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Predicting User's E-Learning Continuance Usage Willingness in China: An Extension of the Technology Continuance Theory

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Abstract. This study investigates the factors influencing users' continuance usage willingness (CUW) of E-Learning platforms in China, focusing on the role of satisfaction and attitude factors. The research employs an extended version of the Technology Continuance Theory (TCT) framework, incorporating new variables such as course trial, perceived cost, and trust. A web-based survey was conducted among 493 Chinese E-Learning users, and the data were analyzed using structural equation modeling (SEM) techniques. The findings reveal that satisfaction and attitude are significant predictors of CUW, while perceived cost and trust are significant antecedents of satisfaction. However, course trial does not have a significant influence on satisfaction. The study contributes to the literature by extending the TCT framework and providing insights into the key factors driving E-Learning continuance usage in China. The findings have important implications for E-Learning platform designers, marketers, and researchers, highlighting the need for strategies that enhance user satisfaction, trust, and positive attitudes toward E-Learning. However, the cross-sectional nature of the study and the use of a non-probability sampling technique limit the generalizability of the findings. Future research should employ longitudinal designs and more representative sampling methods to further validate the proposed model.

Keywords: E-Learning, Continuance Usage Willingness (CUW), Course Trial, Technology Continuance Theory (TCT), Perceived Cost, Trust.

1. Introduction

The popularity of B2C E-Learning in China has reached an unprecedented height with the outbreak of COVID-19 and post-pandemic (Wang & Zhang, 2022; Common Research Network, 2023). Compared with the traditional learning system, E-Learning offers the benefits of scattered learning time, unlimited study locations, high efficiency, and repeatable learning, which assumes a pivotal role in driving the transformation from the traditional "passive" classroom teaching mode to "interactive" E-Learning (Zhou & Li, 2022). Scholars pointed out that E-Learning is gradually becoming a new way of education with the rapid Internet growth and the massive popularity of intelligent terminal devices like 5G cell phones in China (Hoon et al., 2023). Currently, the domestic B2C E-Learning market was 432.8 billion RMB (66.5 billion USD) in 2020, up 24.79% from 346.8 billion RMB (53.4 billion USD) in 2019. In 2023, there will be 325 million users, and the market will be valued at 62.21 billion USD (Leadleo; 2023).

Currently, the domestic E-Learning market can be divided into language learning, early childhood education, K12 education, study abroad consulting, vocational education and skills upgrading, examination and certification training. Meanwhile, the B2C mode (Business to Customer) refers to the transaction mode in which educational and training services provided by enterprises are oriented toward individuals. The B2C model has a wide user base, with the number of users reaching millions and the market capacity reaching billions, which strongly attracts capital. Since 2010, B2C online education has been rapidly developing as a new method of learning (Zhu, Cao, Wang, & Ouyang, 2020). The market size of E-Learning in 2013 was less than 100 billion RMB. Meanwhile, China's E-Learning market is expected to reach 420 billion RMB by 2023 (Common Research Network, 2023). Currently, many E-Learning structures belong to the B2C model in terms of nature, and the representative platforms are Tencent Education, Yuanfudao, New Oriental Online, HuJiang class, CCTalk, and study.163.com.

However, competition in China's B2C E-Learning market is intensifying. Homogenization problems of products and the low willingness of newly registered users in the E-Learning industry are also becoming more prominent (Shi, 2021). Meanwhile, the imperfection of E-Learning products greatly reduces users' interest in accepting services, while online marketing increases information asymmetry between providers and users, resulting in users' mistrust (Hu, 2022). Chinese learners' acceptance of E-Learning is not high. According to a survey by iResearch Consulting, only 23% of respondents currently use E-Learning courses. An additional 34.2% chose traditional forms of training, and another 49.2% of respondents said they did not understand E-Learning courses or did not like this mode (iResearch, 2020).

While B2C E-Learning is booming, the problem of its low learner retention rate is becoming increasingly evident (Mu et al., 2017). E-learning platforms have launched many courses priced at 1 yuan (1 RMB or 0.15 USD) or even free courses to seize the market at low prices. Long-term low-price strategies can easily lead to doubts about the teaching quality of online platforms. After selling products at low prices for a period of time, if the platform wants to increase prices and increase profits, the number of users will inevitably decrease. Discounts and push notifications will cause dissatisfaction among old users and affect the further expansion of the E-Learning platform (Hu, 2022). A survey shows the attrition rate of learners from E-Learning providers in China has also been as high as 15-40% (Tan et al., 2013). E-learning companies in China face a major challenge of student attrition (Qiu & Du, 2021).

The traditional technological, social, and behavioral science theories might fail to clarify critical theoretical issues. Research has been done on continuance usage willingness within the context of mobile Internet during the COVID-19 (Kassim et al., 2022; Koch et al., 2020; Yanxia, 2022; Manegre & Sabiri, 2022). Most studies on this topic did not focus on the CUW for a specific application category (B2C E-Learning). Compared to other forms of internet applications, such as gaming applications,

social media applications, and business applications, B2C E-Learning applications have more complex interfaces and functionality, longer usage times, and more complex interactions (Manegre & Sabiri, 2022; Hammouri et al., 2021). Research gaps exist in identifying how course trial, perceived cost, and trust factors impact CUW behavior in the E-Learning platform.

Continuance usage willingness is the primary explanatory variable of usage behavior, and the experience needs to be continuously tried by the user. If the trial experience is better, it will lead to a positive evaluation of the platform, which will lead to usage intention (Crespo & Rodríguez, 2008). Chen et al. (2019) and Panigrahi et al. (2021) research showed trial have a negative effect on satisfaction, while trial benefits have a positive effect on satisfaction. Panigrahi et al. (2021) research showed that the trialability of product innovation has a positive influence on customer satisfaction. We need further research on the contradictory conclusions.

Many studies have found that perceived cost and satisfaction are either directly or indirectly connected (Chen et al., 2019; Setiawati et al., 2021). Chen examined the relationship between satisfaction and perceived cost (Chen et al., 2019). However, the evidence supporting this claim remains limited (Tang et al., 2020). Reducing the cost of an application is not a temporary solution, and reducing the selling price or even free is meaningful for initially attracting users but does little to ensure sustained adoption of applications (Hsu & Lin, 2015). There is a research gap in understanding how perceived cost affect satisfaction towards impact the decision making process of individuals when it comes to continue using the platform. This information is essential for businesses to adapt to changing consumer preferences.

During the E-Learning selection and usage process, trust is directly linked to satisfaction towards CUW. This is especially important in light of the growing worries about internet purchasing and security. Trust could explain the use of E-Learning systems (Sarosa & Setyowati, 2022). In short-term relationships, initial trust might be more important than in long-term ones (Zhou, 2016). Consequently, studies indicate that trust requires time to grow (Filieri et al., 2015), which corresponds with the amount of time required for a user to determine whether to keep using a particular technology or not. In the study, we need further research on trust.

Based on the background introduction, there is a lack of willingness to continue using the E-Learning platform. This research seeks to unravel the impact of key factors, namely course trial, perceived cost, and trust on satisfaction and attitude towards CUW. The current research discovered the new variables that explain the characteristics of E-Learning, meanwhile using the TCT theory as a conceptual model in order to thoroughly investigate the primary factors influencing E-Learning adoption in the B2C market in China. It is crucial in examining the variables that influence users' CUW in this competitive environment, increase customer satisfaction, and adjust to shifting consumer preferences and regulatory landscapes. Moreover, it helps platform companies make data-driven decisions that are advantageous to sellers as well as users and offer additional theoretical support for the body of existing literature.

2. Literature Review

Considering the information systems literature, the adoption and continuous use of technology can be explained in two stages (Hsu & Lin, 2004). Continuous use is considered an extension of the initial adoption. In this perspective, continuous use refers to users adopting technology as a regular part of their daily routines (Cooper & Zmud, 1990). The field of IS has produced a number of theoretical models attempting to forecast and explain the willingness of users to continue using IT systems. Studies representing the individual level of acceptance theory include TAM, TTF, TPB, UTAUT, IS Success model, and many theoretical models relevant to information system (IS) acceptance, like the Technology Continuance Theory (TCT) model. The TCT model is the most suitable given the conditions of this study. The TCT outperforms other models by a significant margin from a number of

research on users' CUW and continuous usage because of higher explanatory power for satisfaction, attitude, and behavioral intention. This study will discuss the classical model later.

2.1. Technology Continuance Theory (TCT)

Previous theories could not explain enough variance. For example, the TAM and UTAUT models exclude attitude and satisfaction and have lower explanations about suitability for consumers at various phases of the adoption life cycle; the ECM and COG model provides reduced ability to explain behavioral intention, attitude, and satisfaction rather than the TCT model. TPB model, with the core factor 'attitude', has not considered the different stages of adoption and also has lower predictive power compared to TCT. The TCT, a more powerful theory that integrates the cognitive model of decision-making, ECM, and TAM, is a more comprehensive behavior model to study the behavior needs of consumers (Liao et al., 2009). TCT made a substantial contribution by integrating satisfaction and attitude within a unified continuance model, elucidating the impact of various technology factors on user attitude (a longer-lasting overall impression) and satisfaction (a short-term variable) (Liao et al., 2009). Regarding utility and ability to explain, the Technology Continuance Theory model exhibits a substantial advantage over the COG, TAM, and ECM models, and additionally, the model outperforms the previously listed models because it can be applied to various adoption life cycles (initial, short-term, and long-term) (Liao et al., 2009).

The TCT, which was modified from Liao et al. (2019), was employed in Nurdin et al.'s research (2023) to investigate students' motivation to stick with a teaching and learning application. It validated TCT's strong exploratory power in elucidating factors influencing users' ongoing intentions to use the apps. Meanwhile, numerous researchers have examined the underlying mechanisms of TCT. A study by Alraimi et al. (2015) revealed that user satisfaction and perceived usefulness have a positive impact on users' intentions to continue using technology in the context of online learning. According to Liao et al. (2009), Executives and trainers need to focus on the finding that both attitude and satisfaction are important determinants to ensure users' CUW of the learning services. In summary, the longer-lasting utilization of a service, rather than its initial acceptance, serves as the primary determinant of its success. TCT represents a significant advancement over the COG models, TAM, and ECM models, both in terms of quantitative and qualitative aspects.

2.2. Conceptual Framework

After comprehensively reviewing the theories and a critical evaluation of the research issue under investigation, TCT is chosen as the dominant theory in this research. When it comes to application and explanatory power, the TCT performs significantly better than the conventional models (Liao et al., 2009). This research aims to evaluate the integrated model presented below. The model contains six variables: the independent variables include course trial, perceived cost, trust, satisfaction, and attitude (shown in Figure 1). The previous model on continuance usage willingness could not explain enough variance; therefore, adding new variables (course trial, perceived cost, and trust) can improve the variance explained. The model also sets continuance usage willingness in place of the dependent variable. This serves as the foundation for the current study, combining model and variables to provide a robust framework. The relationship and hypothesized correlation between the variables are discussed in the following subsections.

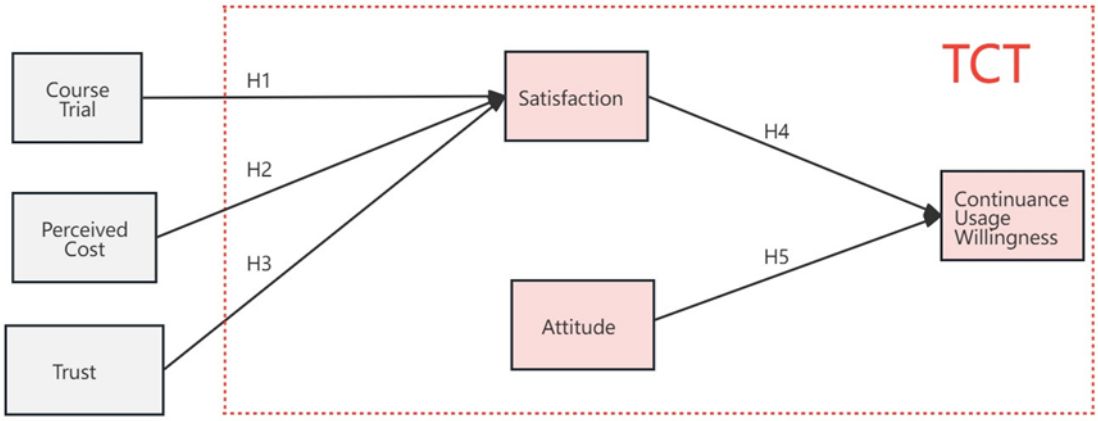

Fig. 1: Research Framework

2.3. Course Trial (CT)

Course trial, an important component of E-Learning platform, means an opportunity to test something out. Trialability is defined as "the extent to which an innovation can be tested on a limited basis" (Rogers, 2003). Purchase intention is the primary 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 & Rodríguez, 2008). Chen et al. (2019) showed trial costs have a negative impact on satisfaction, while trial has a positive impact on satisfaction. Panigrahi 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 willingness to continue use. Consequently, the researcher suggests that:

H1: Course trial positively influences satisfaction towards continuance usage willingness.

2.4. Perceived Cost (PC)

Perceived costs are the perceived payoffs individuals make by evaluating a product or service before consumption (Huang, 2018). Many have explained the role of perceived cost as one of the perceived barriers to adopting E-Learning innovations. Individuals have more positive attitudes toward paying for knowledge for the first time if they are more sensitive to the cost, and perceived cost negatively affects individual first-time use behavior (Bhattacherjee & Lin, 2015). Past research shows the lower the perceived costs, the greater the satisfaction of the customer (Berne et al., 2018). 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 that there was a significant influence between the perception of the cost of education on 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, while perceived price as an antecedent to satisfaction indirectly affects E-Learning continuance usage willingness. Consequently, the researcher suggests that:

H2: Perceived cost positively influences satisfaction towards continuance usage willingness.

2.5. Trust (TRU)

Trust is a belief that something is reliable, good, and honest. Trust is defined as the trustor's willingness to place themselves in a vulnerable position according to the anticipation that the opposing side shall fulfill a specific action that holds significance for the trustor (Mayer et al., 1995). Various studies highlighted the role of trust as a direct determinant of satisfaction (Ginting et al., 2023; Susanta, 2022; Sarkar et al., 2020), and past research found that trust only affects continuance usage willingness via

user's satisfaction (Cao et al., 2018). Sarkar's studies on mobile commerce have demonstrated a strong positive correlation between satisfaction and trust (Sarkar et al., 2020). Other results showed that there was a significant influence between trust on student satisfaction (Syafriani et al., 2021). In this study, we set trust as a direct determinant of satisfaction. Consequently, the researcher suggests that:

H3: Trust positively influences satisfaction towards continuance usage willingness.

2.6. Satisfaction (SAT)

Satisfaction is defined as the overall evaluation of the users' experience and usage effect after using the E-Learning platform. Many studies have confirmed that evaluating user usage satisfaction is a crucial determinant of the CUW of online learners to stick with the platform (Bhattacherjee, 2001). Various types of research on satisfaction were found in the E-Learning or mobile app environment (Foroughi et al., 2023). E-learning studies on satisfaction have demonstrated that learner satisfaction can positively impact continuous learning intention (Wang et al., 2023; Amin et al., 2023). More recently, Shen & Liu (2022) developed a conceptual model by integrating the perceived usefulness, perceived switching cost, and satisfaction to interpret the continuance usage willingness of users of virtual E-Learning platforms. The study's findings indicate that satisfaction is the most important component of CUW. Consequently, the researcher suggests that:

H4: Satisfaction positively influences continuance usage willingness.

2.7. Attitude (ATT)

Attitude refers to an individual's sentiments about engaging in a particular target behavior whether favorable or unfavorable. Numerous studies have been conducted that explain how attitude plays a part in information system studies. CUW may be directly predicted by attitude (Kassim & Ramayah, 2015; Kasilingam & Krishna, 2022; Normalini et al., 2024). Al-Rahmi et al. (2021) found a positive relationship between attitude and CUW of MOOC. Additionally, research findings showed that students' attitudes could have a positive and significant impact on their CUW of MOOC (Shami et al., 2022). This finding highlights the significant role of attitude, which contributes significantly to the expansion and advancement of MOOCs. In general, one of the key determinants of users' CUW of mobile learning is their attitude toward E-Learning (Saleem et al., 2023; Liu & Pu, 2023). Consequently, the researcher suggests that:

H5: Attitude positively influences continuance usage willingness

3. Research Methodology

This research's unit of analysis is Chinese users who are 18 years old and above and used B2C E-Learning platforms before. This research was done from September 2023 to November 2023 through an online survey. Because the B2C E-Learning users' sampling frame is missing, this study uses a non-probability sampling design. After that, respondents were selected based on the aforementioned criteria using a purposive sampling procedure. Four hundred ninety-three replies from Chinese living in all of the country's cities were gathered in accordance with the quota chosen earlier to fairly reflect the population (iiMedia, 2021). Survey questions are listed in Table 1. A seven Likert scale measurement (seven = strongly agree; four = neutral point "neither agree nor disagree"; one = strongly disagree) is employed for all independent variables. The dependent variable (CUW) uses a 5-point Likert scale, which ranges from (1) strongly disagree to (3) = neither agree nor disagree to (5) strongly agree. The two Likert scale types are applied in this study to remedy procedural errors (Malhotra et al., 2017). The research started the pre-test to verify the content validity after the questionnaire design, invited three academic experts and three industrial experts for the pre-testing phase to provide validity, and nine respondents were involved in the pre-test stage. The pre-test showed there were no more problems with the questionnaires. Through a variety of social media channels, the link to the online questionnaire was distributed to an unlimited number of potential respondents and remained live until the necessary number of samples were collected. All of the survey questionnaires were required questions. Screening

and cleaning are necessary to check if all the data have been entered correctly. Following collection, the data will be processed and prepared using IBM SPSS. There are some guidelines between CB-SEM and PLS-SEM (Gefen et al., 2000). The situation in China's E-learning market is rapidly changing, and the framework integrates the new variables to develop the new framework; PLS-SEM is better at exploring or developing existing theories than CB-SEM. The model measurement and assessment analysis were done through the computation of the data in SmartPLS 4.1.0.0, which was guided by the structural equation modeling methods using partial least squares (PLS-SEM) (Shurovi et al., 2024).

Table 1: Survey questions and measurement items

Constructs	Questionnaire Items	Source
Course Trial (CT)	**CT1:** Before having to use the E-Learning platform and make a more sensible purchase decision, I was able to properly try them out.	Montoya et al., 2010
	CT2: Before having to use the E-Learning platform and being satisfied with the video quality, I was able to properly try out the course.	
	CT3: Before having to use the E-Learning platform, I was able to properly try out the course (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.	
Trust (TRU)	**TRU1:** Based on my experience with the E-Learning platform in the past, I know it is honest.	Gefen et al., 2003
	TRU2: Based on my experience with the E-Learning platform in the past, I know it cares about customers.	
	TRU3: Based on my experience with the E-Learning platform in the past, I know it is not opportunistic.	
	TRU4: Based on my experience with the E-Learning platform in the past, I know it is predictable.	
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.	
Attitude (ATT)	**ATT1:** Using the E-Learning platform for learning would be a good idea.	Liao et al., 2009
	ATT2: Using the E-Learning platform for learning would be a wise idea.	
	ATT3: I like the idea of using the E-Learning platform for learning.	
	ATT4: Using the E-Learning platform would be a pleasant experience.	
Continuance Usage	**CUW1:** I intend to continue using the E-Learning system to learn.	Bhattacherjee, 2001
	CUW2: I want to use the E-Learning system regularly in the future.	
	CUW3: I intend to always use the E-Learning system in the future.	

Willingness (CUW)	**CUW4:** My preference is to continue to study with the E-Learning system and not to use other alternatives.	

4. Analysis and Results

4.1. Demographic Profile

Four hundred ninety-three respondents answered the research questionnaire, and 55 replies were disregarded since the answer was "less than 18 years old or never used E-Learning before." As a result, this study employed 438 valid data for further analysis. The initial screening contains blank responses screening, straight lining, checking missing values using E-M algorithm (Zakarie, 2018), and verified outliers by Box-Whisker plot (Shiau-Wen-Lung, 2023). A total of 365 cases remain.

In the present study, common method variance (CMV) was assessed because the data came from a single source. To lower the CMV, the study used Harman's single-factor test, and the findings showed that there are 14 components more than 1%, which accounts for 83.860% of the variance overall, with the largest factor contributing 36.983% of the variance, less than 50% of the cutoff value proposed by Podsakoff et al. (2003). Therefore, in our survey, CMV is not an issue. The normality test chose the Shapiro-Wilk test as ($p < 0.01$), indicating that the data was not normal. PLS is a suitable analysis method for the study since the model is predictive and the data are not normal (Hair et al., 2019). This study tested the proposed hypotheses by employing the partial least squares (PLS) approach with SmartPLS 4.1.0.0.

Table 2 lists the demographic details of the filtered respondents, who are primarily (88.48%) between the ages of 18 and 40, are married (57.80%), are female (54.30%), are Han (45.3%), have a diploma (98.90%), have work experience (84.66%), and have Internet experience (99.73%). The age range of males and females who answered the questionnaire was 18-25 years (18.08%), 26-30 years (16.98%), 31-40 years (53.42%), 41-50 years (8.22%), 51-60 years (3%), and above 60 years (0.3%). The largest percentage of people of all ages are those between the ages of 31 and 40. Among the 365 respondents, most respondents used E-Learning for 1-5 years (67.95%) and had experience with the Internet for more than one year (99.73%). This combination shows that the study's conclusions about continuance usage willingness are not skewed by users' demographic characteristics.

Table 2: Profile of Demographic

Demographic	Categories	Frequency	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
Ethnicity	Han	341	93.43
	Man	9	2.47
	Menggu	7	1.92
	Tujia	3	0.82
	Hui	2	0.55
	Zhang	1	0.27
	Miao	1	0.27
	Yi	1	0.27
Marital Status	Single	150	41.10
	Married	211	57.80
	Others.	4	1.10
City	Megacity (Beijing, Shanghai,	101	27.67

	Shenzhen)		
	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
	Post-graduate	142	38.90
Income	< 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 Platform Usage Experience	Less than 1 year	99	27.13
	1-5 years	248	67.95
	6-10 years	16	4.37
	>10years	2	0.55
E-Learning Services	Tencent class	140	38.36
	New Oriental	45	12.33
	HuJiang class	12	3.29
	CCTalk (www.cctalk.com)	24	6.57
	study.163.com	46	12.60
	Keke English (www.kekenet.com)	20	5.48
	Other class.	78	21.37
Total		365	100.00

4.2. Assessment of the measurement model

This research's measurement model was assessed in four steps: internal consistency reliability, indicator reliability, convergent validity, and discriminant validity. The assessment is followed by the guideline of Hair et al. (2019). First, the study assessed the internal consistency validity of the constructs by evaluating Cronbach's α scores and composite reliability (CR). This study's Cronbach's α scores range from 0.809 to 0.964. The CR suggests that the acceptable value for reliability is above 0.7 (Hair et al., 2020). The CR scores range from 0.875 to 0.972, meeting the minimum threshold value of 0.7 (shown in Table 3). Next, the indicator reliability recommended items are generally advised to be 0.708 or higher (Hair et al., 2016), and the PC3 indicator when it is loading (0.237) is below 0.5, below the recommended value (Hair et al., 2016). The research removed the PC3 indicator, and with all other loadings scores more than 0.5, enhancing the estimate's reliability and demonstrating satisfactory indicator reliability. The average variance extracted (AVE) was then used to test the convergent validity, and the results indicate that every construct recorded AVE values greater than 0.5, showing that there is adequate convergent validity in the study's measuring model. Furthermore, the assessment of discriminant validity is the last stage of measurement model evaluation. It is expected that the correlations with other latent constructs will be less than the square root of the AVE for each construct (Hamid et al., 2017). The assessed latent variables in this study had larger loadings than the other variables, the same as the rules of thumb by Hamid et al. (2017). The results of the Fornell and Lareker Criterion are shown in Table 4. The second discriminant validity criterion is the Heterotrait-Monotrait (HTMT) criterion. The 0.85 HTMT threshold was advised (Henseler et al., 2015), and the results met

the HTMT.85 requirements (displayed in Table 5). In conclusion, discriminant validity was established in the measurement model.

Table 3: Outcomes of Measurement Model

Construct	Item	Loadings	AVE	CR	Cronbach's Alpha
Attitude	ATT1	0.913	0.833	0.952	0.935
	ATT2	0.901			
	ATT3	0.911			
	ATT4	0.924			
Course Trial	CT1	0.898	0.807	0.944	0.920
	CT2	0.904			
	CT3	0.908			
	CT4	0.884			
Continuance Usage Willingness	CUW1	0.834	0.637	0.875	0.809
	CUW2	0.785			
	CUW3	0.857			
	CUW4	0.707			
Perceived Cost	PC1	0.908	0.814	0.929	0.885
	PC2	0.922			
	PC4	0.875			
Satisfaction	SAT1	0.946	0.873	0.972	0.964
	SAT2	0.931			
	SAT3	0.920			
	SAT4	0.937			
	SAT5	0.938			
Trust	TRU1	0.847	0.721	0.912	0.871
	TRU2	0.856			
	TRU3	0.862			
	TRU4	0.831			
Notes: deleted PC3 due to low loadings.					

Table 4: Fornell and Larcker

	ATT	CT	CUW	PC	SAT	TRU
ATT	**0.913**					
CT	0.412	**0.898**				
CUW	0.724	0.405	**0.798**			
PC	0.511	0.346	0.482	**0.902**		
SAT	0.569	0.250	0.549	0.464	**0.934**	
TRU	0.661	0.406	0.582	0.621	0.604	**0.849**
CT: Course Trial. PC: Perceived Cost. TRU: Trust. SAT: Satisfaction. ATT: Attitude. CUW: Continuance Usage Willingness.						

Table 5: Discriminant Validity (HTMT)

	ATT	CT	CUW	PC	SAT	TRU
ATT						
CT	0.447					
CUW	0.821	0.454				
PC	0.562	0.385	0.571			
SAT	0.597	0.264	0.616	0.501		
TRU	0.734	0.456	0.699	0.706	0.656	
CT: Course Trial. PC: Perceived Cost. TRU: Trust. SAT: Satisfaction. ATT: Attitude. CUW: Continuance Usage Willingness.						

Table 6: PLS predict

Item	PLS-SEM_RMSE	LM_RMSE	PLS - LM	Q²predict	Predictive Power
CUW1	0.477	0.449	0.028	0.456	Low Predictive Power
CUW2	0.562	0.586	-0.024	0.281	
CUW3	0.558	0.536	0.022	0.350	
CUW4	0.708	0.701	0.007	0.250	
CUW: Continuance Usage Willingness					

4.3. Assessment of the structural model

The structural model assessment began with a lateral collinearity check. All values within the range of 1.218 to 1.746, which was less than 5 (Ringle et al., 2015), indicating collinearity was not an issue in this research. Next, the SAT and CUW are the endogenous variables, and their respective R^2 values were 0.377 and 0.552. It showed that their predictor constructs (illustrated in Figure 2 and Table 7) account for a sizable portion of the variance. The f^2 calculates a predictor construct's relative influence on endogenous constructs. The effect size f^2 were from 0.000 to 0.560. The next assessment was the Predictive Relevance (Q^2). The endogenous constructs of CUW and SAT were 0.535 and 0.360, respectively. The Q^2 values for this research's structural model were more than zero, which means that the model had a meaningful explanatory and predictive power (Manley et al., 2021). Last, the PLS predict assessed the predictive power of CUW. PLS predict algorithm compares the RMSE values with LM (Shmueli et al., 2019). The guidelines state that the model's predictive power was low (refer to Table 6).

Table 7 and Figure 2 presented the findings from the hypothesis testing conducted for this study. The hypothesis test invoked bootstrapping (Chen-K-Y, 2018). Bootstrapping was the one-tailed test, with sub-samples set at 10000 and a significance level set at 0.05. The research results determined that the predictors could explained 37.7% of the variance in satisfaction and 55.2% of the variance in CUW. The research found that H1 was not supported by an insignificant positive effect of course trail to satisfaction towards continuance usage willingness (β= -0.011, t = 0. 203, p (0. 407) > 0.05). Subsequently, H2 was supported by a significant effect of perceived cost to satisfaction towards CUW (β= 0. 146, t = 2. 283, p (0. 011) < 0.05), and in H3, the direct influence of trust on satisfaction towards continuance usage willingness was supported (β= 0. 518, t = 9. 222, p (0.000) < 0.05). Following that, in H4, it is confirmed that satisfaction had a direct impact on CUW (β= 0.203, t = 4. 389, p (0.000) < 0.05), and in H5, the direct influence of attitude on continuance usage willingness was supported (β= 0.609, t = 13. 972, p (0.000) < 0.05). The result shows that H1 was not supported; meanwhile, H2, H3, H4, and H5 were supported.

Table 7: Hypothesis Testing

Hypothesis	Relationship	Std. Beta	Std Error	t-value	P Values	f^2	Q^2	VIF	R^2	Decision
H1	CT -> SAT	-0.011	0.045	0.203	0.407	0.000	0.360	1.218	0.377	NO
H2	PC -> SAT	0.146	0.064	2.283	0.011	0.021		1.657		YES
H3	TRU -> SAT	0.518	0.056	9.222	0.000	0.246		1.746		YES
H4	SAT -> CUW	0.203	0.046	4.389	0.000	0.062	0.535	1.478	0.552	YES
H5	ATT -> CUW	0.609	0.044	13.972	0.000	0.560		1.478		YES
CT: Course Trial. PC: Perceived Cost. TRU: Trust. SAT: Satisfaction. ATT: Attitude. CUW: Continuance Usage Willingness. Significance level: 0.05. The default specification of a 5% significance level corresponds to a 95% confidence interval.										

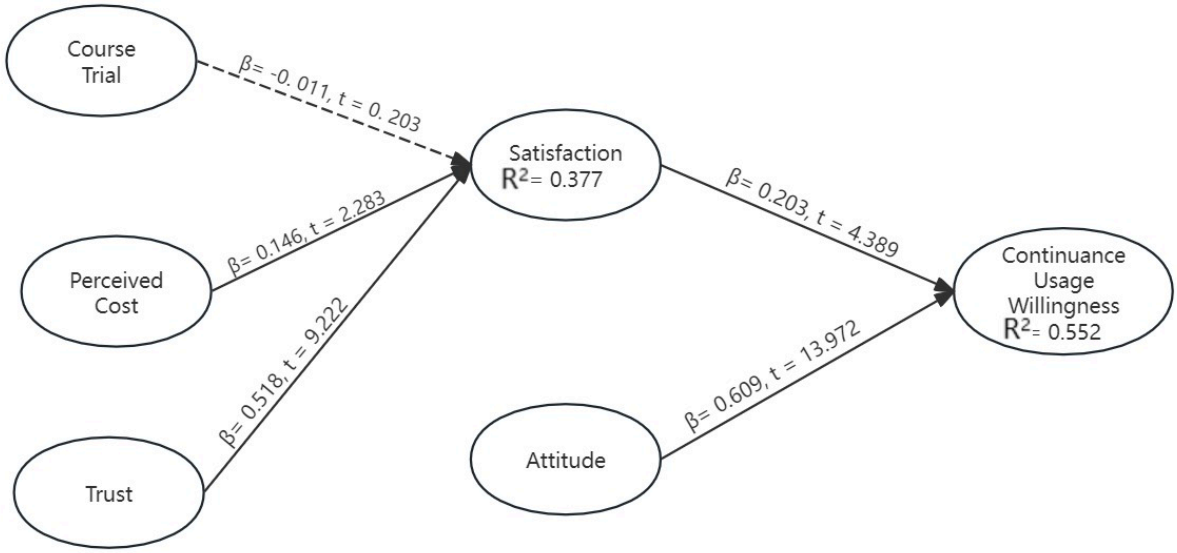

Fig.2: Hypothesis Testing Results

5. Discussion and Implications

5.1. Discussion

This research adopted the TCT model with new variables to predict the determinants influencing the CUW of E-Learning in China. The hypothesis testing showed that the impact of course trial to satisfaction towards continuance usage willingness was insignificant (β= -0. 011, p (0. 407) > 0.05). The research is different from past research (Chen et al., 2019; Panigrahi et al., 2021). It means course trial did not contribute to obtaining user satisfaction, and as a result, users were less willing to accept the innovation. Course trial reduces the users' satisfaction with the product. It can be concluded that, in the competitive market, the trial increases the probability of using E-Learning platforms, but the requirements of the users are still unknown.

Satisfaction was found to be less significantly impacted by perceived cost (β= 0. 146, p (0. 011) < 0.05) than trust (β= 0. 518, p (0.000) < 0.05). The result is similar to the recent research (Rehman et al., 2023), which shows that perceived cost affects satisfaction. This result implies that perceived costs are less significant during the early and late adoption phases of E-Learning. The minor significant relationships in this case could be attributed to the following reasons. Firstly, it might be due to the low price. Nowadays, many E-Learning courses are free, and the cost of paid apps is also low. It may reduce the negative or positive effects of perceived price to insignificance. Second, users consider other aspects, like the expenses of time and effort, to be more significant than financial sacrifices for low-cost products.

Trust in satisfaction was significant, and the findings of this investigation are consistent with studies carried out by Ginting et al. (2023), Susanta (2022), and Ofori et al. (2018). Satisfaction is preceded by trust. Users' perception of the security and privacy of website operations determines their level of trust. One of the most crucial things that users want when using the Internet is website security. E-learning users express satisfaction with service providers due to prior trust in the service provider's ability to deliver dependable and consistent service.

Satisfaction and attitude explained 55.2% of the variance, and both significantly influence the CUW (β= 0.203, (0.000) < 0.05 and β= 0.609, p (0.000) < 0.05). We contend that since users were content with the services (online classes, virtual friend communication, online tests or quizzes, etc.) offered by E-Learning platforms during the pandemic, in line with the findings of recent studies (Joo et al., 2018; Amin et al., 2023; Wang et al., 2023). Users' attitudes toward E-Learning are key factors in their desire for E-Learning. It showed that when users have a positive attitude, they are more likely to adopt

continuous usage. Research about attitude in TCT model and recent research shows user retention may suffer significantly from a post-acceptance mindset (Liao et al., 2009; Saleem et al., 2023; Liu & Pu, 2023; Kasilingam & Krishna, 2022; Haldar & Goel, 2019; Lin et al., 2013; Rahmi et al., 2021; Shami et al., 2022). One important factor influencing the continuance usage willingness to use one-on-one E-Learning is attitude. The more positively learners view a system and believe it to be helpful and easy to use, the more probable it is that they will plan to use it consistently (Liu & Pu, 2023).

5.2. Theoretical Implications

The study provides a number of important theoretical ramifications. The study contributes to the literature that provides determinants of when users continue to use the E-Learning platform, thereby filling a gap in studies examining the ongoing use of applications. This is one of the first studies to develop and test an integrated model that investigates how various information technologies influence continuous usage willingness. The innovative aspect of this research is the integration of TCT and other factors to offer a more thorough examination of users' CUW when using the product. This research makes a substantial contribution to the theory of TCT by extending it to include course trial, perceived costs, and trust (new factors) all at once, which were not previously addressed.

In the TCT model, satisfaction and attitude are the most significant variables. The user's attitude (a longer-lasting overall impression) and satisfaction (a fleeting factor) are also included as determinants that measure the CUW of the B2C E-Learning platform. The finding of this research is consistent with recent studies (Joo et al., 2018; Amin et al., 2023; Wang et al., 2023; Joo et al., 2018). Those two results are in line with most of the earlier studies on satisfaction and attitude in information systems. This research has demonstrated that satisfaction and attitude explain at least 55.2% of the continuous usage willingness. In short, this research provides evidence of the link between the CUW and satisfaction and attitude.

E-Learning is unique because of the specific category of application. However, most studies on this topic did not focus on this particular application. The theoretical contribution of this research is that it presents the influence of the new factors about perceived cost, course trial, and trust towards users' continuance usage willingness of E-Learning. Those factors are new features, and E-Learning contains more personal and interactive information. This study expands on the elements of satisfaction, which advances knowledge by determining perceived cost, course trial, and trust as the antecedents towards continuance usage willingness.

5.3. Practical Implications

In addition to the theoretical advances, the research has a number of consequences for the designer, developers, companies, marketing salesman, and final clients. Competition in China's B2C E-Learning market is intensifying. B2C E-Learning companies can only develop more effective marketing strategies by being aware of the elements that impact users' continued use to truly achieve the purpose of commercializing E-Learning. Companies maintain their advantages in this competitive environment by applying these factors to the application. The company should design new versions of applications and provide a new business model through the factors. The marketing managers can specify the segment market and true customers through these factors (Zhu et al., 2020). This research can help education technology companies improve their products by providing insights that enable them to better meet the core needs of their users.

Second, the course trial is an example of business model innovation. In a competitive market, managers must recognize their client's needs and add value by providing them with innovative products. The majority of domestic E-Learning platforms offer course trial offerings. It can be inferred that, in a competitive market, the trial enhances the likelihood of adopting E-Learning platforms, but the users' requirements remain unknown. Managers must provide more competitive products, such as good service and information quality items that are useful and simple to use, with more inventive features to satisfy people (Panigrahi et al., 2021).

Third, this study discovered that perceived cost has a lesser influence in the initial and post-adoption stages of E-Learning. It could be due to the low price, or clients value other things, such as time and effort expenditures, over monetary sacrifices for low-cost products (Chen et al., 2019). Furthermore, it is probable that some consumers do not consider the price because they had a pleasant experience with the E-Learning platform. Consequently, regardless of a fair pricing differential, these consumers are more likely to be satisfied and plan for later usage of the application. This kind of thinking may also explain the perceived insignificance of costs. In conclusion, users' satisfaction and perceived cost have a strong relationship; consequently, sellers need to understand how important it is to provide a fair value and pricing plan in order to encourage customer satisfaction (Phan-Tan & Le, 2023; Chen et al., 2019).

Fourth, according to research, Chinese people use B2C E-learning platforms for a number of reasons, including studying English and improving their personal lives. With this in mind, E-Learning platforms should include tools that allow users to better manage their learning and lifestyle. These platforms should address customer satisfaction with technology and services, as well as content and pricing (Li, 2023; Xu et al., 2015). Users will be satisfied in both the short and long term, so they will continue to use the E-Learning platform during the initial and long-term usage stages (Jiang, 2023).

Last, this study has found that one of the most important variables influencing user interest in E-Learning is their attitude about it. It showed that when users have a positive mindset, they are more likely to embrace the product and keep using it. According to research on attitudes in the TCT model, post-acceptance user attitudes can have a major impact on user retention. The more learners see a system as easy to use and useful, and the more they have a good attitude toward it, the more likely they are to want to continue using it. Liu & Pu (2023). As a result, strengthening the business model and product, as well as establishing a more positive attitude toward E-Learning, is the method for organizations to sustain the number of users over time.

6. Conclusion, Limitation and Future Studies

This study contributes to the literature on E-Learning continuance usage by extending the TCT framework and identifying the key factors influencing users' CUW in the Chinese context. The findings highlight the critical role of satisfaction and attitude in driving E-Learning continuance usage while also emphasizing the importance of perceived cost and trust as antecedents of satisfaction. The insignificant influence of course trial on satisfaction suggests that E-Learning platforms need to focus on other aspects of the user experience, such as content quality, functionality, and customer support, to enhance user satisfaction and encourage long-term usage.

The study has several practical implications for E-Learning platform providers and marketers. First, the findings underscore the need for strategies that enhance user satisfaction, such as offering high-quality content, easy-to-use interfaces, and responsive customer support. Second, the significant influence of perceived cost on satisfaction suggests that E-Learning platforms should carefully consider their pricing strategies and ensure that users perceive good value for money. Third, the importance of trust highlights the need for E-Learning platforms to prioritize data security, privacy protection, and transparent communication with users.

However, the study has several limitations that should be acknowledged. First, the cross-sectional design of the study does not allow for causal inferences or an examination of the temporal dynamics of E-Learning continuance usage. 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.

In conclusion, this study provides valuable insights into the factors driving E-Learning continuance usage in China and offers a foundation for future research on this important topic. By addressing the

limitations and extending the current findings, researchers can contribute to the development of more effective E-Learning platforms and the promotion of lifelong learning in the digital age.

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