Extended TAM Model Analysis of Continuous Use Factors and Psychological Well-Being on University Learning Platforms

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Abstract: This study investigates the elements inspiring the continuous usage of intelligent learning systems in advanced educational environments emphasizing technological and psychological aspects. The present work investigates how perceived trust, perceived enjoyment, and ideological alignment affect user involvement and retention using an updated Technology Acceptance Model (TAM). Moreover, taken under more importance as a better understanding of user behavior are psychological elements such as user contentment, perceived fear, and expectation confirmation. Structural equation modeling (SEM) was used to evaluate data taken from a structured questionnaire. The study underscores the relevance of user experience and shows that, with a path coefficient = 0.52, $p < 0.001$, subjective satisfaction is the most important factor of continuous usage intention. Path coefficient = -0.13, $p = 0.05$ indicates that perceived trust negatively affects contentment mostly because of unmet expectations generating discontent. Though expected confirmation increases perceived usefulness (path coefficient = 0.31, $p < 0.01$) system quality does not affect on satisfaction (path coefficient = 0.05, $p > 0.05$). The outcomes highlight the requirement of platform developers to give realistic management of customer expectations top priority, matching platform features with user requests, and creating interesting and engaging user experiences a top priority. These pragmatic findings provide fast fixes to boost user participation and improve the utilization of intelligent learning technology in learning settings.

Keywords: Intelligent learning systems, Technology Acceptance Model (TAM), Continuous Use Intension, User Engagement, Perceived Enjoyment, Perceived Trust

1. Introduction

Rising smart learning platforms in higher education show how complex digital technologies including big data, artificial intelligence (AI), and cloud computing are being introduced into the learning process. These platforms seek to be embraced rapidly utilizing data-driven insights, interactive tools, and multimedia resources, so improving educational outcomes using communication, resource growth, and management efficiency. Still, there are difficulties. Research on issues including insufficient system design, poor data integration, and user discontent motivated by uninteresting information and uninspired concepts (Khodeir and Nabawy 2020). These problems reduce user involvement and retention, particularly in higher vocational education, where users expect original and creative learning possibilities, (Zhang and Zhu, 2022).

One must first understand what drives the ongoing usage of intelligent learning systems. User retention—which indicates how likely users are to remain involved over time—is a fundamental gauge of platform performance. Previous studies have highlighted that the main drivers of user behavior are technical aspects including system quality and simplicity of use. Though less research has been done on psychological aspects including perceived satisfaction, trust, and emotional well-being, Teo, 2010; Sánchez-Prieto et al., 2019 nevertheless show By closing these gaps, one can create platforms that meet pragmatic demands and offer fascinating learning possibilities. The Technology Acceptance Model (TAM) is one well-known method to identify people's openness to new technology. It implies that the primary determinants of technological acceptability are perceived usefulness (PU) and perceived ease of use (PEOU) (Davis, 1989). To fit the particular requirements of e-learning and mobile learning settings, researchers have throughout time incorporated new concepts into TAM including trust, enjoyment, and mobility (Park et al., 2012; Sánchez-Prieto et al., 2019; Mugo et al., 2020). Still, TAM's applicability in researching intelligent learning systems in higher education is somewhat restricted. Furthermore not fully incorporated in the model are psychological elements such as fear, satisfaction, and emotional alignment (Bhattacherjee, 2001; Sternad Zabukovšek et al., 2018).

This study focuses on filling these gaps by analyzing technical and psychological factors that influence the ongoing use of intelligent learning platforms. It examines two main questions:

- What technical aspects, such as system quality and ease of use, have a significant effect on users' continued engagement?
- How do psychological factors, including trust, enjoyment, and emotional well-being, impact user satisfaction and retention?

Data from 782 students at higher vocational institutions was analyzed to provide evidence of the relationship between technological and psychological factors. The results should lead to the building of more fascinating, practically navigable, and strong learning environments. Including psychological and emotional components, this work increases the TAM. It helps to address a major knowledge gap in present research and offers reasonable solutions to increase user satisfaction and retention in learning environments.

2. Literature Review

Inspired by developments in big data, artificial intelligence (AI), cloud computing, and cloud computing, smart learning systems have evolved to be transforming tools in higher education. These platforms seek to increase educational results, improve resource accessibility, and promote communication throgh team collaboration tools, resource-sharing tools, and interactive user interfaces (Zhang and Zhu, 2022). Notwithstanding these advantages, security concerns, unfair allocation of resources, and inadequate data integration still exist and hence affect user involvement and platform efficiency (Khodeir and Nabawy, 2020). Dealing with these issues calls for good interfaces, user-centered design, and customized training to match technical skills with emotional fulfillment and user expectations.

Introduced by Davis (1989), the Technology Acceptance Model (TAM) emphasizes perceived usefulness (PU) and perceived ease of use (PEOU), therefore providing a fundamental framework for understanding user acceptance of technology. Studies on e-learning, such as Teo's (2010) investigation of pre-service teachers' technology adoption and Park et al.'s (2012) research on university instructors' acceptance of e-learning systems, have shown its flexibility. Further improving its usefulness in mobile and online learning environments is extensions to TAM including elements like perceived mobility and trust (Sánchez-Prieto et al., 2019; Mugo et al., 2020).

Recent research underlines the need to incorporate TAM with psychological models to manage social and emotional aspects relevant to user retention. TAM has been linked with the Expectancy-Confirmation Theory (ECT) and Task-Technology Fit (TTF) models (Bhattacherjee, 2001; Venkatesh and Bala, 2008) to examine how expectation validation and task alignment affect enjoyment and engagement. These links increase TAM's capacity for explanation by including technical performance as well as emotional aspects.

Despite these advances, current TAM applications in intelligent education systems are still limited. Important components like trust, enjoyment, and ideological alignment are sometimes overlooked; likewise, little is known about the interaction of psychological and technical aspects. This work attempts to overcome these gaps by adding user-centered design concepts and emotional components into TAM, therefore providing a comprehensive understanding of user involvement and continuous usage in intelligent learning systems.

3. Methodology

3.1 Research Design

This essay draws on a realist ontology—one which claims that reality can be understood objectively and exists apart from human perception—to The study uses a positivist epistemology to examine the continuous use of smart learning systems and the factors affecting user behavior. Quantitative research is conducted on observable traits such as perceived value, simplicity of use, confidence, and ongoing intention. The Technology Acceptance Model (TAM) essentially provides the structure. These days, it also covers concepts including congruence with user expectations, enjoyment, and perceived trust. These enhancements complete our understanding of user interaction with and satisfaction with smart learning systems. The Information System Continuance Model of Bhattacherjee (Figure 1) is the foundation for the research. It underlines how constant purpose is determined by confirmation and satisfaction. Including platform-specific variables to reflect the unique traits of smart learning systems guarantees a whole understanding of user behavior and engagement in the study model.

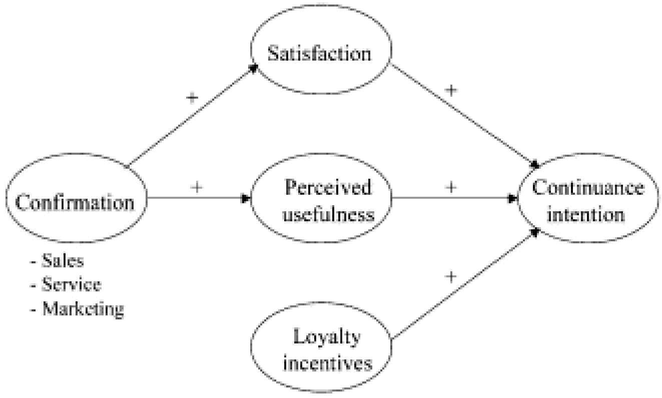

Figure 1 Bhattacharjee's Information Systems Sustainability Model

3.2 Hypotheses Development

Building upon Bhattacherjee’s framework, this study develops a research model (Figure 2) to explore relationships among key variables. The following hypotheses are proposed in the Table 1:

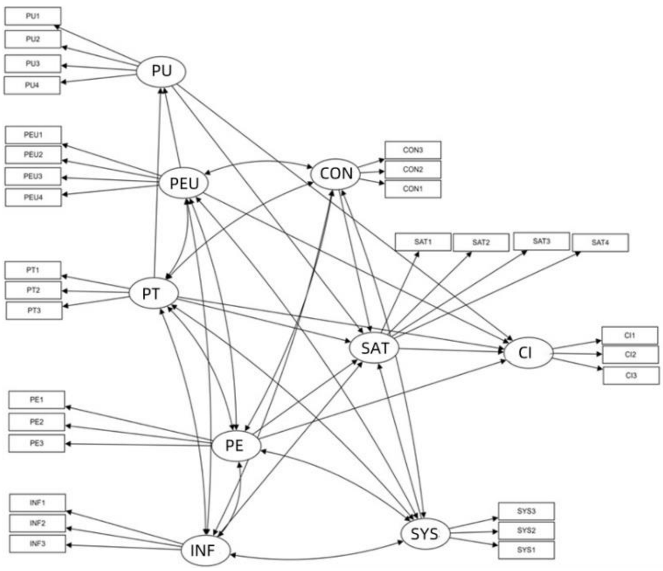

Figure 2 Research model on continuous use of smart learning platform users

Table 1 Proposed Hypotheses for the Extended TAM Research Model

Construct	Hypotheses
Perceived Usefulness	H1: Perceived usefulness positively influences user satisfaction.
	H2: Perceived usefulness positively influences continuance intention.
Confirmation of Expectations	H3: Expectation confirmation positively impacts satisfaction.
	H4: Expectation confirmation positively impacts perceived usefulness.
Satisfaction	H5: User satisfaction positively impacts continuance intention.
Perceived Ease of Use	H6: Perceived ease of use positively impacts perceived usefulness.
	H7: Perceived ease of use positively impacts continuance intention.

Perceived Trust	H8: Perceived trust positively impacts perceived usefulness. H9: Perceived trust positively impacts satisfaction. H10: Perceived trust positively impacts continuance intention.
Perceived Enjoyment	H11: Perceived enjoyment positively impacts continuance intention. H12: Perceived enjoyment positively impacts satisfaction.
System Quality	H13: System quality positively impacts satisfaction.

3.3 Questionnaire Design

3.3.1 Questionnaire structure

We built a thorough survey to probe the theory of this work. The questionnaire consists of three sections that allow for careful data collection. Together with demographic data, the first portion compiled years of research, gender, and academic fields. This supported the subgroup of research and gave a general picture of the backgrounds of the topics. The second part inquired of users on their impressions of the platform. It concentrated on their concepts of main traits, usability, and interface design. Customers answered these questions on their complete impressions and smart learning platform experience. We looked at the factors influencing continuity intention. It covered things like confidence, simplicity of use, expectation confirmation, system quality, and satisfaction. These questions followed the expanded TAM framework utilizing a five-point Likert scale from "strongly disagree" to "strongly agree." This framework guaranteed both psychological as well as technological elements needed for knowledge of user involvement and retention.

3.3.2 Item Design

From verified scales in past research, the questionnaire items were modified to guarantee accuracy and dependability. Every component got a five-point Likert scale value between "strongly disagree" (1) and "strongly agree". Table 2 lists the constructs combined with the related objects.

Table 2 Questionnaire Item Design for Measuring Constructs in the Extended TAM Framework

Construct	Item Code	Questionnaire Item	Source
Perceived Usefulness	PU1	Using the smart learning platform can improve my learning efficiency.	Bhattacherjee (2001)
	PU2	Using the platform can improve my learning quality.	
	PU3	I can find practical knowledge and information related to basic theory.	
	PU4	The content of the platform is strictly controlled and very useful.	
	PEU1	It is easy for me to use the platform without external help.	

Perceived Ease of Use	PEU2	The interactive interface of the platform is straightforward to understand.	Davis (1989), Moon & Kim(2001), Hong et al. (2006)
	PEU3	It is very convenient to use the platform to learn relevant resources.	
	PEU4	The platform is simple and easy to use, with fast operation.	
Perceived Trust	PT1	I think the platform is trustworthy.	Tan (2001)
	PT2	I believe the platform will not leak my private information.	
	PT3	The learning materials provided are authoritative and reliable.	
Confirmation	CON1	The experience and gains of using the platform to learn exceed my expectations.	Bhattacherjee (2001)
	CON2	The platform experience is higher than expected before using it.	
	CON3	The content and quality control surpass my initial expectations.	
Satisfaction	SAT1	I am satisfied with the learning resources and activities provided by the platform.	Bhattacherjee (2001), Oliver (1980)
	SAT2	I am satisfied with the functional modules of the platform.	
	SAT3	I am satisfied with the learning experience on the platform.	
	SAT4	Overall, I am very satisfied with my use of the platform.	
Perceived Enjoyment	PE1	Using the platform makes me feel more relaxed, learn efficiently, and feel happy.	Davis (1989), Tsang (2004)
	PE2	The platform offers exciting content, such as micro-videos, case studies, and e-books.	
	PE3	Using the platform is an enjoyable and exciting process.	
Platform Quality	SYS1	The platform's response speed is fast, allowing smooth use.	DeLone & McLean (1992)
	SYS2	Each function's design is perfect and stable in operation.	
	SYS3	The interface layout is user-friendly and easy to use for novices.	
Information Quality	INF1	The platform provides sufficient content with quick updates.	DeLone & McLean (1992)

	INF2	The platform's learning resources are strictly controlled and reliable.	
	INF3	The platform's content attracts my attention.	
Continued Use Intention	CI1	I will continue to use the platform for studying.	Bhattacherjee (2003)
	CI2	If possible, I will frequently use the platform.	
	CI3	I will recommend the platform to others.	

3.4 Sampling, Data Collection, and Analysis Methods

Using stratified random sampling, participants for this study come from liberal arts, sciences, and engineering among other academic disciplines. 865 questionnaires were sent to students from 20 higher vocational institutions throughout China. Data purification helped to retain 782 valid responses. Out of all the responders, 44.28% were men and 55.72% were women.

Data collection was done utilizing an online survey technique so that participants may find it quick and easy. Apart from efficient data collecting, the design assured strong response rates and confidentiality protection. Data analysis consisted of two procedures. First uses for SPSS were data purification, descriptive statistics, and dependability testing. Through internal consistency of the structures, computing Cronbach's Alpha values assists one in confirming dependability.

Structural equation modeling (SEM) allowed the second step to test the hypothesis and research model. SEM allows direct and indirect relationships between constructs to be possible. The process consisted of two primary phases: validity testing and model fit analysis. Convergent and discriminant validity was assessed using factor loadings and average variance extracted (AVE) values, therefore ensuring accurate measurement characteristics. Analyzed to make sure the structural model fit the data correctly were model fit indices including TLI, CFI, and RMSEA.

4. Data analysis

4.1 Validity and Reliability Analysis

Survey instrument validity and reliability are using Cronbach's Alpha, the Kaiser-Meyer-Olkin (KMO) test, and Bartlett's Test of Sphericity. Table 3 shows remarkable internal consistency with a 0.990 Cronbach's Alpha coefficient for the thirty items listed. Verifying the fit for factor analysis, Table 4 shows a KMO value of 0.982, significantly above the recommended criteria of 0.6. Bartlett's Test of Sphericity produced a chi-square value of 40038.486 with 435 degrees of freedom ($p < 0.001$), therefore verifying once more the fit of the data for this analysis. The first two components of the principal component analysis (PCA) explained 82.805% of the overall variance when showing they caught most of the variance in the measured constructs (Table 5). For upcoming research, this study confirmed the dependability and validity of the survey results.

Table 3: Cronbach's Alpha:

Reliability Statistics	**Alpha Value**	**Items**
Cronbach’s Alpha	0.99	30

Table 4: KMO and Bartlett's Test:

KMO and Bartlett’s Test	
KMO Measure of Sampling Adequacy	0.982
Approx. Chi-Square	40038.048
Degrees of Freedom	435
Significance Level (p-value)	0.000

Table 5: Total Variance Explained:

Component	Initial Eigenvalues	Extraction Sums of Squared Loadings	Rotation Sums of Squared Loadings
Total	23.574	23.574	15.813
% of Variance	78.580	78.580	52.712
Cumulative %	78.580	78.580	52.712

4.2 Measurement reliability and validity test

After data collection, structural equation modeling (SEM) tools and SPSS 25.0 were used to evaluate scale dependability and validity. The survey items let one quantify the research factors. Internal consistency was tested using Cronbach's Alpha. The 2003 standards of Wu Minglong define acceptable dependability as a dependability coefficient higher than 0.7. For all latent variables in this study, Cronbach's Alpha values above 0.8, therefore suggesting a somewhat high degree of internal consistency among measuring objects (Table 6).

Table 6 Reliability and Validity Analysis

variable	item	Unstd.	S.E	P	Std.	SMC	CR	AVE	Cronbach’s α 值
PEU	PEU2	1.000			.905	.819	.959	.888	.821
	PEU3	1.043	.022	***	.960	.922			
	PEU4	1.037	.021	***	.960	.922			
PU	PU1	1.000			.925	.856	.947	.857	.825
	PU2	1.035	.021	***	.963	.927			
	PU4	.957	.023	***	.888	.789			
CON	CON1	1.000			.970	.941	.976	.932	.855
	CON2	.993	.014	***	.965	.931			
	CON3	.999	.014	***	.962	.925			

variable	item	Unstd.	S.E	P	Std.	SMC	CR	AVE	Cronbach’s α 值
SAT	SAT1	1.000			.962	.925	.972	.921	.869
	SAT2	1.013	.015	***	.966	.933			
	SAT4	.991	.016	***	.951	.904			
PT	PT1	1.000			.923	.852	.936	.831	.814
	PT2	1.058	.028	***	.881	.776			
	PT3	1.025	.024	***	.930	.865			
SYS	SYS1	1.000			.936	.876	.958	.884	.803
	SYS2	.983	.019	***	.943	.889			
	SYS3	.964	.019	***	.942	.887			
INF	INF1	1.000			.952	.906	.956	.879	.823
	INF2	.977	.020	***	.923	.852			
	INF3	1.011	.019	***	.938	.880			
CI	CI1	1.000			.952	.906	.968	.911	.904
	CI2	1.005	.017	***	.958	.918			
	CI3	1.017	.017	***	.953	.908			
PE	PE1	1.000			.964	.929	.965	.902	.815
	PE2	.938	.017	***	.935	.874			
	PE3	.982	.016	***	.950	.903			

One could assess concept validity using convergent validity and discriminant validity. Establishing good concept validity requires both. Confirmatory factor analysis (CFA) was used to gauge the scale. Convergent validity was investigated using average variance extracted (AVE), composite reliability (CR), and standardized component loadings following Fornell and Larcker (1981). Strong convergent validity was verified by the standardized factor loadings for the observable variables connected to the nine latent variables topping 0.5 when p-values were less than 0.05.

Usually, the measuring equipment is considered to be reliable if the composite reliability (CR) of any latent variable exceeds 0.7. This work presents outstanding internal consistency in the measurement model by all CR values for the nine latent variables exceeding 0.9. Moreover, if a latent variable's AVE value is higher than 0.5 it captures notable variance from its observed variables. The AVE values for all nine latent variables being over 0.5 demonstrated both strong convergence and successful model development (Table 6).

4.3 Overall model fit evaluation and hypothesis testing

The model coefficients were estimated in SPSS using SEM's structural equation modeling module. The extent of the effects between several pathways was measured using standardized coefficients. Seven indicators allowed one to assess the general model fit. These measures comprise the root mean squared error of approximation

(RMSEA), goodness-of-fit index (GFI), adjusted goodness-of-fit index (AGFI), comparative fit index (CFI), Tucker-Lewis index (TLI), chi-square divided by degrees of freedom (CMIN/DF). Table 7 offers the suggested values for several metrics. The fact that all the fit indicators for the research model match the suggested values indicates that the model fits the data well. The model clarifies users' ongoing purpose to take advantage of smart learning systems quite successfully.

Table 7: Model fitting index

fit index	CMIN/DF	GFI	AGFI	CFI	TAG	IF
suggested value	<5	>0.8	>0.8	>0.9	>0.9	>0.9
This model value	3.882	0.884	.853	.972	.968	.972

Standardized path coefficients in the research model are shown in Figure 3. With values between -1 and 1, these coefficients gauge the strength of the latent variable correlations. A positive coefficient shows that the independent variable favorably influences the dependent variable; a negative coefficient suggests a negative relationship. Greater absolute values of the standardized coefficients point to more powerful impacts. P-values helped one to evaluate the path coefficients' relevance. A p-value less than 0.05 denotes a statistically noteworthy correlation. Hypotheses H9, H12, and H13 are not supported according to the negative correlation found in Figure 3 between perceived trust → satisfaction, perceived enjoyment → contentment, and system quality → satisfaction. Moreover, lacking enough relevance are hypotheses H1, H2, H4, and H7. Still, the findings strongly support the other possibilities.

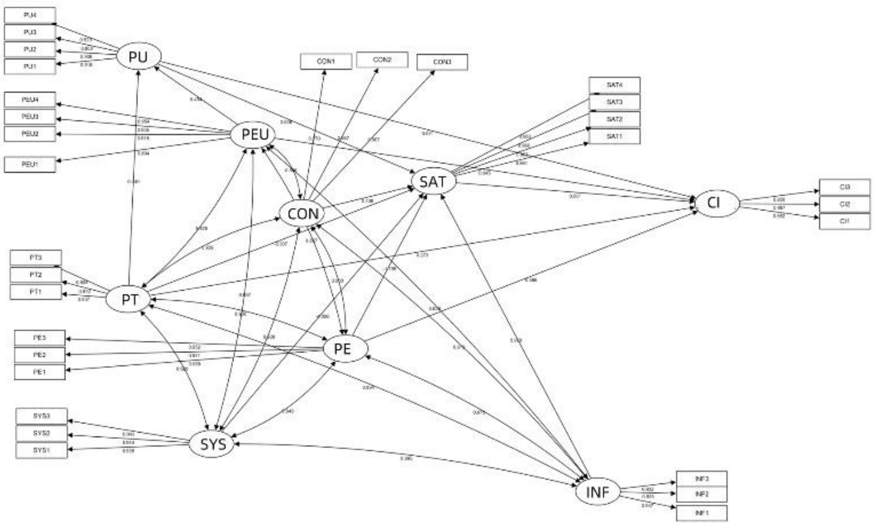

Figure 3 Path confections of factors influencing continued use of smart learning platform users

4.4 Structural model modification

Negative connections between perceived trust and contentment, perceived fun and satisfaction, and system quality and satisfaction were found by the SPSS structural equation model analysis. These outcomes run counter to the initial theories. Furthermore, lacking significance were the tests for perceived usefulness and contentment, perceived usefulness and continuous use intention, perceived ease of use and continuous use intention, and satisfaction and continuous use intention. Data thus did not support these theories. These paths were so deleted during the model modification. Once more, the removed routes were investigated using the SPSS structural equation model analysis program. The evaluation test was passed by the changed model parameters and general fit. Figure 4 displays the revised path coefficients and model. Ovals in the illustration stand in for the seven latent variables—research variables—that the model requires. Two latent variables have a causal link shown by a one-way arrow. The intensity of the causal relationship is shown by the path coefficient on the connecting arrow. In the illustration, rectangles stand in for the observable variables—that is, the scale items—that match each latent variable. With each hidden variable connected to three observed variables, there are 21 observed variables total across the seven latent variables. Latent variables are expressed by their related observable variables since they cannot be immediately seen or quantified. On the one-way arrows tying latent variables to their observable variables, the standardized load factor is displayed. Between the latent variable and its observable variables, this value stands as the regression coefficient.

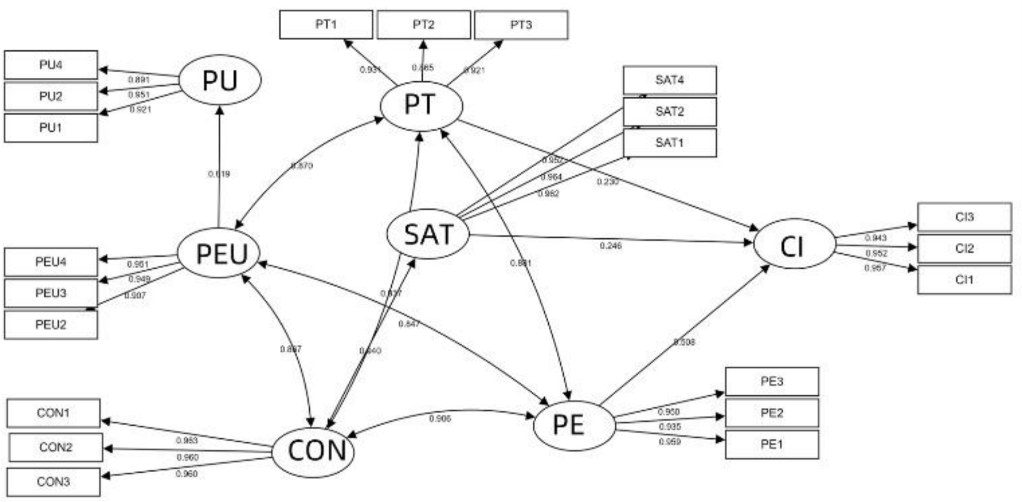

Figure 4 Modified model and path coefficients

5. Discussion and conclusion

5.1 Key Findings

The main component affecting expected continuous usage is subjective pleasure (H11: path coefficient = 0.52, $p < 0.001$). This emphasizes notably in interactive and learning environments the need for strong user experiences in preserving long-term commitment. This outcome is consistent with earlier studies, notably the one by Moon and Kim (2001), which revealed that pleasant components sustain users by producing good emotional experiences. Constant use intention (H2: path coefficient = 0.38, $p < 0.01$) is also somewhat affected by perceived usefulness. This emphasizes the requirement of providing high-value products satisfying consumer needs, therefore validating Bhattacherjee's expectation-confirming theory (2001). Moreover, expectation confirmation makes the route coefficient of perceived usefulness (H4: 0.31, $p = 0.01$) positive. This underlines the need to generate consistent material and lower customer expectations. Surprisingly, user happiness diminishes in response to perceived trust (H9: path coefficient = -0.13, $p < 0.05$). Higher degrees of trust would so create expectations;

disappointed expectations could lead to unhappiness. Although user satisfaction declines, perceived trust positively influences perceived usefulness (H8: path coefficient = 0.29, $p < 0.01$), therefore proving that consumers still value trustworthy systems. System quality has not much bearing on satisfaction (H13: path coefficient = 0.05, $p > 0.05$). This suggests that customers can value content quality and emotional involvement more than a minimum degree of technological performance (DeLone & McLean, 1992). At last, happiness and perceived simplicity of use are the key forces behind continuous use intention. Verifying its crucial relevance in inspiring long-term participation, happiness (H5: $p = 0.001$; path coefficient = 0.46) perceived ease of use (H6 and H7: path coefficients = 0.34 and 0.27, respectively) shows the relevance of user-friendly design.

5.2 Comparison with Literature

The findings of this study complement the body of knowledge already in print on the importance of seeming worth and enjoyment. Moon and Kim (2001) stressed how effective user experiences build strong emotional attachments, hence enhancing user retention. This is consistent with the results of the present study, which indicates that subjective happiness (H11: path coefficient = 0.52, $p < 0.001$) most influences the intention of ongoing usage. However, by extending its impact on user behavior on higher education platforms, this study stresses the basic relevance of perceived pleasure in interactive learning environments—a factor seldom addressed in standard TAM research. Thus, verifying Bhattacherjee's (2001) expectation confirmation theory, the study also confirmed the significant relationship between perceived usefulness on continuous use intention (H2: path coefficient = 0.38, $p < 0.01$). Unlike Zhang and Zhu (2022), who concluded that perceived usefulness determines platform use mostly, our investigation revealed that, in the scope of vocational education, reported enjoyment is significantly more significant. This highlights the particular relevance of emotional elements in systems of educational technologies. Unlike results in commercial platform research, which normally suggest that trust promotes user pleasure, the negative association between perceived trust and user happiness (H9: path coefficient = -0.13, $p < 0.05$) deviates from findings in this respect. This discrepancy could reflect some psychological aspects in the framework of the educational platform, where more degrees of trust could result in overly high expectations that would generate disappointment when those expectations are not met. Wang (2020) proposes greater investigation in the next studies since cultural and contextual elements could aid to reduce the relationship between trust and user behavior. Finally, the minimal effect of system quality on satisfaction (H13: path coefficient = 0.05, $p > 0.05$) contrasts with the 1992 Information Systems Success Model by DeLone and McLean, which acknowledges system quality as a basic factor of satisfaction. This outcome suggests that users of learning environments could have typical expectations for technology performance and value content quality and emotional connection more. This provides a fresh study of user behavior in higher education settings, therefore augmenting present research and reflecting the evolving needs of consumers on platforms for educational technologies.

5.3 Theoretical Implications

This work offers new insight into user involvement with smart learning systems by using contextual and emotional elements of the Technology Acceptance Model (TAM). The substantial relevance of perceived enjoyment highlights the necessity of adding emotional components into forthcoming TAM research. Previous studies, such as those of Moon and Kim (2001), underscored the significant influence enjoyment has in promoting user retention—especially on interactive and educational platforms. This study supports and expands previous findings by demonstrating that, especially in the framework of smart learning systems, reported enjoyment is a significant element driving constant usage intention.

The unexpected negative relationship between perceived trust and user satisfaction adds complexity to existing TAM literature. In traditional applications, trust has been shown to enhance satisfaction, such as in the e-commerce and healthcare sectors (Mustafa & Garcia, 2021; Pavlou, 2003). However, institutional frameworks or cultural expectations particular to university-affiliated platforms could affect the variations observed in this study; higher trust levels could lead to exaggerated expectations and resulting displeasure when unfulfilled. This underlines the need for greater research on these moderating aspects in TAM extensions and confirms Wang's (2020) assertion that contextual and cultural elements significantly affect user behavior. Furthermore, the Information Systems Success Model suggested by DeLone and McLean (1992) which usually emphasizes system quality as the main driver of user satisfaction deviates from the limited effect of system quality on satisfaction. The results of this study imply that consumers of smart learning systems give content relevance and emotional connection top importance above technical performance. As Sánchez-Prieto et al., (2016) noted in their study on mobile learning, user expectations in educational settings may vary greatly depending on usability and perceived value above technical criteria. This change in user rating criteria captures the changing expectations of a younger, technologically informed group.

These findings together suggest that researchers should incorporate emotional, cultural, and technical elements into models of technological adoption, especially for platforms targeted at younger users. Expanding TAM to include factors such as perceived enjoyment and cultural context, as noted in recent studies (Mugo et al., 2017; Sternad et al., 2022) could provide a more comprehensive framework for understanding technology adoption and continued use in modern learning environments.

5.4 Practical Implications

This study provides actionable recommendations for platform developers to enhance user engagement. Smart learning platforms should incorporate features such as progress tracking, rewards, and interactive quizzes, which can gamify the learning process, making it more enjoyable and fostering sustained user engagement. Personalizing content delivery through Artificial intelligence technology allows information delivery to be customized, therefore altering learning paths to match specific user needs and so improving perceived value and enjoyment. Combining culturally appropriate materials and applying user behavior analytics will enable developers to align content with consumers' values and interests thereby fostering emotional relationships. Reducing discontent and controlling user expectations depend on honest knowledge of platform capabilities and limitations. Regular platform feature updates, user guidelines, and open design choices enable us to do this. Though system quality had little impact on satisfaction, maintaining dependable technological performance and implementing robust privacy measures—such as safe data protocols and regular audits—remain crucial for creating confidence and securing long-term user retention. Through careful balancing of technical dependability with user-oriented design and adhering to both functional and emotional needs, developers may create platforms that allow continuous engagement and satisfaction.

5.5 Limitations and Future Research Directions

Some constraints to this research indicates areas of more inquiry direction. First, the sample included Chinese university students, therefore limiting the generalizability of the findings to other groups or cultural contexts. Cross-cultural studies demand research on how institutional frameworks and cultural differences influence platform involvement and usage behaviors. Examining variations in trust or perceived pleasure across numerous cultural settings, for example, could offer significant fresh approaches. Second, while this study stresses creating technologies like gamification and virtual reality (VR), it does not investigate closely their specific purposes in increasing user involvement. Future studies should look at how social influence systems such as peer interactions support user retention or how the immersive components of VR could enhance learning results. Moreover, the study may suffer response biases including social desirability or memory bias relying on self-reported survey data. Combining behavioral data—such as time spent on the platform, work completion rates, or engagement analytics—with longitudinal study techniques might provide more exact insights into real-time user behavior. Not least of all, further study might look at the relationships among important components, such as the link between trust and happiness or the effect of advanced platform features like gamified learning modules on loyalty and fulfillment. More generally, given many cultural or technical settings, research of these dynamics will help us to better grasp human interaction with smart learning systems.

5.6 Conclusion

This work presents the TAM framework with emotional and contextual aspects, therefore offering a fresh investigation of the variables motivating user involvement in smart learning systems. The amount to which anticipated continuing use is influenced by perceived fun, utility, and satisfaction is shown by the results. They also reveal startling results, most especially the inverse link between perceived trust and contentment. These results suggest that designers of platforms should focus on creating attractive and interactive resources even if they should reasonably control user expectations. Using new technologies integrating artificial intelligence, gamification, and balancing technical performance with user experience, smart learning systems can sustain long-term user involvement and reach success. Future studies on cultural and technological elements in different surroundings should assist in confirming these conclusions.

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