Naicker, 2025).

Even after the pandemic began to subside, the use of online educational classes has continued to grow in many institutions. Many universities have recognized the flexibility and accessibility offered by online learning environments, which allow students to access educational resources from different locations and at different times (Rahmani, Groot, & Rahmani, 2024). Online learning can also support blended learning models that combine face-to-face instruction with digital learning experiences. As a result, online education is no longer seen merely as a temporary solution during emergencies but rather as an integral component of modern educational systems. However, the successful implementation of online learning depends not only on technological infrastructure but also on students' willingness to accept and engage with these digital learning environments (Sun, & Shi, 2024; Yindeemak, Limpinan, Pasmala, Nammanee, & Jantakoon, 2025).

While the availability of online learning technologies has increased significantly, their effectiveness largely depends on how learners perceive and interact with these systems. Acceptance of technology plays a crucial role in determining whether students are willing to use online learning platforms as part of their educational experience. If students perceive online educational classes as difficult to use or not beneficial for their learning, they may experience low engagement and reduced motivation. Conversely, when students perceive online learning platforms as useful and easy to use, they are more likely to adopt them and integrate them into their learning activities (Linus, & Aladesusi, 2025; Masalimova, Zheltukhina, Sergeeva, Sizova, Novikov, & Sadykova, 2024). In addition to acceptance, student satisfaction is another critical factor influencing the success of online educational classes. Satisfaction reflects students' overall evaluation of their learning experiences and can influence their continued participation in online learning environments. When students are satisfied with online classes, they are more likely to actively participate in learning activities, complete assignments, and maintain positive attitudes toward digital learning. On the other hand, low satisfaction levels may lead to reduced engagement, poor learning outcomes, and negative perceptions of online education. Therefore, evaluating both acceptance and satisfaction is essential for understanding how students respond to online educational environments and for identifying factors that contribute to successful technology integration in education (Banihashem, Noroozi, den Brok, Biemans, Stevens, & Güney, 2024; Güllü, Kara, & Akgün, 2024).

Pre-service science teachers represent an important group in educational research because they are future educators who will play a critical role in shaping the learning experiences of the next generation of students. As future teachers, they are expected not only to understand scientific concepts but also to be capable of integrating technology effectively into science teaching practices. In the digital era, teachers are increasingly required to utilize online platforms, digital simulations, and other technological tools to enhance science learning. Therefore, examining pre-service science teachers' perceptions of online educational classes can provide valuable insights into their readiness to adopt educational technologies in their future professional careers. Science education often involves complex concepts, experimental activities, and interactive learning processes that may present unique challenges in online learning environments. Pre-service science teachers who experience online educational classes during their training may develop specific perceptions about the effectiveness of such learning methods for teaching science (Han, & Sa, 2022; Mastour, Yousefi, & Niroumand, 2025). Their experiences as students in online classes may influence their attitudes toward technology integration in their future classrooms. If pre-service science teachers perceive online learning environments as effective and beneficial, they may be more willing to incorporate similar technologies into their own teaching practices. Furthermore, understanding the acceptance and satisfaction of pre-service science teachers toward online educational classes can help teacher education institutions design more effective training programs. Teacher education programs must ensure that future educators are equipped with the necessary digital competencies to navigate modern educational environments. By examining how pre-service teachers interact with online learning systems, institutions can identify areas where additional training or support may be required. Consequently, investigating this population is essential for supporting the development of technologically competent educators who can effectively integrate digital tools into science education (Alotaibi, 2026; Bhat, Tiwari, Bhaskar, & Khan, 2026).

One of the most widely used theoretical frameworks for examining technology adoption is the Technology Acceptance Model (TAM). Developed by Davis, TAM explains how users come to accept and use new technologies based on two primary constructs: perceived ease of use and perceived usefulness. Perceived ease of use refers to the extent to which individuals believe that using a particular technology will be free from effort, while perceived usefulness refers to the degree to which individuals believe that the technology will enhance their performance. These perceptions influence users' attitudes, satisfaction, and behavioral intentions to use the technology. Over the past decades, TAM has been widely applied in various educational contexts to analyze students' and teachers' acceptance of digital learning technologies (Li, Numtong, Gan, & Ngern, 2025; Wang, Wang, Zeng, Su, & Li, 2025; Yaldız, & Markoc, 2026).

In the context of online education, TAM provides a useful framework for understanding how students perceive and interact with online learning systems. By examining relationships between perceived ease of use, perceived usefulness, satisfaction, and acceptance intention, researchers can better understand the factors that influence students' willingness to engage with online educational platforms. Such insights are essential for improving the design and implementation of digital learning environments. Despite the growing number of studies examining online learning adoption, many existing studies focus primarily on general student populations or on technology use in higher education without specifically addressing the perspectives of pre-service science teachers (Al-Adwan, Meet, Anand, Shukla, Alsharif, & Dabbaghia, 2025; Vafaei-Zadeh, Ong, Hanifah, & Nikbin, 2026). Furthermore, previous studies often examine technology acceptance or learning satisfaction separately, rather than exploring how these constructs interact within a comprehensive structural model. There is still limited research that simultaneously investigates perceived ease of use, perceived usefulness, satisfaction, and acceptance intention of online educational classes within the context of pre-service science teacher education. Given the increasing importance of digital competence for future educators, a deeper understanding of these relationships is necessary (Waluyo, Hariguna, Saputra, Oktaviana, & Hani, 2025).

Therefore, this study aims to examine pre-service science teachers' acceptance of and satisfaction with online educational classes using the Technology Acceptance Model (TAM). By analyzing the relationships among perceived ease of use, perceived usefulness, satisfaction, and acceptance intention, this study seeks to provide empirical insights into how future science teachers perceive online learning environments. The findings of this study are expected to contribute to the improvement of online educational practices in teacher education programs and to support the development of more effective technology-integrated science learning environments.

METHOD

Research Design

This study employed a quantitative research design using a cross-sectional survey method. A quantitative approach was considered appropriate because the study aimed to examine the structural relationships among the constructs in the Technology Acceptance Model (TAM), namely Perceived Ease of Use (PEU), Perceived Usefulness (PU), Satisfaction (SAT), and Acceptance Intention (AI) toward online educational classes. The cross-sectional design allowed the researchers to collect data from participants at a single point in time and to investigate their perceptions, attitudes, and behavioral intentions regarding online learning (Nainggolan, & Maulana, 2025). This study was explanatory in nature because it sought to test the hypothesized relationships among TAM variables and to determine how perceived ease of use and perceived usefulness influence satisfaction and acceptance of online educational classes. To analyze these relationships, the study applied Structural Equation Modeling (SEM), which is suitable for testing both measurement and structural models simultaneously. SEM was selected because it enables the researchers to assess the validity and reliability of the measurement instrument as well as the direct and indirect effects among latent constructs.

Research Participants

The participants in this study were 193 pre-service science teachers enrolled in a teacher education program. Pre-service science teachers were selected because they represent future educators who are expected to be capable of using digital technology effectively in their professional practice. Their experiences in online educational classes are important to examine, as their perceptions of online learning may influence their future readiness to integrate technology into science teaching. The sample consisted of students who had experienced online educational classes as part of their academic learning process. The participants were selected using purposive sampling, with the main criterion being that they had participated in online classes and were therefore able to provide relevant responses regarding their acceptance of and satisfaction with such learning environments. A sample size of 193 was considered adequate for SEM analysis because it met the minimum recommended sample requirement for examining relationships among multiple latent variables.

Research Instrument

The data were collected using a structured questionnaire adapted from previous studies on the Technology Acceptance Model (TAM) and online learning acceptance. The instrument was designed to measure four latent constructs: Perceived Ease of Use (PEU), Perceived Usefulness (PU), Satisfaction (SAT), and Acceptance Intention (AI). Each construct was represented by four indicators, resulting in a total of 16 items. The PEU construct was measured by items PEU1 to PEU4, the PU construct by PU1 to PU4, the SAT construct by SAT1 to SAT4, and the AI construct by AI1 to AI4. All questionnaire items were assessed using a Likert scale, ranging from 1 = strongly disagree to 4 = strongly agree, depending on the scale format used in the final questionnaire. Before data collection, the instrument was reviewed and adapted to fit the context of online educational classes for pre-service science teachers. Because the questionnaire was adapted from established prior studies, its content was considered theoretically grounded and relevant to the objectives of this study. In addition, minor language adjustments were made to ensure clarity and suitability for the participants' educational context.

Data Collection Procedure

Data collection was conducted by distributing the questionnaire to pre-service science teachers who had participated in online educational classes. The questionnaire was administered after the participants had sufficient experience with online learning, so that they could evaluate the ease of use, usefulness, satisfaction, and acceptance of such classes based on their actual experiences (Adam, Qudratuddarsi, Tari, & Putri, 2024). Ningthias, & Qudratuddarsi, 2025). Participants were informed about the purpose of the study and were asked to complete the questionnaire voluntarily. To ensure ethical research practice, participants were informed that their responses would be kept confidential and used only for academic purposes. They were also assured that their participation was voluntary and that no personal identifying information would be disclosed. After the responses were collected, the data were screened and prepared for further statistical analysis (Lestari, Hasanuddin, Saputri, & Maulidita, 2024).

Data Analysis

The data were analyzed using Structural Equation Modeling (SEM), specifically Partial Least Squares Structural Equation Modeling (PLS-SEM). PLS-SEM was chosen because it is appropriate for predictive research models, can handle relatively small to medium sample sizes, and is suitable for testing complex relationships among latent variables (Qudratuddarsi, & Meivawati, 2025). The analysis was conducted in two stages: measurement model evaluation and structural model evaluation. In the first stage, the measurement model was assessed to determine the reliability and validity of the instrument. Descriptive statistics, including mean, standard deviation, kurtosis, and skewness, were first examined to evaluate the distribution of the data. Indicator reliability was then assessed through factor loadings, with values above 0.70 indicating acceptable item reliability. Internal consistency reliability was evaluated using Cronbach's alpha, rho_A, and Composite Reliability (CR), where values above 0.70 indicated satisfactory reliability. Convergent validity was examined through the Average Variance Extracted (AVE), with values above 0.50 considered acceptable. Discriminant validity was evaluated using the Fornell–Larcker criterion and cross-loading analysis, ensuring that each construct was empirically distinct from the others. In addition, Variance Inflation Factor (VIF) values were examined to detect multicollinearity among indicators, with values below the recommended threshold indicating no serious collinearity issue.

In the second stage, the structural model was evaluated to test the hypothesized relationships among the constructs. Model fit was examined using indices such as the Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). Path coefficients were then analyzed to determine the strength and significance of the relationships between constructs. The significance of the direct and indirect effects was tested using the bootstrapping procedure, which generated t-statistics and p-values for hypothesis testing. Through this analysis, the study assessed not only the direct effects of perceived ease of use and perceived usefulness on satisfaction and acceptance intention, but also the mediating role of satisfaction and usefulness in the TAM framework.

Validity and Reliability of the Instrument

The validity and reliability of the measurement model were supported by the SEM results. All indicator loadings were above the acceptable threshold, indicating that the items were strong measures of their respective constructs. The values of Cronbach's alpha, rho_A, and composite reliability for all constructs exceeded the recommended level, confirming good internal consistency. Likewise, the AVE values for all constructs were above 0.50, indicating adequate convergent validity. The Fornell–Larcker criterion also showed that the square root of AVE for each construct was greater than its correlations with other constructs, confirming discriminant validity. These results indicate that the instrument used in this study was both reliable and valid for measuring pre-service science teachers' acceptance of and satisfaction with online educational classes.

RESULT AND DISCUSSION

Normality and Descriptive Statistics

Normality and descriptive statistics describe the central tendency, dispersion, and distribution shape of the data, where acceptable normality is typically indicated by skewness within ±2 and kurtosis within ±7. The results show that all items meet these thresholds, indicating that the data are normally distributed and suitable for further parametric analysis. The mean scores for Perceived Ease of Use (PEU) and Perceived Usefulness (PU) range from moderate to slightly high (around 3.0–3.6), suggesting that pre-service science teachers generally perceive online classes as relatively easy to use and useful. In contrast, Satisfaction (SAT) and Acceptance Intention (AI) exhibit lower mean values (around 2.5–3.0), indicating more neutral to slightly positive responses. Standard deviations are relatively consistent (around 0.8–1.0), reflecting moderate variability among respondents. Slight positive skewness in SAT and AI items suggests a tendency toward lower ratings, while PEU and PU are more symmetrically distributed.

Table 1 Normality and Descriptive Statistics

Name	Mean	SD	Kurtosis	Skewness
PEU1	3.328	0.996	-0.110	-0.187
PEU2	3.281	0.981	-0.094	-0.023
PEU3	3.036	1.002	-0.226	0.271
PEU4	3.099	0.960	-0.215	0.084
PU1	3.568	1.034	-0.425	-0.254
PU2	3.266	0.876	0.148	0.155
PU3	3.339	0.949	0.081	-0.025
PU4	3.240	0.976	-0.138	-0.023
SAT1	2.625	0.971	0.184	0.434
SAT2	2.812	0.961	0.162	0.136
SAT3	2.589	0.996	0.098	0.359
SAT4	2.651	0.978	0.065	0.412
AI1	2.938	0.911	0.253	0.124

AI2	3.068	0.985	-0.059	0.094
AI3	2.729	1.010	-0.134	0.229
AI4	2.865	0.959	0.060	0.204

Loading, Reliability and Convergent Validity

Factor loadings, reliability, and convergent validity assess the measurement quality of constructs, where acceptable outer loadings should exceed 0.70, Cronbach's alpha and composite reliability (CR) should be above 0.70, rho_a should be above 0.70, and average variance extracted (AVE) should exceed 0.50. The results indicate that all indicators load strongly on their respective constructs, with loadings ranging from 0.766 to 0.921, satisfying the recommended threshold. Perceived Ease of Use (PEU) and Acceptance Intention (AI) demonstrate particularly high loadings, indicating strong indicator representation. Perceived Usefulness (PU) shows slightly lower but still acceptable loadings, especially PU1 and PU4, which remain above 0.70. Satisfaction (SAT) also presents consistently high loadings, reflecting reliable measurement across its indicators.

Reliability analysis reflects the internal consistency of constructs, where Cronbach's alpha, rho_a, and CR values above 0.70 indicate strong reliability. All constructs meet these criteria, with AI (α = 0.920, CR = 0.944), PEU (α = 0.904, CR = 0.933), PU (α = 0.840, CR = 0.894), and SAT (α = 0.889, CR = 0.923), confirming high internal consistency. Convergent validity is supported by AVE values exceeding 0.50, with AI (0.807), PEU (0.777), PU (0.678), and SAT (0.751), indicating that each construct explains a substantial portion of variance in its indicators. These results demonstrate that the measurement model adequately captures the intended latent constructs with sufficient consistency and validity

Table 2. Loading, Reliability and Convergent Validity

	Loading	alpha	rho_a	CR	AVE
AI1	0.899	0.920	0.921	0.944	0.807
AI2	0.921				
AI3	0.890				
AI4	0.883				
PEU1	0.888	0.904	0.906	0.933	0.777
PEU2	0.880				
PEU3	0.863				
PEU4	0.894				
PU1	0.794	0.840	0.842	0.894	0.678
PU2	0.866				
PU3	0.863				
PU4	0.766				
SAT1	0.789	0.889	0.895	0.923	0.751
SAT2	0.883				
SAT3	0.907				
SAT4	0.884				

Discriminant Validity

Discriminant validity assesses the extent to which a construct is truly distinct from other constructs, commonly evaluated using the Fornell–Larcker criterion, where the square root of the AVE for each construct should be greater than its correlations with other constructs. The results show that all diagonal values (AI = 0.898, PEU = 0.882, PU = 0.823, SAT = 0.867) are higher than the corresponding inter-construct correlations, indicating that each construct shares more variance with its own indicators than with other constructs. The correlations among constructs range from moderate to high, with the strongest relationship observed between Satisfaction (SAT) and Acceptance Intention (AI) at 0.864, suggesting a close association while still maintaining discriminant validity. Similarly, PEU and PU show a relatively strong correlation (0.719), reflecting theoretical alignment within TAM. Lower correlations, such as between PU and SAT (0.549), further support construct distinctiveness

Table 3. Fronell-larcker criterion

	AI	PEU	PU	SAT
AI	0.898			
PEU	0.694	0.882		
PU	0.639	0.719	0.823	
SAT	0.864	0.654	0.549	0.867

Multicollinearity

Variance Inflation Factor (VIF) assesses multicollinearity among indicators, where acceptable values are typically below 5.0, and more conservatively below 3.3, indicating that collinearity does not threaten the estimation of model parameters. The results show that all VIF values range from 1.596 to 3.744, suggesting that multicollinearity is within acceptable limits. Indicators of Perceived Usefulness (PU) and Satisfaction (SAT) generally exhibit lower VIF values, indicating minimal collinearity concerns within these constructs. Perceived Ease of Use (PEU) and Acceptance Intention (AI) show slightly higher VIF values, with AI2 (3.744) and SAT3 (3.177) approaching the conservative threshold, yet still remaining acceptable. These findings indicate that each indicator contributes uniquely to its construct without excessive overlap, and the absence of severe multicollinearity supports the stability and reliability of the measurement model estimation

Table 4. VIF

	VIF
AI1	3.167
AI2	3.744
AI3	2.856
AI4	2.764
PEU1	2.990
PEU2	2.820
PEU3	2.647
PEU4	3.014
PU1	1.855
PU2	2.245
PU3	2.214
PU4	1.596
SAT1	1.784

SAT2	2.697
SAT3	3.177
SAT4	2.609

Hypothesis Testing

The structural model represents the hypothesized relationships among latent constructs within a theoretical framework, where constructs are typically illustrated as circles or ovals and indicators as rectangles, while directional arrows indicate causal paths based on theoretical assumptions. In this figure, the model is grounded in the Technology Acceptance Model (TAM), incorporating four key constructs: Perceived Ease of Use (PEU), Perceived Usefulness (PU), Satisfaction (SAT), and Acceptance Intention (AI). Each construct is measured by multiple indicators, and the connections between them reflect proposed relationships to explain user behavior toward online educational classes. The diagram visually organizes how perceptions of system usability and usefulness are linked to affective responses and behavioral intentions, providing a comprehensive overview of how the measurement and structural components are integrated within a single analytical model

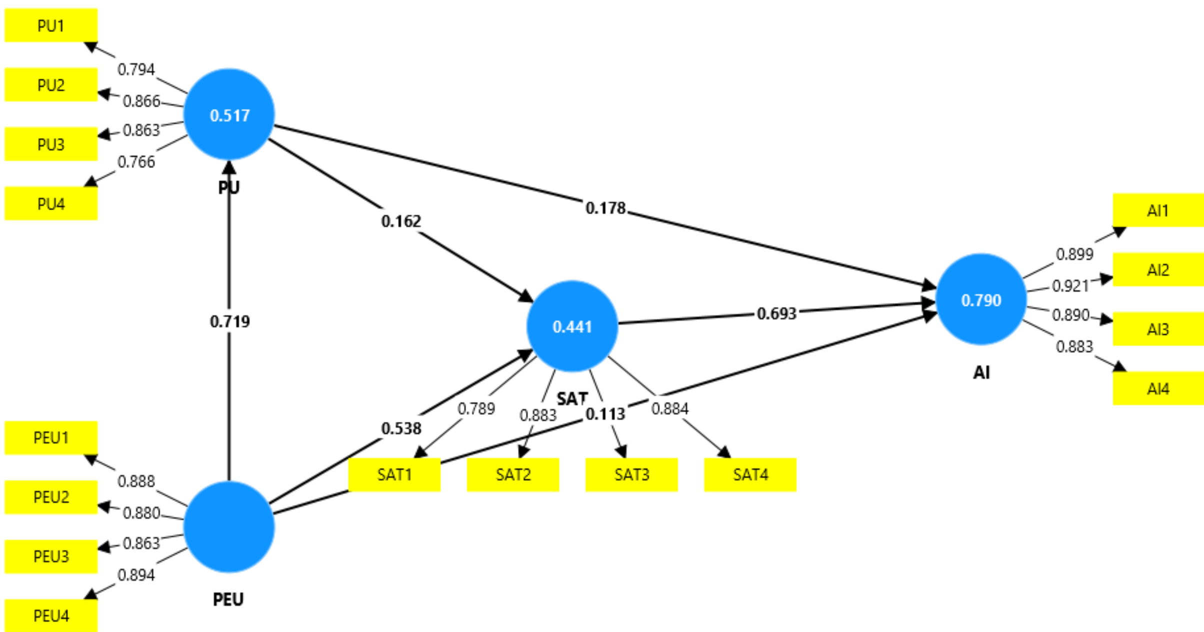

Figure 1. Structural Model of Technology Acceptance Model (TAM)

Model fit indices evaluate how well the proposed structural model represents the observed data, where acceptable thresholds commonly include SRMR ≤ 0.08, lower d_ULS and d_G values indicating better fit, and NFI values approaching or exceeding 0.90. The results show that both the saturated and estimated models produce identical values, suggesting model consistency. The SRMR value of 0.055 falls below the recommended threshold, indicating a good fit between the model and the data. The discrepancy measures d_ULS (0.407) and d_G (0.285) are relatively low, reflecting minimal differences between the empirical and model-implied covariance matrices. The Chi-square value (324.816) represents overall model discrepancy, which is sensitive to sample size but acceptable when supported by other indices. The NFI value of 0.872 is slightly below the ideal 0.90 threshold, suggesting an adequate but not optimal fit, indicating that the model reasonably explains the relationships among PEU, PU, SAT, and AI

Table 5. Model Fit Indices

	Saturated model	Estimated model
SRMR	0.055	0.055
d_ULS	0.407	0.407
d_G	0.285	0.285
Chi-square	324.816	324.816
NFI	0.872	0.872

Hypothesis testing evaluates the relationships between constructs using path coefficients (M), standard deviation (SD), t-statistics, and p-values, where significance is typically determined by $t > 1.96$ and $p < 0.05$. The results indicate that Perceived Ease of Use (PEU) has no significant direct effect on Acceptance Intention (AI) ($t = 1.594$, $p = 0.111$), while it shows strong and significant effects on Perceived Usefulness (PU) ($t = 17.114$, $p = 0.000$) and Satisfaction (SAT) ($t = 6.937$, $p = 0.000$). Perceived Usefulness (PU) significantly influences AI ($t = 2.999$, $p = 0.003$) and SAT ($t = 1.959$, $p = 0.045$), although the latter is marginal. Satisfaction (SAT) demonstrates a strong and significant effect on AI ($t = 13.182$, $p = 0.000$), indicating its central role in shaping acceptance intention.

Mediation analysis examines indirect effects between constructs, where significance is similarly assessed using t-statistics and p-values. The results show that PEU significantly influences AI through SAT ($t = 6.732$, $p = 0.000$) and through PU ($t = 2.888$, $p = 0.004$), indicating meaningful indirect pathways. However, the indirect effect of PEU on SAT through PU ($t = 1.926$, $p = 0.054$) is marginally insignificant. Similarly, the mediation of PU on AI through SAT ($t = 1.921$, $p = 0.055$) does not meet the conventional significance threshold. These findings suggest that while some indirect relationships are statistically supported, others remain borderline, highlighting varying strengths of mediation among PEU, PU, SAT, and AI

Table 6. Hypothesis Testing

	(M)	SD	T statistics	P
PEU -> AI	0.111	0.071	1.594	0.111
PEU -> PU	0.720	0.042	17.114	0.000
PEU -> SAT	0.540	0.078	6.937	0.000
PU -> AI	0.181	0.059	2.999	0.003
PU -> SAT	0.160	0.083	1.959	0.045
SAT -> AI	0.690	0.053	13.182	0.000
PEU -> PU -> SAT	0.115	0.060	1.926	0.054
PEU -> SAT -> AI	0.372	0.055	6.732	0.000
PEU -> PU -> AI	0.131	0.044	2.888	0.004
PU -> SAT -> AI	0.110	0.058	1.921	0.055

This study has several limitations that should be considered when interpreting the findings. First, the use of a cross-sectional design limits the ability to establish causal relationships among the constructs, as data were collected at a single point in time. Second, the sample consisted only of 193 pre-service science teachers from a specific context, which may restrict the generalizability of the results to other populations, disciplines, or educational settings. Third, the data were collected using self-reported questionnaires, which may be subject to response bias such as social desirability or subjective interpretation of items. Additionally, the study focused on four core constructs of the Technology Acceptance Model (TAM), potentially overlooking other relevant factors such as digital literacy, learning engagement, or external support systems. Finally, the reliance on PLS-SEM emphasizes prediction rather than model confirmation, which may limit the depth of theoretical validation.

CONCLUSION

The conclusion of this study summarizes the overall findings based on the analysis of the Technology Acceptance Model (TAM), which explains how perceived ease of use (PEU), perceived usefulness (PU), satisfaction (SAT), and acceptance intention (AI) are interrelated in the context of online educational classes. The results indicate that the measurement and structural models meet acceptable statistical standards, confirming the reliability and validity of the constructs. Empirically, PEU significantly influences PU and SAT, demonstrating that ease of use enhances both perceived benefits and user satisfaction. PU also contributes significantly to AI and SAT, although its effect on satisfaction is relatively weaker. SAT emerges as the strongest predictor of AI, indicating that students' overall learning experience plays a crucial role in shaping their intention to adopt online classes. Direct influence of PEU on AI is not significant, but indirect effects through PU and SAT are evident, highlighting the mediating roles within the model.

Recommendations and future studies emphasize the importance of improving both usability and learning quality in online educational platforms to enhance student satisfaction and acceptance. Educational institutions should focus on designing user-friendly systems, providing adequate technical support, and ensuring meaningful learning interactions to strengthen students' experiences. Teacher education programs are encouraged to integrate digital competencies and pedagogical training that prepare pre-service teachers to effectively utilize online learning technologies. Future research may expand this study by including additional variables such as digital literacy, self-efficacy, or learning engagement, and by applying longitudinal designs to observe changes over time. Studies involving larger and more diverse samples across different disciplines or educational levels could also provide broader insights into technology acceptance in education

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