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Cracking the Code of E-Learning Retention: The Impact of Experience in China Using PLS-MGA

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Abstract

Aim/Purpose	Chinese customers are now employing B2C E-Learning as a novel method to get an education. The issues of product homogenization, low user registration eagerness, and poor retention have become noticeable. The purpose of this research is to identify key elements that influence consumers' intention to continue using E-Learning in China and to examine how user experience moderates the relationship between satisfaction and continuance usage intention (CUI) among users with varying levels of experience. The framework was built by including additional new factors into the Technology Continuance Theory (TCT) theory.
Background	In the present day, B2C E-Learning is expanding quickly, and the E-Learning market is promising and has emerged as a new, widely recognized industry. The post-pandemic period and mobile Internet usage have powered the B2C E-Learning industry's explosive growth. Nonetheless, post-pandemic research on B2C E-Learning is still in its early stages and lacks a complete framework.
Methodology	The framework was built by including additional new factors into the TCT theory. A web-based survey was conducted among 493 E-Learning users in China. Structural equation modeling was conducted, and the results were examined using SPSS and SmartPLS.
Contribution	This research significantly enhances the theory of TCT by incorporating previously unaddressed components (course trial, perceived cost, information quality, and service quality). The novelty of this study is that it focuses on brand-

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new technological factors and identifies key factors. Aside from theoretical implications, the research has several implications for designers, developers, companies, marketing personnel, and end-users.

Findings The results indicated satisfaction is the most significant predictor of continuance usage intention (CUI). Course trials and information quality were insignificant in terms of satisfaction, whereas there was a significant association between perceived cost, service quality, and satisfaction towards CUI. The experience did not moderate the relationship between satisfaction and CUI. The PLS-MGA results show that less experienced and more experienced users have no significant difference in continuance usage intention when they are satisfied.

Recommendations for Practitioners The research results have various implications for designers, developers, businesses, marketing representatives, and end users. Based on these determinants, organizations can develop more effective marketing strategies.

Recommendations for Researchers Researchers on this specific application can make use of the extension of the model. Researchers will have a comprehensive perspective on B2C E-Learning platforms through the holistic new research framework.

Impact on Society According to research, Chinese people use E-learning platforms for many reasons, including studying English and improving their personal lives. With this in mind, E-Learning platforms should include tools that allow users to manage their learning and lifestyle better.

Future Research Future research should employ longitudinal designs to better understand how users' perceptions and behaviors evolve over time. Second, the use of a non-probability sampling technique and the focus on Chinese users limit the generalizability of the findings to other contexts. Future studies should replicate the proposed model in different cultural and educational settings to assess its external validity.

Keywords E-Learning, eLearning, continuance usage intention, course trial, perceived cost, information quality, service quality, satisfaction, technology continuance theory

INTRODUCTION

B2C E-LEARNING IN CHINA

The popularity of B2C E-Learning in China has significantly increased due to COVID-19 and its subsequent effects (Common Research Network, 2023; Y. Wang & Zhang, 2022). E-Learning offers benefits such as the flexibility to choose study periods, the convenience of studying from any location, improved productivity, and the opportunity for repetitive learning. This plays a crucial role in transitioning from conventional classroom instruction to interactive E-Learning (Hameed et al., 2024; Zhou & Li, 2022). Researchers have observed that E-Learning is becoming increasingly popular as a result of the pandemic, the rapid expansion of the Internet, and the widespread use of advanced technology like 5G cell phones in China (Ng & Fang, 2023; Teoh et al., 2023). The domestic B2C E-Learning market had a value of 432.8 billion RMB (66.5 billion USD) in 2020, representing a 24.79% growth compared to its value of 346.8 billion RMB (53.4 billion USD) in 2019. According to iiMedia Research (2021), the market would be valued at 86.12 billion USD in 2021 with 446 million users.

PROBLEM STATEMENT ABOUT E-LEARNING

However, competition in China's B2C E-Learning sector is increasing. Challenges related to the lack of enthusiasm among new consumers in the E-Learning sector are more noticeable (Shi, 2021). Imperfections in E-Learning products decrease user interest in using the services, while online marketing creates information asymmetry between suppliers and users, leading to customer mistrust (Hu, 2022). Chinese users do not have a high level of acceptance towards E-Learning. Only 23% of respondents presently utilize E-Learning courses, as per a poll conducted by iResearch Consulting. 34.2% of respondents preferred traditional training methods, whereas 49.2% did not comprehend or disliked E-Learning courses (iResearch, 2020). The problem of low learner retention rate in the expanding B2C E-Learning sector is increasingly evident (Mu et al., 2017). A survey conducted by Tan et al. (2013) reveals that the attrition rate of learners from E-Learning providers in China ranges from 15% to 40%. Chinese online education companies face a major challenge in retaining students.

A key determinant of the success of any information service is its continued utilization after the first acceptance phase. Understanding users' intention to continue using a product is crucial because getting new customers costs more than retaining current ones. It can cost five to twenty-five times as much to get new clients as it does to keep the ones you already have (Gallo, 2014). Traditional conceptions in technology, social sciences, and behavioral sciences may not sufficiently describe important theoretical concepts. Researchers have investigated the inclination to persist in utilizing mobile Internet during the COVID-19 pandemic (Kassim et al., 2022; Manegre & Sabiri, 2022; Y. Wang & Zhang, 2022). Previous research on this subject did not specifically examine the CUI of the B2C E-Learning application category. B2C E-Learning applications possess more complex interfaces, sophisticated functionality, prolonged usage durations, and more intricate interactions in comparison to other internet programs such as gaming, social media, and business applications (Hammouri et al., 2021; Manegre & Sabiri, 2022).

This research aims to investigate the following: (1) What are the key factors of E-Learning in determining user satisfaction? (2) Does experience moderate the impact of satisfaction on CUI between rich and less experienced users? The novelty of this study is that it will discover new factors that clarify the characteristics of E-Learning. The contribution of this study employed the Technology Continuance Theory (TCT) as a conceptual framework to thoroughly investigate the key factors that influence the different stages of adoption of E-Learning in the B2C sector in China. It is crucial to examine the elements that influence users' continuance usage intention (CUI) in a competitive economy, improve customer satisfaction, and adjust to evolving consumer preferences and regulatory settings. Moreover, it helps platform firms make informed decisions based on data, which benefits both vendors and consumers. It also adds theoretical support to the existing body of literature.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The adoption and continued usage of technology can be explained in two stages according to the information systems literature (Hsu & Lin, 2004). Consistent utilization is viewed as a continuation of the original acceptance. Continuous use in this context means consumers integrate technology into their everyday routines on a regular basis (Cooper & Zmud, 1990). The Information Systems discipline has formulated many theoretical models to forecast and clarify users' inclination to continue using IT systems. Studies at the individual level of acceptance theory encompass several theoretical models such as TAM, TTF, TPB, UTAUT, IS Success, and TCT. The TCT model is the most appropriate for this study's settings. The TCT outperforms other models in multiple research studies on users' CUI and continuous usage because of its superior ability to explain satisfaction, attitude, and intention. This study will then examine the model.

Technology Continuance Theory (TCT)

TCT is a solid theory that incorporates the cognitive decision-making model, ECM, and TAM, offering a comprehensive behavior model for evaluating consumer behavior (Liao et al., 2009). The TCT model better explains initial adopters, as well as short-term and long-term users (Liao et al., 2009). TCT greatly contributed by merging satisfaction and attitude in a unified continuation model, describing the influence of diverse technology features on user attitude (a lasting overall impression) and satisfaction (a short-term variable) (Liao et al., 2009). The TCT model has a notable superiority in utility and explanatory capacity compared to the previous models.

The TCT, originally developed by Liao et al. (2009), was employed in Nurdin et al.'s (2023) research to assess the motivation of students in utilizing a teaching and learning application. The investigation validated TCT's strong capacity to identify the factors that influence users' ongoing intentions to utilize the apps. A multitude of researchers have extensively examined the fundamental mechanics of TCT. Liao et al. (2009) emphasized the importance of executives and trainers recognizing that user happiness is the key determinant in assuring users' intention to continue using learning services. TCT is a major improvement compared to the COG, TAM, and ECM models in both numeric and qualitative aspects.

Conceptual Framework

The research model integrates course trial, perceived cost, information quality, service quality, satisfaction, continuance usage intention, and experience. This model follows the perception-attitude-intention chain, and TCT has been selected as the primary theory for this project. The TCT outperforms traditional models in terms of application and explanatory power (Liao et al., 2009). The research attempts to assess the integrated model provided below. Figure 1 shows our proposed research model. The prior model of CUI was insufficient in explaining variance. Therefore, incorporating additional variables such as course trial, perceived cost, information quality, and service quality can enhance the explained variance. The model additionally sets CUI in place of the dependent variable. This is the basis of the present study, which integrates a model and variables to establish a strong framework. The subsequent sections will cover the relationship and proposed correlation between the variables.

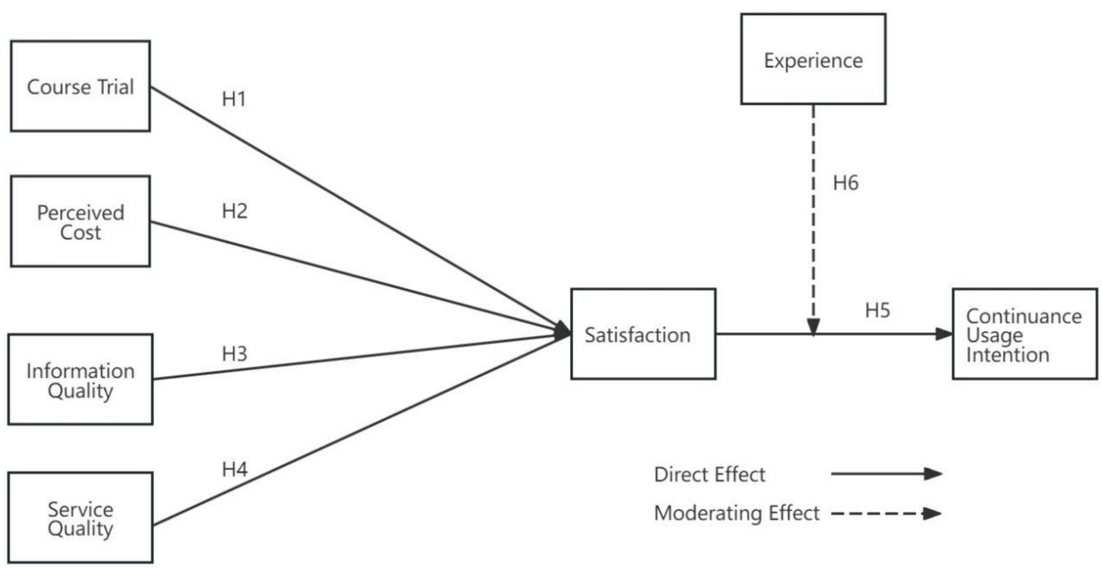

Figure 1. Research framework

Course Trial (CT)

Course trial, a crucial element of the E-Learning platform, refers to the chance to experiment or evaluate something. Trialability refers to the degree to which an idea can be tried on a small scale (Rogers, 2003, Chapter 1). Purchase intention is the main explanatory variable of purchase behavior, and the experience needs to be continuously experienced and tried by the user. If the experience is better, it will lead to a positive evaluation attitude of the individual, which will lead to purchase intention (Herrero Crespo & Rodríguez del Bosque, 2008). H. Chen et al. (2019) showed trial costs have a negative impact on satisfaction, while trial has a positive impact on satisfaction. Past research, such as Panigrahi et al. (2021) and Winarti et al. (2021), showed that the trialability of products positively influences customer satisfaction. Considering the use of the TCT model, the course trial in this study is an antecedent to satisfaction, thus indirectly influencing the intention to continue use. Consequently, the researcher suggests that:

> **H1:** Course trial positively influences satisfaction towards continuance usage intention.

Perceived Cost (PC)

Perceived costs are the perceived payoffs individuals make by evaluating a product or service before consumption (Huang, 2018). Perceived cost is often cited as a significant obstacle to the adoption of E-Learning advances. According to Bhattacherjee and Lin (2015), individuals are more likely to have good attitudes towards paying for information for the first time if they are more aware of the cost. Additionally, the perception of cost has a detrimental impact on an individual's behavior when using a service or product for the first time. Prior studies indicate that when customers perceive lower costs, their satisfaction levels tend to be higher (Berne-Manero et al., 2018; Han et al., 2022). However, research also showed prices positively impact customer satisfaction. The results show that implementing appropriate pricing strategies can positively influence customer satisfaction and attract new customers (Ahmed et al., 2023). In the educational area, results showed a significant influence between the perception of the cost of education and student satisfaction (Syafriani et al., 2021). Considering the TCT model used in this study, perceived price is predicted to have a positive relationship with satisfaction. The researcher suggests that:

> **H2:** Perceived cost positively influences satisfaction towards continuance usage intention.

Information Quality (IQ)

Information Quality (IQ) is a measure of a system's ability to store, transport, or produce data. It is widely used to assess the performance of information systems. In this context, "information" encompasses the content of Internet applications that users, such as clients and organizations, access. Satisfaction and continued usage intention are significantly impacted by the quality of the information offered (Garg & Sharma, 2020). According to Lin and Wang (2012), consumers' perceptions of course content utility in E-Learning services can enhance their expectation confirmation levels when they see the information as rich and high quality. Investigations into the ongoing usage of E-Learning assessed the quality of its material and found a notable positive impact on satisfaction (Nikou & Maslov, 2023; Y.-M. Wang et al., 2023). Consequently, the researcher recommends that:

> **H3:** Information Quality positively influences satisfaction towards continuance usage intention.

Service Quality (SQ)

Reliable and efficient service quality provides a superior experience, enabling consumers to trust the system (W. Wang et al., 2019). Service Quality (SQ) is recognized as a crucial determinant of information system utilization and customer satisfaction in the Information System (IS) success theory, which is driven by emerging technology trends (Ramayah et al., 2010). SQ has been studied in several information system settings. SQ's impact on user satisfaction has been examined in studies by Setiawan and Sfenrianto (2023), Biswas et al. (2024), and Zolotov et al. (2018). A different study on E-

Learning indicates that SQ has a direct impact on user satisfaction (Dağhan & Akkoyunlu, 2016). Past research in various fields has identified service quality as a key factor influencing attitude (Chowdhury, 2023; Hou et al., 2021). The researcher recommends the following:

> **H4:** Service Quality positively influences satisfaction towards continuance usage intention.

Satisfaction (SAT)

Satisfaction is the comprehensive evaluation of users' experience and the influence of using the E-Learning platform. Evaluating user satisfaction is a significant factor in determining the intention of online learners to continue using a platform. The research on satisfaction in the E-Learning or mobile app environment was varied and encompassed a wide range of studies (Foroughi et al., 2023). Studies on the satisfaction of E-Learning have revealed that learner satisfaction can have a beneficial effect on the intention to continue learning (Al Amin et al., 2023; C. Wang et al., 2023). The results of past studies suggest that satisfaction is the primary element of CUI. The researcher recommends that:

> **H5:** Satisfaction positively influences continuance usage intention.

Experience (EXP)

According to Bolen (2020), "experience" can be defined as a skill or knowledge you get by doing something previously. The ability of users is a crucial component of the user process and will evolve as they gain experience. As users gain more IS or IT usage experience, the effects of their beliefs on usage intention may also change (Castañeda et al., 2007; Kim et al., 2009; Saha et al., 2023). Prior investigations have demonstrated that user expertise typically has a positive effect on user loyalty (Till & Busler, 2000). Additionally, other research showed that experience has a moderating effect (Chang et al., 2014; Giannakos, 2013). Research shows that the relationship between satisfaction and continuance usage intention (customer intention to repurchase) is more pronounced for both frequent and seasoned online buyers (Khalifa & Liu, 2007; Saha et al., 2023). As a result, we believe that factors influencing CUI in E-Learning have quite different effects on users with rich and poor experiences. Consequently, the researcher suggests that:

> **H6:** The impact of satisfaction on continuance usage intention will be stronger for more experienced users when compared to less experienced users.

Materials and Methods

The research focuses on Chinese adults aged 18 and above who have previously used B2C E-Learning platforms as the subjects of analysis. This inquiry employed a snowball sampling approach due to the lack of a sample frame for B2C E-Learning customers, and this contributes to enlarging the sample by reaching respondents outside the researchers' contacts (Etikan et al., 2016). Respondents were selected based on certain criteria using a purposive sampling method. A total of 493 replies were obtained from Chinese people residing in different cities around the country, adhering to a predetermined quota to ensure a representative sample of the population (iiMedia Research, 2021). The survey questions are shown in Table 1. A seven-point Likert scale is used to measure all independent variables, with seven representing "strongly agree" and one representing "strongly disagree." The dependent variable (CUI) is measured using a five-point Likert scale, ranging from (1) strongly disagree to (5) strongly agree. Two types of Likert scales were used in this study to address procedural errors (Malhotra et al., 2017). The research conducted a pre-test to assess the content validity of the questionnaire design. Three academic experts and three industrial experts, along with nine respondents, were invited to participate in the pre-testing phase to ensure validity. The preliminary assessment indicated that there were no further issues with the questionnaires. The link to the online questionnaire was shared across many social media platforms to reach a wide audience of possible responders. All survey forms had mandatory questions. Verification and purification are essential to ensure the accuracy of all entered data. After gathering the data, it was analyzed and organized using IBM SPSS. The model's measurement and assessment analysis were conducted by computing the data in SmartPLS 4.1.0.2, following the structural equation modeling methodologies utilizing partial least squares (PLS-SEM) described by Shurovi et al. (2024). The analysis plan is given in Figure 2.

Table 1. Survey questions and measurement items

Constructs	Questionnaire items	Source
Course Trial (CT)	**CT1:** Before using the E-Learning platform and making a more sensible purchase decision, I was able to try them out properly.	Montoya et al. (2010)
	CT2: Before using the E-Learning platform and being satisfied with the video quality, I was able to try out the course properly.	
	CT3: Before using the E-Learning platform, I was able to try out the course properly (the teacher's instructional approach to the trial course could attract me).	
	CT4: In short, the course trial effect will affect my satisfaction.	
Perceived Cost (PC)	**PC1:** I think the fee that I paid for the use of this E-Learning platform is acceptable.	Xu et al. (2015)
	PC2: I think the fee that I paid for the use of this E-Learning platform is reasonable.	
	PC3: I think the fee I paid for the use of this E-Learning platform is high.	
	PC4: I am pleased with the fee that I paid for the use of this E-Learning platform.	
Information Quality (IQ)	**IQ1:** The E-Learning course content is high quality and can meet my learning needs.	Lin and Wang (2012)
	IQ2: The course structure of the E-Learning platform is reasonable and can meet my learning needs.	
	IQ3: The E-Learning platform course content is moderate in length and fits my learning habits.	
	IQ4: The E-Learning platform has an online test function, which is helpful for my learning effect.	
Service Quality (SQ)	**SQ1:** The E-Learning platform provides on-time services.	Zhou (2013)
	SQ2: The E-Learning platform provides prompt responses.	
	SQ3: The E-Learning platform provides professional services.	
	SQ4: The E-Learning platform provides personalized services.	
Satisfaction (SAT)	**SAT1:** I am satisfied with the functions provided by the E-Learning platforms.	Wan et al. (2020)
	SAT2: I am satisfied with the services provided by the E-Learning platforms.	
	SAT3: I am satisfied with the contents of E-Learning platforms.	
	SAT4: I am satisfied with the quality of E-Learning platforms.	
	SAT5: Overall, I am satisfied with the E-Learning platforms I use.	
Continuance Usage Intention (CUI)	**CUI1:** I intend to continue using the E-Learning system to learn.	Bhattacherjee (2001)
	CUI2: I want to use the E-Learning system regularly in the future.	
	CUI3: I intend to always use the E-Learning system in the future.	
	CUI4: My preference is to continue to study with the E-Learning system and not to use other alternatives.	

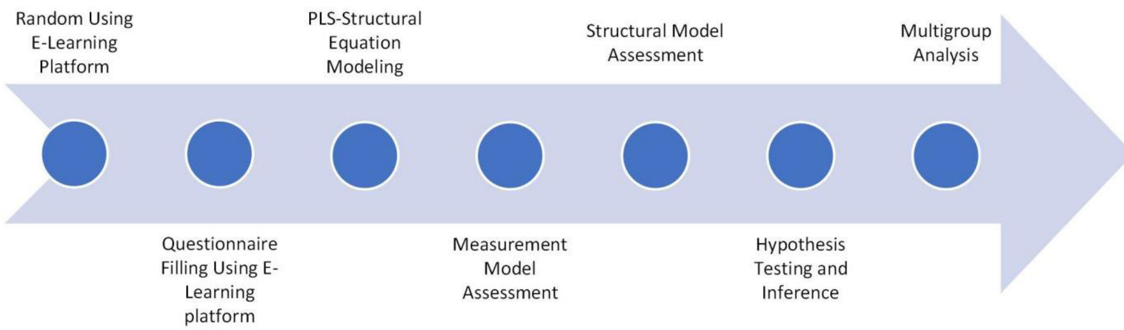

Figure 2. Analysis plan

Analysis and Results

Demographic Profile and Technology Usage

The target sample consisted of individuals who had previous experience with B2C E-Learning platforms. A total of 493 respondents completed the research questionnaire, with 55 responses being excluded because they indicated either being under 18 years old or lacking prior experience with E-Learning. Therefore, 438 valid data points were used for further investigation. The initial screening process involved identifying blank responses, detecting straight lining, checking for missing values using the E-M algorithm (Hashi, 2018), and confirming outliers through a Box-Whisker plot (Shiau, 2023). After this screening, there were 365 instances remaining. The study analyzed common method variance (CMV) caused by the data originating from one source. The study minimized CMV using the marker variable technique. A t-test was used to test the non-response bias (Sekaran & Bougie, 2009). The results show that there was no significant difference between early and late responses. Four items were adapted from Oreg (2003) that are unrelated to the study. The addition of marker variables does not significantly alter either the Beta (β) value (differences between 0.000 and 0.133) or the R^2 changes (the difference between 0.000 and 0.114). Both the regression paths were significant. Thus, CMV is not an issue in our survey. The normality test employed the Shapiro-Wilk test with a significance level of $p < 0.01$, indicating that the data deviated from a normal distribution. Partial least squares structural equation modeling is an effective analysis technique for this study due to its prediction model and the non-normal distribution of the data (Hair et al., 2019). The study investigated the proposed hypotheses using the Partial Least Squares (PLS) approach with SmartPLS 4.1.0.2.

Table 2 presents the demographic information of the chosen participants. The majority of them, accounting for 88.48%, were aged between 18 and 40. Additionally, 57.80% of the participants are married, 54.30% are female, 98.90% possess a diploma, and 99.73% have prior experience using the Internet. This combination illustrates that the study's conclusions about users' CUI are not influenced by their demographic characteristics.

Table 2. Demographic profile

Demographic	Categories	Frequency (N = 365)	Percentage (%)
Age	18-25	66	18.08
	26-30	62	16.98
	31-40	195	53.42
	41-50	30	8.22
	51-60	11	3.00
	> 60	1	0.30
Gender	Male	167	45.70
	Female	198	54.30

Demographic	Categories	Frequency (N = 365)	Percentage (%)
Marital Status	Single	150	41.10
	Married	211	57.80
	Others.	4	1.10
City	Megacity (Beijing, Shanghai, Shenzhen)	101	27.67
	Second-tier cities (Chengdu)	150	41.10
	Others	114	31.23
Highest Academic	Middle school or lower	1	0.27
	High school	3	0.83
	Junior college	80	21.92
	Undergraduate	139	38.08
	Postgraduate	142	38.90
Income (CNY)	< 1000	41	11.23
	1000-5000	51	13.97
	5000-10000	152	41.65
	> 10000	121	33.15
Internet Experience	Less than 1 year	1	0.27
	1-5 years	25	6.85
	6-10 years	72	19.73
	11-15years	114	31.23
	16-20 years	96	26.30
	>20 years	57	15.62
E-Learning Experience	0-2 years	177	48.50
	2 years above	188	51.50
Total		365	100.00

Assessment of the Measurement Model of Complete Data

The evaluation of the measurement model is based on the guidelines provided by Hair et al. (2019). The study initially assessed the internal consistency validity of the constructs by evaluating Cronbach's α scores, rho A, and composite reliability (CR). The study's Cronbach's α values range from 0.809 to 0.964. The coefficient of dependability suggests that the minimum acceptable value should exceed 0.7 (Hair et al., 2020). In accordance with the Sarstedt et al. (2021) study, the rho_A statistic, which is conceptually positioned between Cronbach's alpha and composite reliability, offers a more accurate indication of internal consistency and typically surpasses the 0.7 cut-off criterion. The CR values vary from 0.875 to 0.972, above the minimum threshold of 0.7 stated in Table 3. The minimum acceptable level of reliability for items is typically 0.708 or greater (Hair et al., 2016). The PC3 indicator loading of 0.381 is lower than the minimum needed value of 0.5 (Hair et al., 2016). The investigation excluded the PC3 indication, whereas all other loading values over 0.5 indicated reliable indicators. The convergent validity was assessed using the average variance extracted (AVE). All constructs exhibited AVE values of more than 0.5, demonstrating satisfactory convergent validity in the study's measurement methodology. The evaluation of discriminant validity is the final step in analyzing a measuring model. The Heterotrait-Monotrait (HTMT) criterion serves as the standard for assessing discriminant validity. The study followed the recommended 0.85 HTMT threshold proposed by Henseler et al. (2015), and the results met the HTMT 0.85 criterion, as indicated in Table 4. The measurement model confirmed the discriminant validity.

Table 3. Outcomes of measurement model (complete data)

Construct	Item	Loadings	AVE	CR	rho A	Cronbach's Alpha
Course Trial	CT1	0.898	0.807	0.944	0.925	0.920
	CT2	0.904				
	CT3	0.908				
	CT4	0.884				
Perceived Cost	PC1	0.908	0.814	0.929	0.885	0.885
	PC2	0.922				
	PC3	0.875				
Information Quality	IQ1	0.848	0.695	0.901	0.869	0.852
	IQ2	0.845				
	IQ3	0.889				
	IQ4	0.745				
Service Quality	SQ1	0.802	0.717	0.910	0.878	0.868
	SQ2	0.860				
	SQ3	0.889				
	SQ4	0.832				
Satisfaction	SAT1	0.946	0.873	0.972	0.965	0.964
	SAT2	0.929				
	SAT3	0.920				
	SAT4	0.938				
	SAT5	0.938				
Continuance Usage Intention	CUI1	0.824	0.637	0.875	0.819	0.809
	CUI2	0.776				
	CUI3	0.859				
	CUI4	0.727				
Delete PC3 due to indicator at 0.381						

Table 4. Discriminant validity (HTMT)

	CT	CUI	IQ	PC	SAT	SQ
CT						
CUI	0.454					
IQ	0.383	0.469				
PC	0.385	0.571	0.522			
SAT	0.264	0.616	0.377	0.501		
SQ	0.300	0.503	0.665	0.590	0.428	

Assessment of the Measurement Model of Less Experience and Rich Experience Group Data

First, the data was divided into two groups based on the respondents' level of experience (measured in terms of years of E-Learning use) by performing a median split (Pappas et al., 2014). We examined the measurement model for the less experience group data and rich experience group data separately. In this study, the SRMR values were 0.080 for the less experienced group data and 0.079 for the rich experience group data, which indicated an acceptable model. Table 5 shows that all the composite reliability values for the less experienced and rich experience group data were above 0.70, indicating reliable constructs. The AVE values of all constructs were above 0.50 for the less experience group and rich experience group data, indicating convergent validity. In sum, all these results show that the research model had acceptable reliability and validity for both the less experienced group and the rich experience group data.

Table 5. Measurement model evaluation (less experience versus rich experience)

Construct	Item	Loadings		AVE		CR		Cronbach's alpha	
		less exp	rich exp	less exp	rich exp	less exp	rich exp	less exp	rich exp
Course Trial	CT1	0.893	0.909	0.821	0.795	0.948	0.939	0.928	0.915
	CT2	0.908	0.901						
	CT3	0.909	0.914						
	CT4	0.915	0.840						
Perceived Cost	PC1	0.885	0.929	0.800	0.819	0.923	0.932	0.875	0.889
	PC2	0.921	0.919						
	PC3	0.877	0.867						
Information Quality	IQ1	0.842	0.933	0.661	0.720	0.886	0.911	0.828	0.871
	IQ2	0.793	0.933						
	IQ3	0.877	0.933						
	IQ4	0.734	0.933						
Service Quality	SQ1	0.650	0.891	0.635	0.775	0.873	0.932	0.806	0.903
	SQ2	0.813	0.893						
	SQ3	0.904	0.879						
	SQ4	0.799	0.857						
Satisfaction	SAT1	0.938	0.954	0.873	0.873	0.972	0.972	0.964	0.964
	SAT2	0.939	0.920						
	SAT3	0.921	0.918						
	SAT4	0.942	0.938						
	SAT5	0.933	0.943						
Continuance Usage Intention	CUI1	0.896	0.678	0.715	0.543	0.909	0.825	0.866	0.719
	CUI2	0.787	0.750						
	CUI3	0.918	0.796						
	CUI4	0.773	0.718						

CT: Course Trial. PC: Perceived Cost. IQ: Information Quality. SQ: Service Quality. SAT: Satisfaction. CUI: Continuance Usage Intention. *p<0.05; **p<0.01; ***p<0.001. exp: experience

Assessment of the Structural Model and Hypothesis Testing

The assessment of the structural model commenced with a lateral collinearity verification. The results fall within the range of 1.000 to 1.694, which is less than 5 (Ringle et al., 2015), suggesting that collinearity is not a concern in this study. The endogenous variables were SAT and CUI, with R^2 values of 0.257 and 0.303, respectively. The predictor constructs, as shown in Figure 3 and Table 6, explain a significant amount of the variance. The f^2 quantifies the impact of a predictor construct on endogenous constructs. The effect sizes ranged from 0.005 to 0.434. The upcoming evaluation is the predictive relevance (Q^2). Coefficients for the internal structures SAT and CUI are 0.233 and 0.220, respectively. The Q^2 values of the structural model in this research were more than zero, indicating that the model possessed significant explanatory and predictive capabilities (Manley et al., 2021). Lastly, the PLS model evaluated the prediction capability of CUI. The assessment is to assess the predictive power of the theoretical model when using the PLSpredict algorithm comparing the RMSE (or MAE) values with LM (Shmueli et al., 2019). According to the rules, because the majority of the dependent construct indicators in the PLS-SEM analysis produce higher prediction errors than the naive LM benchmark, the model has low predictive power (Table 7).

Table 6 and Figure 3 display the results of the hypothesis testing done in this study. The hypothesis test employed bootstrapping, as outlined by K. Y. Chen in 2018. The bootstrapping procedure involved a one-tailed test with sub-samples of 10,000 and a significance level of 0.05. The research findings indicated that the predictors accounted for 25.7% of the variance in satisfaction and 30.3% of the variance in CUI. The study revealed that in Hypothesis 1, the relationship between course trial and satisfaction was not statistically significant ($\beta = 0.069$, $t = 1.445$, $p\ (0.074) > 0.05$). In H2, the relationship between perceived cost and satisfaction towards CUI was statistically significant ($\beta = 0.317$, $t = 5.087$, $p\ (0.000) < 0.05$). In H3, the study found that the difference between information quality and satisfaction was not statistically significant ($\beta = 0.084$, $t = 1.459$, $p\ (0.072) > 0.05$). Service quality in H4 showed a significant direct effect on satisfaction ($\beta = 0.164$, $t = 2.306$, $p\ (0.011) < 0.05$). In hypothesis H5, the direct impact of satisfaction on CUI was statistically significant ($\beta = 0.550$, $t = 12.091$, $p\ (0.000) < 0.05$).

Table 6. Hypothesis testing

Hypothesis	Relationship	Std. Beta	Std Error	t-value	P Values	f^2	Q^2	VIF	R^2	Decision
H1	CT -> SAT	0.069	0.048	1.445	0.074	0.005	0.233	1.195	0.257	No
H2	PC -> SAT	0.317	0.062	5.087	0.000	0.095		1.510		Yes
H3	IQ -> SAT	0.084	0.057	1.459	0.072	0.009		1.616		No
H4	SQ -> SAT	0.164	0.071	2.306	0.011	0.025		1.694		Yes
H5	SAT -> CUI	0.550	0.046	12.091	0.000	0.434	0.220	1.000	0.303	Yes
CT: Course Trial. PC: Perceived Cost. IQ: Information Quality. SQ: Service Quality. SAT: Satisfaction. CUI: Continuance Usage Intention. *p<0.05; **p<0.01; ***p<0.001										

Table 7. PLS predict

Item	PLS-SEM_RMSE	LM_RMSE	PLS - LM	Q^2predict	Predictive Power
CUI1	0.886	0.833	0.053	0.165	Small Predictive Power
CUI2	0.927	0.938	-0.011	0.129	
CUI3	0.963	0.936	0.027	0.140	
CUI4	1.145	1.103	0.042	0.128	
CUI: Continuance Usage Intention					

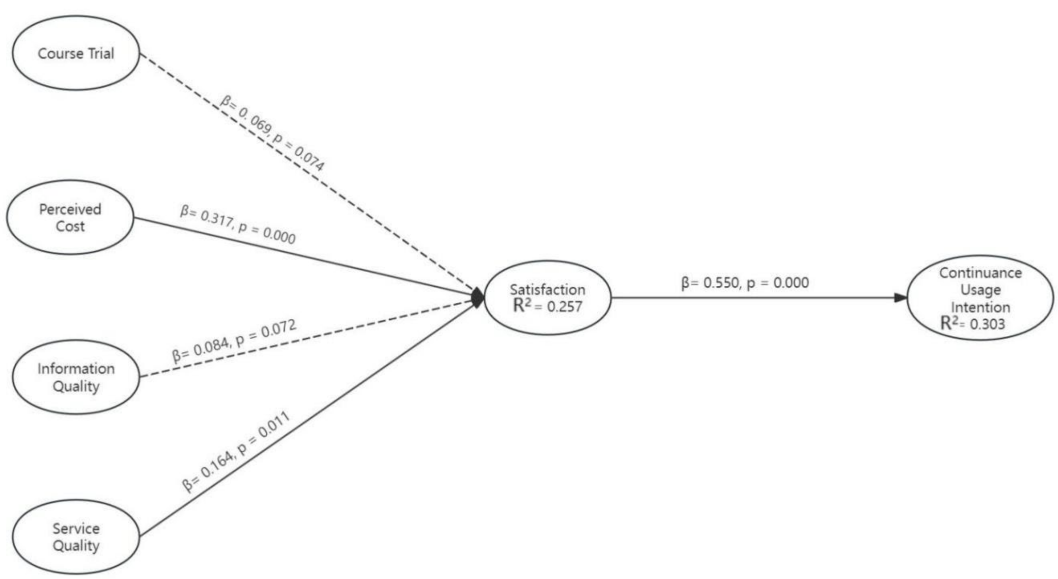

Figure 3. Results of the structural model of complete data

Assessment of the Structural Model of Less Experience and Rich Experience Group Data

For the less experienced data, the results showed a variance of 28.0% for satisfaction and 34.8% for continuance usage intention (Figure 4). For the rich experience data, the results showed a variance of 24.9% for satisfaction and a variance of 25.3% for continuance usage intention (Figure 5). The bootstrapping results showed that course trials had no influence on satisfaction among the less experienced users. Perceived cost influenced both less and richer experienced users' satisfaction. Information quality affects less experienced users' satisfaction but not rich experience users' satisfaction. Service quality significantly affected rich experience user satisfaction, but not less experienced user satisfaction. Satisfaction influenced both less and rich experienced users' intention to continue using. The results of the hypothesis testing are presented in Table 8.

Course trial had no impact on satisfaction for either the less experienced users (H1 (less experience): $\beta = 0.020$, p (0.388) > 0.05) or the rich experience users (H2 (rich experience): $\beta = 0.099$, p (0.076) > 0.05) users. This finding is contrary to prior research, which has found that trial is a strong reason for satisfaction (Winarti et al., 2021). Course trial is a kind of business model innovation. Trialability contributes to developing comfort among consumers. However, non-significant means course trials did not contribute to achieving satisfaction among the users. It can be concluded that, in the competitive market, the trial increases the probability of using E-Learning platforms, but the requirements of the less experienced and rich experience users are still unknown.

The perceived cost had an impact on satisfaction for both the less experienced users (H2 (less experience): $\beta = 0.335$, p (0.000) < 0.05) and the rich experience users (H2 (rich experience): $\beta = 0.258$, p (0.002) < 0.05) users. This is consistent with existing findings (Ahmed et al., 2023). The significant relationships in this case could be attributed to the following reasons. First, it could be because of the low price. Nowadays, many E-Learning courses are free, and the cost of paid apps is also low. It might encourage the relevance of the perceived price's benefits and impacts. Moreover, it's not impossible that some users simply do not give the price much thought because they initially had a positive experience with the E-Learning platform. Consequently, regardless of a fair price variation, these consumers are more likely to be happy with the app and want to keep using it. This line of reasoning may also account for the perceived insignificance of costs. In conclusion, perceived value is highly tied to customer satisfaction.

Information quality had a significant influence on satisfaction for the less experienced users (H3 (less experience): $\beta = 0.271$, p (0.002) < 0.05), but not for the rich experience users (H3 (rich experience): $\beta = 0.016$, p (0.404) > 0.05). This finding is different from prior research, which has found that information quality is a strong reason for satisfaction in both high-level and low-level experience groups (Biswas et al., 2024). The significant relationships in this case could be attributed to the following reasons. In an E-Learning market, post-paid service is used by most users (after trialing the courses or trying other platforms) and then visit the current platform; they might not care about brands and information quality regarding tangibles and empathy (Chakraborty & Sengupta, 2014).

Service quality had a significant influence on satisfaction for the rich experience users (H4 (rich experience): $\beta = 0.253$, p (0.000) < 0.05), but not for the less experienced users (H4 (less experience): $\beta = -0.003$, p (0.487) > 0.05). This finding is different from prior research, which has found that service quality is a strong reason for satisfaction in both high-level and low-level experience groups (Biswas et al., 2024). The significant relationships in this case could be attributed to the following reasons. Due to the intangibility of the service, E-Learning users may base their opinions on factors other than the results of receiving a particular service.

The perceived cost had an impact on satisfaction for both the less experienced users (H5 (less experience): $\beta = 0.590$, p (0.000) < 0.05) and the rich experience users (H5 (rich experience): $\beta = 0.503$, p (0.000) < 0.05) users. This is consistent with existing findings (Ahmed et al., 2023). The significant relationships in this case could be attributed to the following reasons. Satisfaction is a transient factor. Satisfaction with CUI is stronger for less experienced users than for rich experience users. This is likely due to the correlation between satisfaction and intention weakening as the duration of the E-Learning usage.

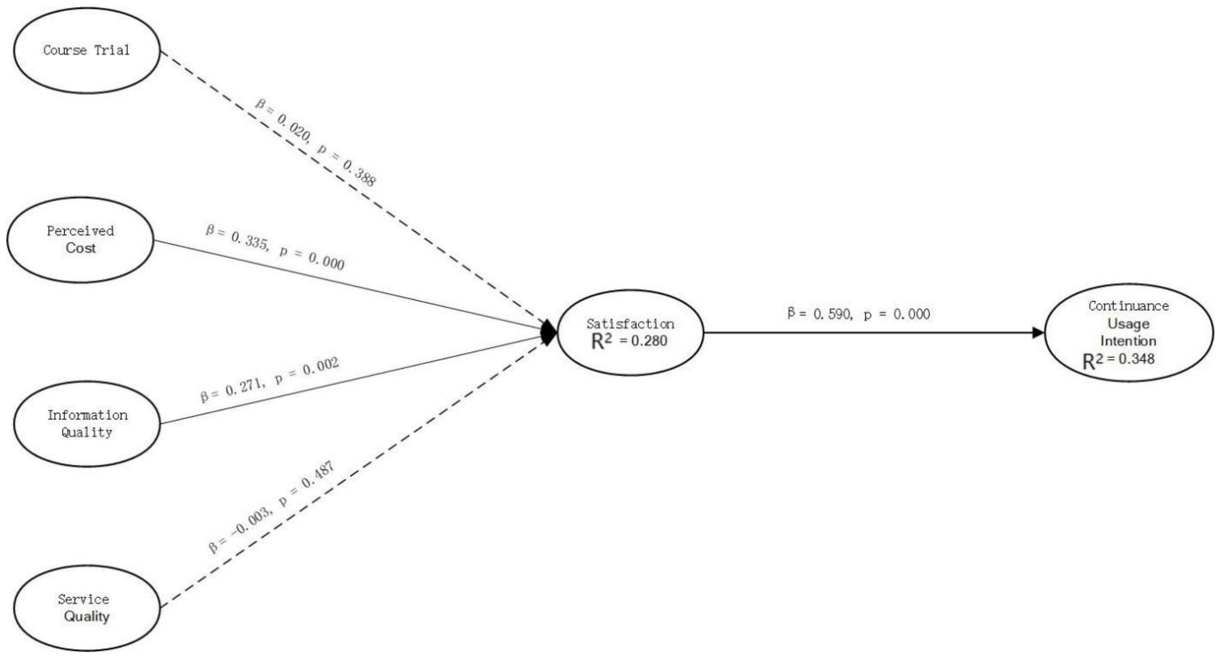

Figure 4. Results of the structural model of less experience data

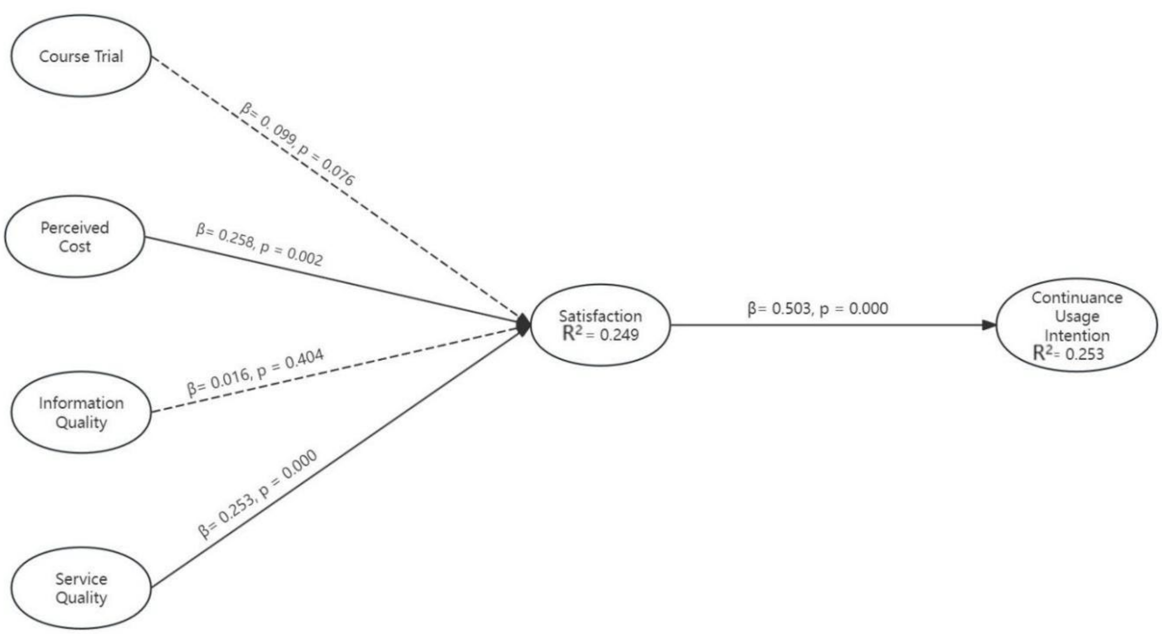

Figure 5. Results of the structural model of rich experience data

Table 8. Results of hypothesis testing (less experience versus rich experience)

Hypo-thesis	Relationship	Std. Beta		t-value		P Values		Decision	
		Less exp	Rich exp	Less exp	Rich exp	Less exp	Rich exp	Less exp	Rich exp
H1	CT -> SAT	0.020	0.099	0.285	1.433	0.388	0.076	No	No
H2	PC -> SAT	0.335	0.258	3.737	2.813	0.000	0.002	Yes	Yes
H3	IQ -> SAT	0.271	0.016	2.907	0.242	0.002	0.404	Yes	No
H4	SQ -> SAT	-0.003	0.253	0.033	2.565	0.487	0.000	No	Yes
H5	SAT -> CUI	0.590	0.503	10.258	7.208	0.000	0.000	Yes	Yes

CT: Course Trial. PC: Perceived Cost. IQ: Information Quality. SQ: Service Quality. SAT: Satisfaction. CUI: Continuance Usage Intention. *p<0.05; **p<0.01; ***p<0.001. exp: experience

Multigroup Analysis

Measurement invariance

According to the MICOM procedure, all results met the compositional invariance criteria, and two composites had equal mean values and variances, indicating partial measurement invariance (Table 9). Therefore, we carried out a multigroup analysis (MGA) by comparing standardized coefficients (Henseler et al., 2016).

Table 9. The compositional invariance and the equality of composite means and variances

Composite	c value (=1)	95% confidence interval	Compositional invariance?
Course Trial	0.997	[0.991;1.000]	Yes
Perceived Cost	1.000	[0.997;1.000]	Yes
Information Quality	0.994	[0.989;1.000]	Yes
Service Quality	0.997	[0.994;1.000]	Yes
Satisfaction	1.000	[1.000;1.000]	Yes
Continuance Usage Intention	0.996	[0.994;1.000]	Yes
Composite	**Difference of the composite's mean value (=0)**	**95% confidence interval**	**Equal mean values?**
Course Trial	0.048	[-0.177;0.177]	Yes
Perceived Cost	-0.372	[-0.183;0.170]	No
Information Quality	-0.142	[-0.175;0.166]	Yes
Service Quality	-0.214	[-0.175;0.180]	No
Satisfaction	-0.258	[-0.177;0.173]	No
Continuance Usage Intention	-0.289	[-0.165;0.169]	No
Composite	**Difference of the composite's variance (=0)**	**95% confidence interval**	**Equal variance?**
Course Trial	0.149	[-0.312;0.303]	Yes
Perceived Cost	0.090	[-0.321;0.316]	Yes
Information Quality	-0.115	[-0.282;0.285]	Yes
Service Quality	-0.495	[-0.291;0.316]	No
Satisfaction	-0.074	[-0.272;0.295]	Yes
Continuance Usage Intention	0.523	[-0.489;0.439]	No

PLS-MGA results

In this study, the PLS-MGA results show that less experienced and more experienced users have no significant difference in continuance usage intention when they are satisfied with the E-Learning platform (Table 10). Thus, H6 was not supported. This finding is different from the prior research that confirms the moderating effect of experience on the relationship between satisfaction and continuance usage intention for E-Learning platforms (Pappas et al., 2014; Saha et al., 2023). “Experience” is defined as a skill or knowledge you get by doing something previously. The ability of the user is a crucial component of the user process and evolves with experience. However, satisfaction is a transient factor. In this research, the fundamental cause may be rooted in accumulated experience. A course trial and usage may gather enough experience, and the assessment or decision is already made. The relationship between satisfaction and CUI for less and rich experience groups is likely the result of this assessment.

Table 10. PLS-MGA results

Hypothesis	Relationship	Path coefficients of less exp	Path coefficients of rich exp	Path coefficients diff (| less exp -rich exp|)	T Parametric (less exp vs. rich exp)	Supported
H6	SAT -> CUI (moderator experience)	0.590	0.503	0.087	0.955	No
SAT: Satisfaction. CUI: Continuance Usage Intention. *p<0.05; **p<0.01; ***p<0.001. exp: experience						

DISCUSSION AND IMPLICATIONS

THEORETICAL IMPLICATIONS

The study provides a number of important theoretical ramifications. The study adds to existing literature by identifying factors that influence user’s continued use of the E-Learning platform, addressing a gap in research on sustained application usage. This study is among the first to create and evaluate an integrated model that explores the impact of different information technologies on the intention to continue using them. This research is unusual since it integrates TCT and new elements to provide a comprehensive analysis of users’ CUI when using the product. Satisfaction is the most crucial variable in the TCT model and transit determinant. This study has shown that satisfaction accounts for a minimum of 30.3% of the CUI of the E-Learning platform. This study significantly enhances the idea of TCT by simultaneously incorporating course trials, perceived costs, service quality, and information quality, aspects that were previously overlooked.

Furthermore, E-Learning is notable for its unique classification within the realm of applications. The majority of studies on this subject did not precisely examine this particular application. This study offers a theoretical examination of the influence of course trials, perceived cost, service quality, and information quality on consumers’ intention to sustain their usage of E-Learning. The determinants consist of novel characteristics, whereas E-Learning provides customized and interactive content. This study investigates the impact of satisfaction and many parameters such as course trial, perceived cost, service quality, and information quality on the propensity to continue using an E-Learning service.

PRACTICAL IMPLICATIONS

In addition to its theoretical advancements, the research has significant implications for designers, developers, companies, marketing experts, and end clients. The level of competition in China’s B2C E-Learning business is increasing. In order to establish a competitive advantage, E-Learning firms must have a comprehensive understanding of the elements that influence customers’ long-term engagement with their products and services. The organization should build updated versions of software and introduce a new business strategy based on these aspects. Marketing managers can specify the target market segment and specific clients by taking into account several factors (Zhu et al., 2020). This research can aid education technology companies in refining their products by delivering insights that allow them to more effectively satisfy the core requirements of their users.

Studies suggest that Chinese citizens employ E-learning platforms for many purposes, including acquiring English language skills and improving their overall personal welfare. With this in mind, E-Learning platforms should contain characteristics that allow users to better manage their personal learning and lifestyle. The platforms should prioritize consumer happiness in relation to technology, services, content, and price (Li, 2023; Xu et al., 2015). Users will have satisfaction in both the short and long term, which will lead to their ongoing use of the E-Learning platform throughout the initial and extended periods of usage (Jiang, 2023).

This study found the course trial has no influence on satisfaction towards CUI. This means that course trials did not contribute to achieving satisfaction among the users, and the users later became less willing to adopt the innovation. This study also found that perceived cost has a reduced impact during the first and post-adoption phases of E-Learning. This may be because customers prioritize factors like time and effort spent above financial savings when choosing products rather than solely focusing on low prices. Additionally, some consumers may not take the price into account due to their positive experience with the E-Learning platform. Therefore, despite a fair cost difference, these users are more likely to be content and intend to use the application in the future. Therefore, sellers must recognize the significance of offering trial and equitable value and pricing strategies to promote customer satisfaction (Panigrahi et al., 2021; Phan Tan & Le, 2023).

Information systems are usually evaluated based on information quality and service quality metrics. Market consumers usually opt for post-paid services after thoroughly researching the options available. They may not place high importance on the quality of information or the recognition of their brand in terms of practical considerations and empathy. E-Learning providers can distinguish themselves by delivering short-term flexibility, meeting general criteria, and competitive prices while focusing on long-term functional excellence to adapt to consumer expectations. Because service quality is not easily measurable, customers of E-Learning may form their opinions based on aspects that go beyond the results of the service being provided. The B2C business model heightened the user's impression of separation. Engaging a service provider who possesses a nice, knowledgeable, and polite demeanor will significantly improve the customer's service experience in contrast to interacting with impolite and impatient personnel. Managers must provide competitive items that are accompanied by high-quality service, extensive expertise, and user-friendly features in order to fulfill client satisfaction.

CONCLUSION

This research provides crucial insights into the factors that impact the ongoing utilization of E-Learning in China and serves as a foundation for future research in this important field. Researchers can optimize E-Learning platforms and facilitate lifelong learning in the digital era by surmounting limitations and building upon current findings.

Although the contributions stated earlier are noteworthy, they also come with certain limits that can be explored further in future research. The impact of different types of E-Learning content should be examined beyond the B2C E-Learning. The potential boundary conditions or contextual factors may influence the generalizability of the findings to other E-Learning platforms or user populations. For example, the research could consider the role of cultural factors, such as collectivism and power distance, in shaping users' perceptions and behaviors related to E-Learning. The study's cross-sectional approach hinders generating causal inferences or studying the temporal dynamics of E-Learning's continued usage. Future research should include longitudinal designs in order to acquire a more profound comprehension of how users' perceptions and behaviors evolve over time. The findings may not be generalizable to other contexts due to the use of a non-probability sampling technique and the concentration on Chinese users. Future research should reproduce the recommended model in numerous countries, cultures, and educational environments to test its external validity.

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