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Factors Affecting Undergraduate's Perceived Usefulness and Satisfaction with E-learning platform in Yibin, China

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Abstract

This study examines the key factors influencing undergraduate students' perceived usefulness and satisfaction with E-learning platforms in Yibin, China. Integrating the Technology Acceptance Model (TAM), Expectation Confirmation Model (ECM), and Unified Theory of Acceptance and Use of Technology (UTAUT), the proposed framework includes five independent variables: Self-Efficacy (SE), Perceived Ease of Use (PEU), Facilitating Conditions (FC), Social Influence (SI), and Confirmation (CON); one mediating variable Perceived Usefulness (PU), and one dependent variable: Satisfaction (SAT). A structured questionnaire was distributed to 500 senior undergraduates from four majors at Sichuan University of Science & Engineering (Yibin campus). Structural Equation Modeling (SEM) and Confirmatory Factor Analysis (CFA) were used for data analysis and model validation. Findings confirmed all six hypotheses. PU emerged as a central mediating factor, while CON and FC were found to significantly enhance student SAT. The study offers insights into optimizing support systems, usability, and learner engagement in digital education environments.

Keywords: Perceived Usefulness, Satisfaction, E-Learning, Technology Acceptance

Introduction

E-learning, encompassing online and distance education, has transformed traditional learning by enabling flexible, self-paced access to educational resources across time and space (Bouchrika, 2025). Its adoption, driven by multimedia integration, cost-effectiveness, and adaptability, has fueled rapid growth: the global E-learning industry has expanded by 900% between 2000 and 2020, with corporate uptake continuing to rise (Elearning, 2025). In higher education, E-learning platforms not only enhance efficiency and reduce costs (Welsh et al., 2003) but also support blended learning through tools for content management, interactive discussions, assessments, and scheduling, thereby strengthening communication between instructors and students, particularly in remote settings (Zhong et al., 2022).

In China, government initiatives such as the Smart Education China (SEC) platform have significantly accelerated the advancement of E-learning. By the end of 2023, the platform had connected 519,000 institutions and 293 million students, offering a vast array of resources from primary to higher education (Imarc, 2025). These efforts reflect China's strategic emphasis on educational equity, innovation, and lifelong learning.

Although E-learning has been widely adopted, undergraduates still face low engagement, dropout risks, and dissatisfaction due to limited real-time interaction, distractions, and uneven digital literacy (Dong et al., 2020; iiMedia, 2023). Infrastructure constraints, particularly in regional contexts such as Yibin, further hinder effective participation. While TAM (F. D. Davis, 1989), UTAUT (Venkatesh et al., 2003), and ECM (Bhattacherjee, 2001) have explained technology adoption and continuance, little is known about how these frameworks jointly clarify undergraduates' perceived usefulness and satisfaction. This study addresses this gap by integrating these models, positioning satisfaction as the core outcome and highlighting the mediating role of perceived usefulness.

Given the rapid expansion of digital education, particularly within higher education institutions, it is imperative to examine the underlying factors that shape students' satisfaction with E-learning environments. Drawing on TAM, UTAUT, and ECM, this study investigates senior undergraduates in Yibin, China, to explore how SE and PEU affect PU, and how PU, FC, SI, and CON influence SAT. Six hypotheses are proposed and tested through SEM. The findings are expected to validate the conceptual framework while offering practical guidance for platform design and policy, contributing to the sustainable development of E-learning in Chinese higher education.

Literature Review

Self-Efficacy (SE)

SE, a construct derived from Bandura's (1982) social learning theory, is conceptualized as an individual's cognitive appraisal of their capability to organize and execute specific actions necessary for attaining targeted goals. It encompasses not only the perceived competence to perform tasks but also the confidence to overcome potential challenges and persist in the face of difficulties. Within the framework of technology adoption, SE extends beyond technical skills to encompass users' confidence in effectively employing digital tools for task completion (Compeau & Higgins, 1995; Tarhin et al., 2017). Within E-learning environments, SE plays a pivotal role in determining learners' ability to navigate platforms and achieve academic objectives (Liaw, 2008; Shen et al., 2013). Learners with higher SE tend to engage more effectively with educational technologies, allocate fewer cognitive resources to system navigation, and focus more on learning tasks (Marakas et al., 1998).

Substantial research consistently indicates a significant positive association between SE and PU within E-learning contexts. Empirical evidence reveals that learners demonstrating higher levels of SE are more likely to perceive digital learning platforms as beneficial tools for achieving learning objectives (Bailey et al., 2017; Sinha & Bag, 2023). In the context of MOOCs, students with greater SE demonstrate higher appreciation for platform features, resulting in elevated PU (Fianu et al., 2018; Shao, 2018). This relationship is further supported by findings from Alqurashi (2016) and Chao et al. (2017), who identify SE as a significant predictor of PU within technology-mediated learning spaces. Moreover, Womble (2007) identified a reciprocal association between SE and PU, emphasizing their interdependence in shaping learners' engagement with E-learning systems.

H1. SE has significant impact on PU.

Perceived Ease of Use (PEU)

Within technology adoption literature, PEU constitutes a fundamental construct denoting an end-user's subjective assessment of the extent to which interacting with a technological system necessitates negligible cognitive or physical exertion (F. D. Davis et al., 1989). This construct captures users' perceptions of system simplicity, clarity, and adaptability (Ha & Stoel, 2009; Tubaishat, 2018). PEU is often associated with learners' confidence in navigating platforms without cognitive overload (K.-M. Lin et al., 2011; B. Wu & Chen, 2017; Yang & Su, 2017). Studies also highlight that users with lower technical proficiency tend to perceive greater difficulty, highlighting the influence of prior experience on the formation of PEU (Sparks et al., 1997).

Within the TAM, PEU is a critical antecedent of perceived usefulness (PU), influencing users' evaluations of system effectiveness (F. D. Davis et al., 1989). When systems are easy to operate, users require less time and effort to achieve their objectives, thereby enhancing performance perceptions (Tung et al., 2008). Empirical evidence from E-learning and other domains (e.g., e-portfolios and biometric systems) consistently demonstrates the favorable impact of PEU on PU (Abdullah et al., 2016; Tan & Kim, 2015). Thus, PEU exerts a dual influence on technology acceptance, affecting both the initial adoption decision and the sustained intention to use, by augmenting users' perceived value and overall assessment of the system.

H2. PEU has significant impact on PU.

Facilitating Conditions (FC)

FC, a key construct in the UTAUT, have evolved from earlier models such as the Theory of Planned Behavior, where they align with perceived behavioral control (Ajzen, 1991). Venkatesh et al. (2003) conceptualized FC as an individual's perceived availability of sufficient institutional resources and technological frameworks that enable the effective utilization of target systems, a definition widely adopted across subsequent studies. Taylor and Todd (1995) emphasized both resource-based (e.g., time, money) and technological compatibility factors in shaping FC. In E-learning and mobile learning contexts, FC encompass users' beliefs in self-efficacy and the availability of institutional and technical support (Jeong et al., 2019; Lwoga & Komba, 2015; Samsudeen & Mohamed, 2019).

Recent studies have expanded FC to include perceptions of resource accessibility, knowledge availability, and professional support, particularly in emerging digital environments (Arora et al., 2022; Cheong et al., 2008; Nikou, 2021). FC are considered pivotal in reducing perceived task difficulty and fostering favorable user evaluations.

Empirical evidence consistently links FC to user satisfaction. When supportive conditions are present, users exhibit more positive attitudes and higher satisfaction levels (Chan et al., 2011; Festinger, 1957; Su & Tong, 2021). In digital service environments such as MOOCs and social media platforms, FC enhance users' sense of control, convenience, and engagement (Alalwan, 2020; Shah & Khanna, 2023; Yen, 2005). Furthermore, post-adoption satisfaction is often amplified when support exceeds expectations, reinforcing the mediating role of FC in technology acceptance (Qiao et al., 2021; Venkatesh et al., 2011).

H3. FC has significant impact on SAT.

Perceived Usefulness (PU)

PU, a central construct in the TAM, denotes an end-user's conviction that the adoption of particular technological systems will optimize task execution outcomes (F. D. Davis, 1989; Ifinedo, 2017). It reflects users' expectations regarding the technology's potential to increase effectiveness, provide timely information, or support academic and work-related outcomes (Agudo-Peregrina et al., 2014; K. J. Davis & Gerlach, 2018). In educational settings, PU is often associated with learners' belief that a system facilitates task completion and enhances learning effectiveness (Al Natour & Woo, 2020; Q. Chen et al., 2007). This theoretical framework has been expanded to various digital environments, including social media (Izuagbe et al., 2019), mobile payments (J. Wu et al., 2017), and online shopping (Moslehpour et al., 2018).

PU has been consistently identified as a key antecedent of both user satisfaction and the ongoing intention to utilize a system. Higher PU tends to promote favorable user attitudes, facilitating stronger satisfaction and ongoing intention to use (Bhattacherjee & Premkumar, 2004; Masrani et al., 2023). In the domain of MOOCs and E-learning platforms, PU has been empirically validated to positively influence satisfaction and learning outcomes (Daneji et al., 2019; Hadji & Degoulet, 2016). Empirical studies further confirm that PU significantly shapes users' post-adoption evaluations across diverse domains, such as mobile commerce (Lee & Jun, 2007), online health communities (Limayem & Cheung, 2008), and service technologies (Li & Liu, 2014; Thong et al., 2006). Therefore, PU constitutes a pivotal antecedent influencing both initial technology assimilation and subsequent continuous utilization behaviors.

H4. PU has significant impact on SAT.

Social Influence (SI)

SI, a pivotal construct underpinning the UTAUT framework, refers to the level at which individuals' technology adoption decisions are shaped by the perceptions, expectations, or behaviors of significant others (Venkatesh et al., 2003). It encompasses external pressures or normative beliefs emerging from one's socio-cultural setting—such as peers, family, mentors, and institutions—that can directly or indirectly impact technology usage intentions (Lwoga & Komba, 2015; Riquelme & Rios, 2010; Venkatesh & Davis, 2000). In contexts such as mobile payments and E-learning, SI is often operationalized as the influence exerted by others within a social network who encourage or support system use (Qasim & Abu-Shanab, 2016; Williams et al., 2015).

Empirical studies have consistently shown a favorable relationship between SI and user satisfaction across various digital platforms. In MOOCs and E-learning, social validation and peer encouragement significantly enhance learners' satisfaction and engagement (S. Liu et al., 2022; Shah & Khanna, 2023). Alqahtani et al. (2022) further highlighted that SI, along with PEU and PU, mediates satisfaction through perceived support and enjoyment. In addition, SI contributes to user satisfaction in online environments such as mobile shopping and social communication platforms, where trust in peers and group consensus influence user perceptions

(Iranmanesh et al., 2022; Tao, 2019). However, its impact may vary by context; for example, Madani et al. (2023) found SI to be an insignificant predictor of satisfaction among educators using online learning tools.

Overall, SI serves as a vital psychosocial factor in shaping users' behavioral responses and satisfaction levels across technology-mediated environments.

H5. SI has significant impact on SAT.

Confirmation (CON)

CON represents the evaluative outcome where users judge a system's actualized performance to be congruent with or exceeding their antecedent expectations (Bhattacherjee, 2001; Rahi & Abd. Ghani, 2019). Within the E-learning context, CON reflects the perceived congruence of learners' post-use experiences with their pre-use expectations regarding online platforms, particularly during disruptions such as the pandemic (Alami & El Idrissi, 2022; Mellikeche et al., 2020). When system quality surpasses expectations, users experience positive confirmation, especially among those with modest initial expectations (C.-P. Chen et al., 2015).

Expectation-Confirmation Theory (ECT) posits that CON is a key predictor of users' satisfaction, influencing PU and PEU (Cheng, 2020; B. Wu & Chen, 2017). Empirical findings in diverse learning environments, such as MOOCs, cloud-based systems, and blended formats, consistently demonstrate that confirmation is a pivotal factor influencing users' satisfaction levels and their propensity to maintain continued engagement with the system (Cheng, 2019; Daneji et al., 2019). In particular, the realization of anticipated benefits reinforces positive evaluations of the system, whereas unmet expectations may result in dissatisfaction or discontinuation (Bhattacherjee, 2001; Foroughi et al., 2019).

Studies also confirm the relevance of confirmation across different platforms, including educational blogs and social media-enhanced learning, where it significantly influences satisfaction outcomes (Ifinedo, 2017; Larsen et al., 2009; Limayem & Cheung, 2008). Therefore, confirmation serves as a pivotal post-adoption construct, directly shaping users' satisfaction with and continued engagement in E-learning environments.

H6. CON has significant impact on SAT.

Satisfaction (SAT)

Satisfaction (SAT) is commonly conceptualized as the user's evaluative judgment regarding a product, service, or system, reflecting the extent to which it meets expectations and fulfills needs (Goodhue, 1998; Kotler et al., 2014; Oliver, 2014). In educational contexts, satisfaction pertains to learners' overall contentment with the learning environment and perceived achievement (Sanchez-Franco, 2009; Sun et al., 2008; Sweeney & Ingram, 2001). It is often regarded as the positive effect arising when user goals and expectations are met (Baber, 2020; Haddad et al., 2014; Szymanski & Hise, 2000).

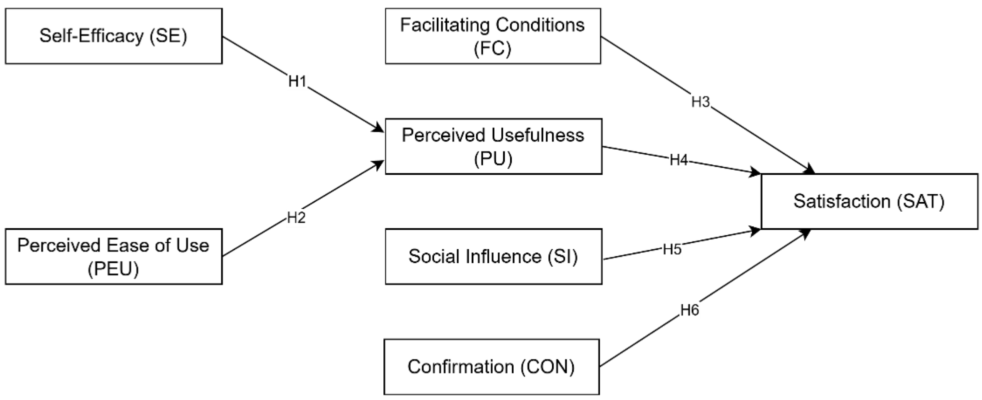
SAT is a critical determinant of continued technology use; applications that satisfy user needs are more likely to retain users (H.-H. Lin & Wang, 2006; Rezaei & Valaei, 2017). Factors such as system quality, and platform openness serve as major factors influencing SAT in online learning environments, including MOOCs (Khurana et al., 2019). Additionally, satisfaction is closely linked to utilitarian value, which underscores its importance in shaping user performance and behavioral intention (Babin et al., 1994). Recent studies emphasize student satisfaction as a key predictor of effective online learning outcomes (Hamdan et al., 2021).

Conceptual Framework

Drawing upon established theoretical models such as UTAUT, TAM, and ECM, this current research establishes a theoretical framework to assess factors influencing undergraduates PU and SAT with E-learning platforms in Yibin, China. The framework is informed by three key prior studies. First, researchers such as Shah and Khanna (2023) examined post-adoptive intention toward MOOCs, incorporating six predictors - performance expectancy (PE), FC, SI, effort expectancy (EE), hedonic motivation (HM), and personal innovativeness (PI)—with satisfaction as a mediating variable. Second, other researchers such as Singh and Sharma (2021) investigated MOOC acceptance as an alternative to internships, focusing on SI, FC, and self-regulation (SR), mediated by SE, PU, and PEU. Third, Cheng (2020) explored the impact of interactivity (Int), course content quality (CCQ), and course design quality (CDQ) on continuance intention (CI), through the mediating roles of PU, confirmation (CON), and SAT.

Figure 1

Conceptual Framework



Building on these frameworks, the present study develops a model (Figure 1) incorporating five independent variables—self-efficacy (SE), PEU, FC, SI, and CON—one mediating variable (PU), and one dependent variable (SAT). Six hypotheses are formulated: two test the influence of SE and PEU on PU; one examines the effect of PU on SAT; and three assess the direct impacts of FC, SI, and CON on SAT.

Research Methodology

Research Design

This study utilized a quantitative research approach, applying a non-probability sampling method to recruit participants. Data acquisition was carried out via structured questionnaire surveys distributed online to the designated sample population. The participants comprised undergraduate students of Sichuan University of Science and Engineering (Yibin campus) who had been engaging with an E-learning platform for at least one academic semester.

The survey instrument consisted of three sections: (1) screening items to ensure respondent eligibility, including questions to select target respondents, (2) measurement items using a five-point Likert scale to assess the core constructs, covering all variables in the study:

PEU, PU, SE, FC, SI, CON, and SAT, and (3) demographic information, including gender, age, frequency of platform use per week, and monthly expenditure on the E-learning service. To facilitate comprehension and accurate responses, the questionnaire was translated into Chinese. Within the methodological framework, the investigator operationalized five theoretically grounded independent variables through a five-point bipolar continuum. This Likert-type metric anchored opposing poles at 1 (strongly inconsistent) and 5 (strongly consistent), generating interval-scaled measurements. These empirically quantified constructs subsequently underwent statistical assessment to examine six predefined research hypotheses.

Ethical considerations were strictly observed in this study. All participants provided informed consent prior to data collection, were assured of confidentiality, and were informed of their right to withdraw from the study at any time without penalty.

This methodological approach facilitated a systematic examination of the predictors of student satisfaction within the E-learning context. The insights derived from the analysis are expected to inform strategies for enhancing learner satisfaction and optimizing the implementation of online education platforms. To ensure methodological parsimony, primary data acquisition was exclusively implemented via structured questionnaire deployment.

Research Population and Sample

The target population comprised senior undergraduates actively engaged with E-learning platforms at Sichuan University of Science & Engineering in Yibin, China. High-year students were selected due to their greater academic experience and familiarity with E-learning tools, which allows for more informed evaluations of perceived usefulness and satisfaction compared with lower-year students. A purposive sampling strategy was employed to ensure disciplinary diversity and include students with substantial experience in E-learning platforms. This approach enhances the relevance of findings for technology-focused majors while targeting key constructs such as PU and SAT. However, it may limit generalizability to undergraduates from other disciplines or lower academic years. On this basis, the researcher selected participants from four technology-focused majors: Computer Science & Technology, Electronic Information Engineering, Vehicle Engineering, and Electrical Engineering and Automation. Inclusion criteria mandated: (1) current or recent platform usage experience, and (2) senior academic standing. Data collection proceeded through academic advisors to ensure sample representativeness of the study's core constructs: PU and SAT with E-learning systems. The resultant sample structure is detailed in Table 1.

Table 1

Sample Units and Sample Size

Four Main Subjects	**Number of Senior Undergraduate Students**	**Proportional Sample Size**
Computer Science & Technology	409	186
Electronic Information Engineering	282	128
Vehicle Engineering	254	115
Electrical Engineering and Automation	156	71
Total	**1,101**	**500**

Data Analysis

This study employed a cross-sectional quantitative research design utilizing survey methodology to methodically address the research objectives. Prior to primary data collection, content validity was established through Item-Objective Congruence (IOC) evaluation by three domain experts, with all items exceeding the 0.60 benchmark. Subsequent pilot testing (n=50) confirmed instrument reliability, demonstrating Cronbach's α coefficients >0.70, consistent with psychometric standards (Babin et al., 1994). Data analysis was conducted using SPSS and JAMOVI for preliminary measurement evaluation, followed by AMOS 26.0. To substantiate the measurement model and empirically explore the theorized relationships among constructs, CFA and SEM were applied.

Demographics of Participants

As delineated in Table 2, the study cohort exhibited a pronounced gender imbalance, with male respondents constituting 77% of the sample (n = 500) compared to a 23% representation of female participants. Concerning the age composition, the majority (96.4%) were between 21 and 24 years old, while 2.0% were aged 18-20, and 1.6% were above 24. Regarding frequency of E-learning platform usage, 7.6% of respondents reported using the platform less than twice per week, whereas 50.4% used it 3-4 times, 33.2% reported 5-7 times, and 8.8% indicated usage exceeding 7 times per week. In terms of academic discipline, the highest proportion of participants were from Computer Science & Technology (37.2%), followed by Electronic Information Engineering (25.6%), Vehicle Engineering (23.0%), and Electrical Engineering and Automation (14.2%).

Table 2

The demographic data

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	385	77.0%
	Female	115	23.0%
Major	Computer Science & Technology	186	37.2%
	Electronic Information Engineering	128	25.6%
	Vehicle Engineering	115	23.0%
	Electrical Engineering and Automation	71	14.2%
Age	18- 20 years old	10	2.0%
	21- 22 years old	272	54.4%
	23-24 years old	210	42.0%
	More than 24 years old	8	1.6%
Number of learn with E-learning platform a week	less than 2 times	38	7.6%
	3 - 4 times	252	50.4%
	5 - 7 times	166	33.2%
	more than 7 times	44	8.8%

Results and Discussion

CFA, as defined by Hoyle (2011), quantifies latent constructs by analyzing variance-covariance patterns across multiple observed indicators to derive a parsimonious set of latent factors. This methodology is essential for empirically validating the structural relationships among underlying factors within scale items. Empirical results (Table 3) demonstrate composite reliability (CR) exceeding 0.7, factor loadings surpassing 0.5, and average variance extracted (AVE) values greater than 0.5 (Hair et al., 2014). The analysis also revealed that Cronbach's α values ranged from 0.849 to 0.898, which exceeds the commonly accepted threshold of 0.70 proposed by Nunnally (1978), indicating that all measurement scales demonstrated strong internal consistency.

Table 3

CFA Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variable	Source of Questionnaire	No. of Item	CA	Factors Loading	CR	AVE
Perceived Ease of Use (PEU)	Singh and Sharma (2021)	4	0.876	0.775-0.844	0.876	0.639
Perceived Usefulness (PU)	Cheng (2020)	4	0.885	0.781-0.834	0.886	0.661
Self-efficacy (SE)	Lwoga and Komba (2015)	6	0.898	0.751-0.811	0.898	0.596
Facilitating Conditions (FC)	Shah and Khanna (2023)	4	0.888	0.803-0.825	0.888	0.666
Social Influence (SI)	Alami and El Idrissi (2022)	4	0.884	0.781-0.838	0.885	0.658
Confirmation (CON)	Cheng (2020)	3	0.849	0.782-0.853	0.851	0.656
Satisfaction (SAT)	Cheng (2020)	4	0.884	0.794-0.884	0.885	0.658

In accordance with the discriminant validity criterion established by Fornell and Larcker (1981) , the square root of the AVE for each latent construct must demonstrate statistical superiority over all bivariate correlation coefficients between that construct and other latent variables within the structural model. Empirical evidence from Table 4 confirms that the AVE values for all constructs were substantially higher than their corresponding inter-construct correlations. These results collectively support both convergent and discriminant validity, empirically validating the robustness of the structural model.

Table 4

Square roots of AVEs and correlation matrix

	SE	FC	SI	CON	PEU	PU	SAT
SE	**0.772**						
FC	0.290	**0.816**					
SI	0.174	0.288	**0.811**				
CON	0.231	0.203	0.212	**0.810**			
PEU	0.300	0.322	0.224	0.287	**0.799**		

	SE	FC	SI	CON	PEU	PU	SAT
PU	0.444	0.294	0.273	0.285	0.451	**0.813**	
SAT	0.319	0.374	0.345	0.468	0.338	0.464	**0.811**

Table 5 highlights that the model demonstrates excellent alignment with the patterns observed in the data: χ^2/df = 1.156, GFI = 0.949, AGFI = 0.937, NFI = 0.952, CFI = 0.993, TLI = 0.992, and RMSEA = 0.018. All values meet or surpass established statistical thresholds (Hu & Bentler, 1999; Kline, 1998), providing robust empirical substantiation for both convergent and discriminant validity of the measurement model. This evidence confirms the framework's psychometric rigor and demonstrates precise construct operationalization within the target sample.

Taken together, these results enable meaningful interpretation of the hypothesized relationships, showing that the observed associations among constructs align with the research questions and are consistent with prior findings in TAM, UTAUT, and ECM literature, thereby supporting the theoretical framework of the study.

Table 5

Goodness-of-Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Al-Mamary & Shamsuddin, 2015)	1.156
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.949
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.937
NFI	≥ 0.80 (J. H. Wu & Wang, 2005)	0.952
CFI	≥ 0.80 (Bentler, 1990)	0.993
TLI	≥ 0.80 (Sharma et al., 2005)	0.992
RMSEA	< 0.08 (Pedroso et al., 2016)	0.018
Model summary		**In harmony with empirical data**

Structural Equation Modeling (SEM)

SEM constitutes a comprehensive statistical framework for validating theoretical constructs and testing hypotheses through integrated measurement (CFA) and structural models (Hair et al., 2014). This methodology enables simultaneous assessment of indirect variable relationships and global model fit (Kline, 2023), with model adequacy evaluated via established benchmarks including χ^2/df, CFI, RMSEA, and additional indices specified by Hadji and Degoulet (2016).

Empirical results revealed strong model-data alignment: χ^2/df = 1.844, GFI = 0.907, AGFI = 0.891, NFI = 0.921, CFI = 0.962, TLI = 0.958, RMSEA = 0.041 (Table 1). All metrics conform to psychometric thresholds (Hu & Bentler, 1999; Schreiber et al., 2006), indicating acceptable-to-optimal model fit. As shown in Table 6, these findings substantiate the measurement model's efficacy in operationalizing theoretical constructs within the empirical context.

Table 6

Goodness-of-Fit for Structural Model

Index	Acceptable Values	Fit Index
CMIN/DF	< 3.00 (Al-Mamary & Shamsuddin, 2015)	1.844
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.907
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.891
NFI	≥ 0.80 (J. H. Wu & Wang, 2005)	0.921
CFI	≥ 0.80 (Bentler, 1990)	0.962
TLI	≥ 0.80 (Sharma et al., 2005)	0.958
RMSEA	< 0.08 (Pedroso et al., 2016)	0.041
Model summary		**Acceptable Model Fit**

Hypothesis Outcomes

The hypothesized causal pathways between independent and dependent constructs underwent empirical assessment through regression coefficients and standardized path estimates. As detailed in Table 7, six proposed hypotheses received robust cross-dataset confirmation, evidencing statistically significant relationships across all substantiated paths.

Building on the validated measurement and structural models, the findings can be translated into actionable insights for E-learning platform development and higher education policy. Among the significant predictors, PU exhibited the strongest effect on student SAT, followed by FC, SI, and CON, highlighting their relative importance in shaping learners' experiences. Mediation analysis further confirmed that PU serves as a critical conduit through which SE and PEU influence SAT, emphasizing the central role of perceived utility in driving engagement and positive perceptions. Practically, these results suggest that platform developers should prioritize intuitive, user-friendly features that enhance learners' perceived benefits, while institutional policies should support technical infrastructure, guidance, and peer encouragement to maximize adoption and satisfaction. By linking statistically substantiated effects to concrete recommendations, this approach bridges the gap between empirical findings and practical decision-making, thereby aligning research outcomes with the study's overarching objectives.

Table 7

Summary of hypothesis tests

Hypothesis	Standardized Coefficients (β)	t-value	Result
H1: SE has significant impact on PU.	0.397	8.352***	Supported
H2: PEU has significant impact on PU.	0.420	8.847***	Supported
H3: FC has significant impact on SAT.	0.224	5.000***	Supported
H4: PU has significant impact on SAT.	0.340	7.251***	Supported
H5: SI has significant impact on SAT.	0.184	4.138***	Supported
H6: CON has significant impact on SAT.	0.409	8.272***	Supported

Note: *p<0.05

Discussion

The empirical analysis provides robust support for all posited hypotheses. **H1** is empirically substantiated, indicating that SE exerts a moderate yet statistically significant positive effect on PU (β = 0.397, *t* = 8.352). The effect size can be interpreted as moderate, suggesting that SE holds a meaningful but not dominant influence relative to other predictors. This finding resonates with prior scholarship (Kanwal & Rehman, 2017; Sinha & Bag, 2023), underscoring the pivotal role of SE in shaping learners' evaluations of digital educational tools, confirming that learners with heightened confidence in their domain-specific capabilities exhibit greater propensity to perceive digital learning platforms as instrumental resources for achieving educational objectives.

H2 further validates the influence of PEU on PU (β = 0.420, *t* = 8.847). Based on conventional effect size benchmarks, this coefficient falls within the moderate-to-strong range, indicating that PEU has a substantial practical bearing on students' PU. This corroborates the TAM (Venkatesh & Davis, 2000) and is supported by empirical findings from Gallego et al. (2008) and I.-F. Liu et al. (2010). These results highlight that a user-friendly interface enhances the perceived utility of the system.

With regard to **H3**, the significant positive effect of FC on SAT (β = 0.224, *t* = 5.000). This effect is relatively modest in magnitude, implying that although FC are not the strongest determinant, their presence still makes a noticeable contribution to students' satisfaction. This observation aligns with the assertions of Festinger's cognitive consistency theory (1957) and is echoed in more recent studies (Alalwan, 2020; Su & Tong, 2021), emphasizing that accessible support infrastructures are instrumental in fostering positive learning experiences.

H4 demonstrates that PU significantly contributes to SAT (β = 0.340, *t* = 7.251). The standardized path coefficient suggests a moderate influence, signaling that PU plays a central—though not exclusive—role in shaping satisfaction outcomes. This result is consistent with prior literature (Bhattacherjee & Premkumar, 2004; Masrani et al., 2023), indicating that students who perceive clear functional benefits from the system report greater satisfaction. The result further validates the assumptions of the TAM and highlights the practical importance of enhancing PU to strengthen learners' overall experiences in digital learning environments.

H5 also establishes SI as a meaningful predictor of SAT (β = 0.184, *t* = 4.138). The relatively low coefficient size positions SI as a weaker predictor compared with other constructs, yet its statistical significance affirms that peer norms and expectations cannot be disregarded. This supports findings by Hsiao et al. (2016) and S. Liu et al. (2022), suggesting that peer norms and social expectations meaningfully shape learners' attitudes toward online platforms. The result underscores that satisfaction in digital learning is affected not only by system attributes but also by the surrounding social context.

Lastly, **H6** confirms that CON significantly influences SAT (β = 0.409, *t* = 8.272), in accordance with ECT (Bhattacherjee, 2001; Cheng, 2014). The coefficient is indicative of a moderate-to-strong effect, reflecting that CON constitutes one of the more influential factors driving student satisfaction. This finding highlight that the degree to which learners' initial expectations regarding system functionality and learning outcomes are met by actual performance serves as a critical determinant of their satisfaction. In other words, when perceived experiences align closely with prior expectations, students are more likely to develop positive evaluations of the E-learning platform, thereby reinforcing continued acceptance and sustained engagement in technology-mediated learning environments.

In summary, all hypothesized paths were statistically validated, reinforcing both TAM and ECT frameworks. The findings contribute to the growing body of literature on E-learning adoption and provide actionable insights for improving user satisfaction and system effectiveness in the context of Chinese higher education.

Conclusions

This study investigated the key determinants influencing undergraduate students' perceived usefulness and satisfaction with E-learning platforms in Yibin, China. Drawing upon an integrated framework that synthesizes the TAM, ECM, and UTAUT, the research examined both direct and mediating effects of SE, PEU, FC, SI, and CON on PU and SAT.

Empirical data collected from 500 science and engineering students were analyzed using SEM. The reliability and validity of the measurement model were confirmed through CA, CR, AVE, and CFA, while expert review and pilot testing strengthened the instrument's design and applicability.

The results confirm that SE and PEU significantly influence PU, which, in turn, serves as a key mediator in predicting satisfaction. Additionally, FC, SI, and CON directly affect satisfaction, underscoring the combined influence of individual cognitive beliefs and contextual support. The mediating role of PU reinforces its centrality in technology acceptance, consistent with prior research emphasizing its predictive power for both satisfaction and continued use.

By integrating three major theoretical models, this study contributes a unified and empirically validated framework that enhances understanding of E-learning adoption in the Chinese higher education context. The findings emphasize the importance of both pre-adoption beliefs and post-adoption experiences in shaping students' satisfaction, offering valuable insights into the mechanisms driving long-term engagement with digital learning platforms.

Practically, the study suggests that universities should focus on enhancing students' digital self-efficacy through targeted training, simplifying platform usability, and improving technical infrastructure and support. Encouraging positive peer and instructor engagement with E-learning systems can also strengthen social influence and satisfaction outcomes. While the study provides a robust model, its generalizability is limited by the focus on a single academic discipline and region. Future research should broaden the scope across diverse fields and locations, incorporate additional psychological constructs, and adopt longitudinal designs to examine evolving user experiences over time.

Meanwhile, this study advances the literature by integrating TAM, ECM, and UTAUT into a unified framework, empirically demonstrating how individual cognitive factors (SE, PEU) and contextual elements (FC, SI, CON) jointly influence PU and SAT. By confirming the mediating role of PU, the research clarifies the mechanisms through which pre-adoption beliefs translate into post-adoption satisfaction, extending prior findings in the Chinese higher education context. Furthermore, the study provides evidence that both direct and indirect effects should be considered in modeling technology acceptance, offering a theoretically grounded model that can guide future research on E-learning adoption and technology-mediated learning environments.

In sum, this research affirms the central role of perceived usefulness in bridging user perceptions and satisfaction, offering a theoretically grounded and practically relevant model for improving student engagement in E-learning environments. These findings contribute to the ongoing development of learner-centered digital education systems that foster both immediate acceptance and sustained participation.

Recommendations

Drawing on empirical evidence from 500 senior undergraduate science and engineering students in Yibin, China, this study confirms that SE, PEU, FC, SI, and CON significantly affect PU and SAT with E-learning platforms. These findings, grounded in TAM, ECM, and UTAUT, offer several actionable recommendations.

As for short-term priorities, first, given PU's central mediating role between user perceptions and satisfaction, platform designers and university IT teams should initially focus on features that directly enhance learning efficiency. This includes implementing adaptive learning pathways, intelligent assessment tools, and real-time feedback systems aligned with national STEM standards to maximize perceived educational value.

Second, to strengthen SE and PEU, immediate measures such as interactive tutorials, formative assessments, and peer collaboration modules should be provided to boost learner confidence and reduce cognitive load, facilitating intuitive platform use.

Third, addressing FC and CON in the short term involves ensuring stable internet access, device compatibility, and timely technical support, while reinforcing students' expectations through clear learning objectives, consistent content updates, and personalized progress tracking.

As for long-term priorities, fourth, as SI significantly influences satisfaction, institutions should cultivate a supportive social environment by engaging instructors and influential peers to actively promote the platform. Long-term strategies can include community ratings, student testimonials, and peer recognition systems (e.g., leaderboards) to sustain engagement.

Fifth, continuous improvement should be institutionalized. Regular usability audits, ongoing student satisfaction surveys, and staff development programs will ensure the platform evolves alongside user needs and pedagogical goals.

Collectively, by sequencing these interventions—short-term measures to rapidly enhance usability, confidence, and satisfaction, followed by long-term strategies to reinforce social support and iterative improvement—stakeholders can systematically cultivate a more effective and engaging E-learning environment for STEM students in higher education.

Limitations and Further Study

Notwithstanding the valuable empirical evidence contributed by this study regarding the determinants influencing perceived usefulness and satisfaction with E-learning platforms among undergraduate students in Yibin, it is imperative to delineate several inherent methodological and contextual limitations. These identified constraints not only contextualize the current findings but also explicitly demarcate fertile ground for subsequent scholarly inquiry.

First, the sample was limited to senior students from four majors within a single university, which may restrict the generalizability of the findings. Given disciplinary and institutional differences in digital learning experiences, future studies should incorporate broader samples across multiple universities and academic fields to enhance external validity.

Second, employing a cross-sectional approach restricts the potential to infer causality or capture temporal dynamics in user satisfaction. Since user perceptions may evolve due to platform updates or pedagogical shifts, longitudinal designs are recommended to examine changes in satisfaction and related behaviors over time.

Third, due to practical constraints, the model included only seven constructs derived from ECM, TAM, and UTAUT. Other influential variables—such as content relevance, instructor support, learner autonomy, or emotional engagement—were not addressed. Future research could expand the framework by integrating additional predictors and testing potential moderating or mediating relationships.

Fourth, the study focused solely on user satisfaction without exploring continuance intention or actual usage behavior. As satisfaction is a key antecedent but not a comprehensive indicator of post-adoption engagement, subsequent studies should include continuance intention and usage frequency to provide a more holistic understanding of user behavior.

Finally, the exclusive reliance on quantitative methods may have overlooked rich qualitative insights. Incorporating mixed-methods approaches—such as interviews or focus groups—could offer deeper understanding of students' experiences, expectations, and contextual influences on satisfaction with E-learning systems.

Future research that systematically addresses these limitations is likely to yield a more nuanced and contextually sensitive understanding of technology acceptance processes as well as patterns of student engagement within digital learning environments. By overcoming the current constraints, subsequent studies can generate deeper theoretical insights and provide more robust empirical evidence, thereby strengthening both the explanatory power and the practical implications of technology-enhanced education research.

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