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Factors Impacting Chinese College Students' Perceived Usefulness and Continuance Intention Toward an Online Learning Platform in Yibin, China

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Abstract

This study investigates the factors influencing Chinese college students' perceived usefulness and continuance intention regarding an online learning platform in Yibin, China. Based on the Expectation Confirmation Model (ECM) and Technology Acceptance Model (TAM), a conceptual framework was developed with five independent variables (Information Quality (IQ), System Quality (SQ), Perceived Ease of Use (PEU), Social Influence (SI), and Interactivity (INT)), one mediating variable - Perceived Usefulness (PU), and one dependent variable - Continuance Intention (CI)). A structured questionnaire was distributed to 500 senior undergraduate students from four majors at Sichuan University of Science & Engineering (Yibin campus). Empirical findings indicate that all five independent variables—IQ, SQ, PEU, SI, and INT—positively and significantly affect PU. Furthermore, both PU and PEU have significant direct impacts on CI. PU plays a key mediating role, linking system and social factors to usage behavior. These observations reaffirm prior scholarly work in technology adoption and on learning, supporting the premise that students' judgments of content quality, platform usability, social environment, and interactive features critically shape their evaluation of usefulness, which in turn influences their CI to use online learning platforms. The findings offer practical insights for improving online learning platforms through enhanced quality, interactivity, and social engagement features.

Keywords **:** Perceived Usefulness, Continuance Intention, Online Learning Platforms, Technology Adoption

Introduction

With the rapid advancement of Internet and communication technologies, online learning has increasingly evolved into a dominant mode of education, offering greater flexibility and convenience compared to traditional classroom-based instruction. It empowers learners to access educational content at any time and from any location, thereby supporting both structured formal instruction and self-paced independent learning (Guo et al., 2023). Internet technology has removed time and space constraints, enabling global integration of education and promoting open sharing of resources. Online education has significantly transformed traditional classroom models and teaching methods, with evolving content and functionalities. Technological advances have expanded its application across personal learning, corporate training, and institutional curricula, introducing concepts such as internet-based open learning that support learner autonomy and flexible pacing. This growth also offers opportunities for institutions to develop more adaptable systems, foster educational innovation, and enhance comprehensive student development (L. Zhang, 2023). In response to this need, numerous online learning platforms—such as Coursera, edX, and China's XuetangX—have been extensively adopted across various regions and disciplines. According to recent projections, the global population of online learners is expected to reach approximately 57 million by 2027, while the market value of the e-learning industry is anticipated to exceed 370 billion U.S. dollars by 2026 (Peck, 2025). Despite the rapid expansion and widespread adoption of digital learning systems, sustaining long-term learner engagement and promoting continuance intention remain significant challenges for educators, platform developers, and policymakers.

Prior studies have highlighted the importance of perceived usefulness—students' belief that using a platform enhances learning performance—functioning as a principal influence on users' willingness to retain platform usage. For example, Marandu et al. (2023) proved that satisfaction (SAT) serves as a significant antecedent of CI, indicating that higher levels of user SAT contribute positively to users' willingness to continue engaging with the platform, while Aldholay et al. (2019) emphasized the roles of compatibility, transformational leadership, and network quality. Other studies have explored how ease of use, content quality, and interaction features impact engagement (Ghosh et al., 2023). In China, researchers have examined student cognition, online environments, and emotional engagement. Zhu et al. (2022) stressed the importance of learning resources and interaction in promoting behavior change, while Xu et al. (2023) found that teacher-student and teacher-parent interaction significantly enhance continued use. However, few studies have focused on second-tier cities like Yibin, where the adoption of online learning is growing but remains under-researched.

Given these gaps and drawing on technology acceptance and user behavior theories, this study aims to investigate how PU, PEU, IQ, SQ, INT, and SI affect learners' CI toward online learning platforms in Yibin, China.

Literature Review

Information Quality (IQ)

IQ denotes users' perceived quality of information as accurate, timely, relevant, complete, and well-organized (H. Lee et al., 2007). With respect to computer-assisted learning systems, IQ emphasizes the quality of content provided by platforms and its alignment with learners' needs (Y.-M. Cheng, 2014; Yakubu & Dasuki, 2018). McKinney et al. (2002) and Y.-M. Cheng (2012) further noted that learners are more likely to value platforms that deliver up-to-date, flexible, and contextually relevant content.

Empirical studies have consistently shown that IQ significantly influences learners' PU of online learning systems. Seddon (1997), building on the DeLone and McLean model, emphasized the critical role of IQ in shaping PU and user satisfaction. When the provided content meets or exceeds expectations, learners perceive the platform as more effective (Choi et al., 2007). Y. Lee (2006), and Al-Fraihat et al. (2020) have affirmed that high IQ enhances motivation for continuous use by improving perceived usefulness. E. Lwoga (2014) also highlighted the importance of diverse and tailored content in reinforcing the inclination of learners to participate in digital learning environments. Overall, prior researches have confirmed that improving IQ is essential for enhancing learners' perceptions of usefulness and promoting sustained platform engagement.

Research purpose: H1 examines whether higher IQ directly enhances learners' PU of online learning platforms, validating the theoretical link between content quality and user eng agement. Thus, a research hypothesis H1 is formulated:

H1. IQ has significant impact on PU.

Interactivity (INT)

INT encompasses the users' ability to engage in two-way communication processes, wherein they can not only influence the direction or flow of content but also provide feedback, thereby fostering dynamic and responsive user-system interaction, including control over content and turn-taking (Liu & Shrum, 2002; Williams et al., 1988). It encompasses real-time engagement with both the structure and content of mediated environments (Steuer, 1992), and enables reciprocal interactions among learners and learner-instructor dyads, thereby supporting collaboration and enhancing educational experiences (Barreda et al., 2016; Palloff & Pratt, 1999; Pituch & Lee, 2006).

Effective interactivity—both among learners and learner-instructor dyads—has constituted a core aspect of shaping learners' PU of an online system (Paechter et al., 2010; Pituch & Lee, 2006). When learners can flexibly control elements such as content, pacing, and interaction sequence, and receive timely and relevant feedback, their perception of system usefulness has been enhanced (Y.-M. Cheng, 2012). Direct engagement with instructors, access to up-to-date content, and interactive participation have contributed to higher satisfaction and perceived value (Kuo et al., 2014). Furthermore, positive peer and instructor interactions within the system have fostered collaborative learning and strengthened the intent to remain actively involved with the platform (Lin et al., 2017).

Research purpose: H2 investigates whether higher levels of interactivity increase learners' PU of online learning systems, supporting the role of dynamic engagement in shaping PU.

H2. INT has significant impact on PU.

Social Influence (SI)

SI manifests perceived social sanctioning intensity, wherein individuals cognitively evaluate the level of consensual support from primary referent groups toward designated behavioral implementation (B. Cheng et al., 2012; Davis et al., 1989). With respect to individuals' adoption of technological systems, SI reflects the impact of social norms and the perceived expectations of peers, instructors, or institutional authorities on users' decisions regarding system adoption (Venkatesh & Davis, 2000). It also encompasses how the behavior and opinions of one's social network—such as colleagues, supervisors, or administrators—shape perceptions and intentions related to technologies like e-learning or mobile payment systems (Madani et al., 2023; Qasim & Abu-Shanab, 2016).

Social influence (SI) has been shown to significantly shape learners' perceived usefulness (PU) of online learning platforms such as MOOCs. Learners' perceptions have often been shaped by the views and reinforcement provided by social counterparts, instructors, along with other important members of the social circle (Y.-H. Lee et al., 2013; B. Wu & Chen, 2017). Prior studies have confirmed that SI positively correlates with PU, as external validation reinforces the belief that the system enhances learning effectiveness (Claar et al., 2014; Nikou & Economides, 2017). Karahanna and Straub (1999) emphasized the role of influential referents in forming PU judgments, while Venkatesh and Davis (2000) highlighted that favorable perceptions among important others can enhance users' willingness to adopt the system. B. Wu and Zhang (2014) found SI constitutes a fundamental determinant of students' PU in E-learning 2.0 settings, highlighting the extent to which social pressures and normative beliefs shape users' cognitive evaluations of educational technologies.

Research purpose: H3 aims to examine whether SI positively affects learners' PU, highlighting the role of social norms in shaping technology adoption.

H3. SI has significant impact on PU.

System Quality (SQ)

SQ denotes the technical performance of an e-learning platform, encompassing usability, accessibility, and responsiveness (Zheng et al., 2013). A high-quality system is characterized by well-organized content delivery, user-friendly interfaces, and consistent, timely access to multimedia learning resources (Calisir et al., 2014; Y.-M. Cheng, 2014). SQ also encompasses platform reliability, flexibility, and the system's ability to effectively transmit information, often evaluated through user feedback (Rui-Hsin & Lin, 2018).

High system quality (SQ) in e-learning platforms has enhanced learners' perceived usefulness (PU) by aligning system functionality with their learning needs (Roca et al., 2006).

Reliable performance, real-time responsiveness, and effective communication features have contributed to positive user evaluations (B.-C. Lee et al., 2009). When learners perceive the system as stable, secure, and user-oriented, their assessment of its practicality and usefulness has increased (DeLone & McLean, 1992; Pituch & Lee, 2006). Additionally, SQ has positively influenced PU in both distance education and self-paced learning contexts (Cho et al., 2009). Thus, higher SQ can exceed user expectations, fostering stronger acceptance and continued usage.

Research purpose: H4 tests whether higher system quality positively influences learners' PU, emphasizing the importance of platform stability and usability for perceived effectiveness.

H4. SQ has significant impact on PU.

Perceived Ease of Use (PEU)

PEU captures the perception that minimal effort is needed to interact with the system effectively (Davis, 1989). PEU reflects learners' perceptions of the simplicity and usability of platforms such as MOOCs or virtual classrooms (B.-C. Lee et al., 2009; B. Wu & Chen, 2017). Systems that are intuitive and user-friendly have reduced the time needed to learn their functions, thereby enhancing user engagement and academic performance (Karaali et al., 2011).

According to the TAM, PEU has positively influenced PU in e-learning contexts (Davis, 1989; B. Wu & Chen, 2017). Perceiving the system as easy to use has increased learners' appreciation of its effectiveness and advantages (B.-C. Lee et al., 2009; Ong & Lai, 2006). Prior studies have consistently confirmed that simpler systems enhance users' perceptions of usefulness, thereby increasing acceptance (Venkatesh & Davis, 2000). Empirical evidence also has shown that persons who find e-learning platforms easy to operate tend to report higher PU (Huang et al., 2007).

In technology acceptance research, PEU has emerged as a key predictor influencing users' CI, suggesting that the simpler and more intuitive a system is perceived to be, the more likely users are to sustain their engagement over time (Davis, 1989; Lu, 2014). Empirical studies across e-learning contexts have confirmed the positive association between PEU and CI, indicating that users' willingness to keep using the system increases with perceptions of low effort and high efficiency (Thong et al., 2006). For both educators and students, systems that reduce cognitive load and enhance task performance have contributed to sustained usage intentions (Bajaj et al., 2021; S. Sharma & Saini, 2022). Additionally, when users believe that a platform supports effective learning or information retrieval, their intention to persist increases (Jeong, 2011).

Research purpose: H5 investigates whether learners' PEU positively affects PU, supporting the role of system simplicity in technology acceptance. H7 examines whether learners' perception of system ease and usefulness translates into continued engagement with online learning platforms.

H5. PEU has significant impact on PU.
H7. PEU has significant impact on CI.

Perceived Usefulness (PU)

Within the framework of technology acceptance, PU reflects users' conviction that employing a designated system will facilitate better performance in both professional tasks and academic pursuits (Ajzen, 1991; Davis, 1989). In technology adoption, users have tended to embrace systems they regard as beneficial and conducive to improved performance (Q. Chen et al., 2007; Ifinedo, 2017). As for e-learning, PU is closely linked to students' beliefs about the platform's ability to improve learning outcomes (Dorobăţ et al., 2019).

PU has been empirically confirmed to represent a critical predictor of CI in technology adoption (Bhattacherjee, 2001). Empirical studies in e-learning have consistently reported a positive association between PU and CI (Kim et al., 2019). Researchers have shown that learners are inclined to maintain usage of e-learning platforms when they perceive the system as effective in supporting academic performance (Chauhan et al., 2022; Y.-M. Cheng, 2012). Similar findings have been reported in the context of MOOCs, where perceived usefulness enhances learners' motivation for continued engagement (Alraimi et al., 2015; Shao, 2018). Overall, when users believe that an e-learning system delivers relevant, high-quality content aligned with their learning needs, their intention to persist has increased significantly (Foroughi et al., 2019; E. T. Lwoga & Komba, 2015).

Research purpose: H6 tests whether PU significantly influences learners' CI, highlighting PU as a mediator between system characteristics and CI.

H6. PU has significant impact on CI.

Continuance Intention (CI)

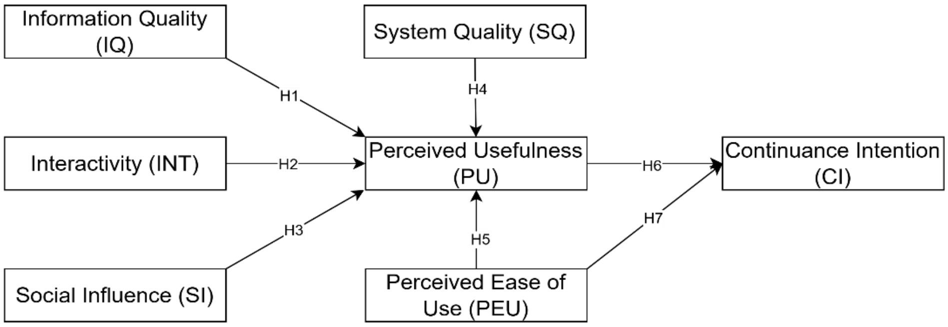
CI captures a learner's commitment and willingness to uphold continued use of a designated product, service, or system beyond the initial adoption phase (Bhattacherjee, 2001; Elsotouhy et al., 2023). It signifies not only sustained engagement but also the cognitive decision to remain with the selected option instead of exploring or switching to alternative solutions (Hellier et al., 2003). Within the scope of electronically supported education, CI specifically refers to students' intention to consistently use online learning platforms over time, often accompanied by favorable attitudes toward the platform and a willingness to recommend it to others (Chang, 2013; Shah & Khanna, 2023). As such, CI serves as a critical indicator of long-term system success and user retention in digital learning environments.

Conceptual Framework

The theoretical model put forward is formulated through the integration of the TAM and the ECM, both of which have been extensively applied in studies examining post-adoption behavior and technology use. Within this framework, five key constructs—SQ, IQ, INT, SI, and PEU—are conceptualized as independent variables that potentially affect users' perceptions and behavioral responses. PU is positioned as a mediating variable, reflecting its theoretical role in linking system-related factors to user continuance outcomes. CI, representing users' sustained willingness to engage with the platform, is designated as the dependent variable.

Figure 1

Conceptual Framework



The analysis proceeds in two main stages. First, the study examines the individual and collective impacts of SQ, IQ, INT, SI, and PEU on PU. This step aims to identify which system and user-experience factors most significantly shape learners' PU of the e-learning platform. Second, the model assesses the influence of PU on CI, thereby establishing the indirect pathways through which initial perceptions translate into continued usage behavior. Furthermore, the model incorporates the direct effect of PEU on CI, acknowledging prior theoretical insights that ease of use can independently affect continuance decisions, beyond its mediated role through PU.

Research Methodology

Research Design

In this paper, a descriptive quantitative survey methodology was adopted to systematically investigate the research objectives. Using a quantitative nonprobability sampling method, sample data were gathered through the administration of a carefully developed structured questionnaire, which underwent rigorous content validity assessment through item-objective congruence (IOC) analysis prior to distribution, ensuring the relevance and clarity of each item in relation to the study constructs. The questionnaire was structured into three sections, comprising a total of 35 items. The first section contained three screening questions designed to identify the target respondents. The second section encompassed the measurement of all study variables, including IQ, SQ, PU, INT, PEU, SI, and CI, with 27 items adapted from Y.-M. Cheng (2014), Y.-M. Cheng (2020), and Alami and El Idrissi (2022). The final section addressed demographic characteristics, consisting of five questions. All variables were assessed using a five-point Likert scale. The survey was distributed to participants via class counselors, with each participant completing a single questionnaire to provide individual-level responses. Subsequently, the collected data were subjected to comprehensive analyses, including construct validity evaluation and SEM, to rigorously test the hypothesized relationships within the proposed research framework.

Research Population and Sample

The study was designed and implemented at Sichuan University of Science & Engineering (SUSE) in Yibin, China, targeting senior undergraduate students with prior or current experience using online learning platforms. Participants were drawn from four academic majors: Computer Science & Technology, Software Engineering, Vehicle Engineering, and Mechatronics Engineering. The structural model comprised 7 latent variables and 27 observed indicators, with the significance criterion established at 0.05. Based on statistical power considerations and prior research, 425 participants constituted the minimum required sample. To enhance reliability, 500 valid responses were collected, meeting the recommended threshold for SEM, as 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	187
Software Engineering	222	101
Vehicle Engineering	254	116
Mechatronics Engineering	211	96
Total	**1,096**	**500**

Data Analysis

Before the data gathering process, three subject-matter experts evaluated content validity using the IOC index; all questionnaire items outperformed the threshold criterion of 0.6. Subsequently, a pilot research phase including 50 respondents demonstrated satisfactory reliability, with CA coefficients surpassing 0.7, aligning with Nunnally and Bernstein's (1994) criterion. Data analysis employed AMOS 26.0. To substantiate the measurement model and empirically explore the theorized relationships among constructs, CFA and SEM were applied.

Demographics of Participants

Table 2 reveals a gender distribution, indicating that 78.6% of participants were male, while females accounted for 21.4%. Among all respondents, the majority of students (95%) were aged 21-24 years old. Regarding academic disciplines, Computer Science and Technology and Vehicle Engineering were the most frequently represented fields, constituting 37.4% and 23.2% of the sample, respectively. Importantly, all participants (100%) reported having prior experience with online learning platforms, highlighting their familiarity with digital educational tools. Additionally, a significant majority (92.2%) of the students use online learning platforms more than three times per week, suggesting a high level of engagement with such technologies. These demographic details not only contextualize the sample but also provide essential background information that supports the interpretation and generalizability of the study's findings.

Table 2

The demographic data

Demographic and Behavior Data (N=500)		Frequency	Percentage
Gender	Male	393	78.6%
	Female	107	21.4%
Major	Computer Science & Technology	187	37.4%
	Software Engineering	101	20.2%
	Vehicle Engineering	116	23.2%
	Mechatronics Engineering	96	19.2%
Age	18- 20 years old	15	3.0%
	21- 22 years old	267	53.4%
	23-24 years old	208	41.6%
	More than 24 years old	10	2.0%
Number of learn with online learning platform a week	less than 2 times	39	7.8%
	3 - 4 times	258	51.6%
	5 - 7 times	162	32.4%
	more than 7 times	41	8.2%

Results and Discussion

To validate the uniqueness of each latent construct, CFA was carried out as a methodological approach for establishing discriminant validity. Each construct demonstrated internal consistency, with Cronbach's alpha values greater than the 0.70 criterion, confirming satisfactory reliability (refer to Table 3) (Nunnally & Bernstein, 1994). The results indicated that all factor loadings met the significance criterion and were above the 0.30 cutoff (Hair et al., 2007), indicating acceptable item representation. Furthermore, all constructs met the recommended criteria for composite reliability (> 0.70) and average variance extracted (AVE > 0.50), supporting convergent validity (Fornell & Larcker, 1981).

Table 3

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

Variable	Source of Questionnaire	No. of Item	CA	Factors Loading	CR	AVE
Information Quality (IQ)	Y.-M. Cheng (2014)	4	0.874	0.793-0.801	0.875	0.637
Interactivity (INT)	Y.-M. Cheng (2020)	3	0.845	0.780-0.823	0.847	0.649
Social Influence (SI)	Alami and El Idrissi (2022)	4	0.870	0.772-0.817	0.871	0.628
System Quality (SQ)	Y.-M. Cheng (2014)	4	0.860	0.760-0.799	0.861	0.608
Perceived Ease of Use (PEU)	Alami and El Idrissi (2022)	4	0.884	0.762-0.829	0.885	0.658
Perceived Usefulness (PU)	Y.-M. Cheng (2014)	4	0.901	0.838-0.894	0.903	0.699
Continuance Intention (CI)	Y.-M. Cheng (2014)	4	0.890	0.787-0.839	0.891	0.672

As outlined by Fornell and Larcker's (1981) criterion, the establishment of discriminant validity requires that the square root of a construct's AVE exceed the strength of its associations with all other latent variables included in the analysis. As shown on Table 4, the AVE square roots for all constructs exceeded their respective inter-construct correlations. Results from this analysis supported both convergent and discriminant validity, reinforcing the soundness of the structural model employed.

Table 4

Square roots of AVEs and correlation matrix

	IQ	INT	SI	SQ	PEU	PU	CI
IQ	0.798						
INT	0.215	0.806					
SI	0.332	0.239	0.792				
SQ	0.318	0.306	0.257	0.780			
PEU	0.236	0.135	0.240	0.281	0.811		
PU	0.486	0.405	0.419	0.479	0.403	0.836	
CI	0.226	0.141	0.253	0.221	0.453	0.470	0.820

Based on the fit indices in Table 5, the measurement model demonstrated a strong degree of fit within the sampled population. Specifically, fit indices indicated a strong model fit, with values reported as follows: CMIN/df was 1.135; GFI reached 0.953; AGFI was 0.942; NFI equaled 0.957; CFI achieved a value of 0.995; TLI was 0.994; and RMSEA was notably low at 0.016, suggesting minimal approximation error. These indicators not only meet but surpass the conventional thresholds widely accepted in the field, offering compelling support for both the convergent and discriminant validity of the measurement structure. Such consistently high model fit values across all indices suggest that the observed data are well explained by the hypothesized constructs.

Table 5

Goodness-of-Fit for Measurement Model

Index	Acceptable Values	Statistical Values
CMIN/DF	< 3.00 (Al-Mamary & Shamsuddin, 2015)	1.135
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.953
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.942
NFI	≥ 0.80 (J. H. Wu & Wang, 2005)	0.957
CFI	≥ 0.80 (Bentler, 1990)	0.995
TLI	≥ 0.80 (G. P. Sharma et al., 2005)	0.994
RMSEA	< 0.08 (Pedroso et al., 2016)	0.016
Model summary		**In harmony with empirical data**

Structural Equation Modeling (SEM)

Hair et al. (2014) stated that both for concepts, theory development tests and error handling and hypothesis statistical tests need to be analyzed and evaluated by measurement models (CFA) and structural models. SEM is a statistical testing method that focuses on examining indirect relationships among variables and the fit with the overall model (Kline, 2023). Hadji and Degoulet (2016) pointed out that SEM is based on multiple indicators, including the Normed Fit Index (NFI), chi-square statistic ($\chi 2$), degrees of freedom (df), Comparative Fit Index (CFI), Non-Normed Fit Index (NNFI), Root Mean Square Residual (RMR), Goodness of Fit Index (GFI), and Root Mean Square Error of Approximation (RMSEA).

The empirical findings yielded the following results: CMIN/df = 1.914, with GFI at 0.909 and AGFI at 0.892. Additional fit metrics include a NFI of 0.924, a CFI of 0.962, and a TLI of 0.958. As shown in Table 6, all values were within the acceptable or recommended thresholds for good model fit, indicating that the proposed structural model provides a satisfactory representation of the observed data.

Table 6

Goodness-of-Fit for Structural Model

Index	Acceptable Values	Fit Index
CMIN/DF	< 3.00 (Al-Mamary & Shamsuddin, 2015)	1.914
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.909
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.892
NFI	≥ 0.80 (J. H. Wu & Wang, 2005)	0.924
CFI	≥ 0.80 (Bentler, 1990)	0.962
TLI	≥ 0.80 (G. P. Sharma et al., 2005)	0.958
RMSEA	< 0.08 (Pedroso et al., 2016)	0.043
Model summary		**Acceptable Model Fit**

Hypothesis Outcomes

To assess the hypothesized associations among the independent and dependent constructs, the researcher employed standardized path coefficients alongside regression coefficients as indicators of relationship magnitude. As evidenced by the statistical outcomes displayed in Table 7, the findings consistently validated seven hypotheses across the two distinct groups of data.

Table 7

Summary of hypothesis tests

Hypothesis	Standardized Coefficients (β)	t-value	Result
H1: IQ has significant impact on PU.	0.339	7.480***	Supported
H2: INT has significant impact on PU.	0.273	6.069***	Supported
H3: SI has significant impact on PU.	0.230	5.264***	Supported
H4: SQ has significant impact on PU.	0.303	6.711***	Supported
H5: PEU has significant impact on PU.	0.271	6.127***	Supported
H6: PU has significant impact on CI.	0.333	6.803***	Supported
H7: PEU has significant impact on CI.	0.359	7.211***	Supported

Note: *p<0.05

Discussion

To begin with, Hypothesis **H1** is validated, showing that IQ exerts a statistically positive influence on PU. The corresponding standardized coefficient is 0.339, with a t-value of 7.480. This aligns with foundational and recent studies (Choi et al., 2007; Seddon, 1997), underscoring the crucial role of content accuracy, relevance, and clarity in shaping users' cognitive evaluations of platform utility.

Hypothesis **H2** is also supported by the data. The construct of INT significantly affects PU, yielding a standardized coefficient of 0.273 and a t-statistic of 6.069. This empirical pattern corroborates the findings of Y.-M. Cheng (2021), and B.-C. Lee et al. (2009), all of which stress the importance of bidirectional communication, user engagement, and system responsiveness in enhancing perceived effectiveness.

Regarding Hypothesis **H3**, SI is identified as a meaningful antecedent of PU, with a standardized coefficient of 0.230, accompanied by a t-value of 5.264, demonstrating statistical significance. Such findings are in agreement with the assertions of Y.-H. Lee et al. (2013), B. Wu and Chen (2017), and Nikou (2021), who highlight the impact of peer recommendations and subjective norms in shaping users' beliefs about the platform's value.

With respect to Hypothesis **H4**, the study confirms the impact of SQ on PU. This path exhibits a normalized coefficient value of 0.303, accompanied by a t-value of 6.711. This result aligns with the conclusions drawn by Roca et al. (2006), and Cho et al. (2009), supporting the notion that the technical performance of the platform—including stability, reliability, and user interface quality—substantially influences users' perceptions of usefulness.

Further, Hypothesis **H5** reveals that PEU is a significant determinant of PU, with a parameter estimate of 0.271 with a t-score reaching 6.127. This relationship is consistent with the TAM, as described in Davis's (1989) seminal contribution, with corroboration from empirical studies such as those by Ong and Lai (2006), and Huang et al. (2007).

Turning to Hypothesis **H6**, the analysis provides strong support for the mediating role of PU in shaping CI. The standardized regression weight reached 0.333, with a t-value of 6.803 indicating statistical significance. This is in line with the ECM framework and reinforced by Kim et al. (2019), and Gupta et al. (2021), affirming that when students perceive tangible benefits, they tend to sustain platform use over time.

Lastly, Hypothesis **H7** is upheld, revealing that PEU significantly contributes to the prediction of CI through a direct path. This is exemplified by a standardized parameter estimate of 0.359 and a t-statistic of 7.211, highlighting strong significance. The result is consistent with earlier findings from Davis (1989), Mailizar et al. (2021), and Jeong (2011), all of whom point out that platforms perceived as easy to navigate contribute positively to users' willingness to continue usage.

Conclusions

This study investigated factors impacting on Chinese college students' PU and CI with online learning platform in Yibin, China. The proposed conceptual framework was grounded in the ECM and the TAM. By integrating constructs such as IQ, SQ, PEU, SI, INT, PU, and CI. This study was designed to offer an in-depth and systematic examination of the key factors influencing students' post-adoption behavior in the context of e-learning systems. By exploring a broad range of determinants—spanning technological, cognitive, and social dimensions—the research seeks to elucidate how these variables collectively impact students' continued usage intentions and sustained engagement with online learning platforms following their initial acceptance. Through this comprehensive approach, the study contributes to a more nuanced understanding of the mechanisms driving learner persistence, which is critical for optimizing e-learning system design and enhancing educational outcomes in higher education settings.

Using a structured questionnaire based on a five-point Likert scale, 500 valid responses were collected from senior undergraduates majoring in science and engineering disciplines. The instrument was pre-tested and verified through expert consultation using the Index of IOC, and pilot-tested to ensure item clarity and content validity. CFA and SEM were employed to assess the model's validity and test the proposed hypotheses. Specifically, reliability was evaluated using CA and CR, while construct validity was examined through the AVE. The results from these tests confirmed that the scales exhibited satisfactory internal consistency and strong construct validity, thereby ensuring the robustness and credibility of the measurement model employed in this study.

Empirical findings indicate that all five independent variables—IQ, SQ, PEU, SI, and INT—positively and significantly affect PU. Furthermore, both PU and PEU have significant direct impacts on CI. These observations reaffirm prior scholarly work in technology adoption and e-learning, supporting the premise that students' judgments of content quality, platform usability, social environment, and interactive features critically shape their evaluation of usefulness, which in turn influences their CI to use online learning platforms (Alraimi et al., 2015; Sun et al., 2008).

Among all predictors, perceived usefulness played a dual role, serving as both a direct antecedent to CI and a mediating variable between system-related factors and behavioral outcomes. This finding reaffirms the centrality of usefulness perceptions in post-adoption behavior, particularly in online learning contexts where self-regulated engagement is essential. Notably, interactivity—a relatively underexplored construct in traditional TAM—exhibited a strong effect on perceived usefulness, suggesting that active engagement features (e.g., discussion forums, real-time Q&A, feedback mechanisms) substantially enhance students' value perceptions. Moreover, PEU demonstrated significant direct effects on both PU and CI. This underscores the pivotal role of system usability in shaping not only students' evaluation of platform effectiveness but also their sustained engagement and behavioral intentions toward continued use. Consequently, platforms that optimize ease of interaction can simultaneously enhance perceived value and foster long-term user retention in online learning environments.

Recommendations

Drawing on the SEM analysis of 500 senior science and engineering undergraduates in Yibin, this study confirms that PU, shaped by IQ, SQ, PEU, SI, and INT, is the primary driver of CI toward online learning platforms. Taking into account the present study's findings, the following strategic recommendations are formulated:

1. Enhance Functional Relevance: To strengthen PU, platform developers and academic institutions should integrate features that directly support students' academic needs in STEM fields, such as simulation tools, interactive problem-solving environments, and access to discipline-specific databases.

2. Improve Usability: As PEU significantly influences both PU and CI, user-centered design is essential. Platforms should offer intuitive navigation, responsive interfaces, mobile compatibility, and simplified access to learning resources and communication tools.

3.Ensure Content and System Quality: High IQ and SQ are critical for platform credibility. This includes providing accurate, up-to-date, and comprehensive content, alongside stable system performance, low latency, and efficient technical support. Regular evaluations and user feedback should inform continuous improvement.

4. Promote Social and Interactive Features: Given the influence of SI and INT, e-learning environments should encourage collaboration and communication through tools such as discussion forums, group workspaces, peer reviews, and real-time instructor interaction, especially in project-based learning contexts.

5. Support User Onboarding and Engagement: Institutions should implement training modules and orientation programs to familiarize students with platform functionalities. Digital literacy workshops and integrated tutorials can boost both PEU and PU.

The effectiveness of these recommendations can be assessed through pilot implementations, followed by user surveys, learning analytics, and key performance indicators such as engagement and retention rates. Continuous monitoring and iterative refinement will ensure their sustained relevance and impact. By aligning platform design with these recommendations, universities and developers can strengthen CI, thereby enhancing user satisfaction, promoting sustained engagement, and supporting academic success.

Limitations and Further Study

While this study provides valuable insights through the use of a comprehensive analytical framework, several methodological and contextual limitations should be acknowledged. Specifically, potential biases in the research design, limited generalizability due to the single-institution sample, and context-specific conditions may have influenced the findings. Addressing these issues in future studies can improve the reliability and applicability of results. The following sections highlight five key limitations and suggest directions for further research.

First, the study population consisted of students from a single university in Yibin, limiting institutional diversity. Although the sample size was adequate, broader sampling across multiple institutions or regions is recommended to enhance generalizability.

Second, the employment of a cross-sectional approach impedes causal inference between studied constructs, as it captures participants' perceptions and intentions at only one point in time. This temporal limitation hinders the examination of dynamic changes in learners' behavioral intention toward online learning platforms. To address this issue, future studies are encouraged to employ longitudinal tracking or controlled experimental methods, which would enable a deeper and more nuanced exploration of the temporal dynamics underlying changes in user perceptions and continuance intentions. Such longitudinal insight is critical for capturing the progression and transformation of users' attitudes and behaviors toward sustained technology use, thereby enhancing the ability to identify the key factors that drive long-term engagement and retention.

Third, the model focused on seven variables derived from TAM and ECM, omitting other potentially relevant factors such as learner motivation, instructor presence, or content relevance. Expanding the model with additional or moderating variables may improve explanatory power.

Fourth, the exclusive use of quantitative methods via structured surveys may restrict deeper exploration of students lived experiences. Future studies could adopt qualitative or mixed-methods approaches to capture more nuanced insights.

Lastly, as the findings are context-specific to students in Yibin, caution is advised in generalizing results across different cultural or institutional settings. Replication studies in diverse geographic and educational contexts are encouraged to substantiate and further develop the current evidence.

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