IMPACT OF UNIVERSITY STUDENTS' ONLINE EDUCATION USER EXPERIENCE ON CONTINUING INTENTION

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Abstract

Online education platforms are the main way for users to learn online, and user experience will affect users' continuing intention. Studying the influencing factors of users' willingness to continue using online education platforms from the perspective of user experience can not only enrich theoretical research in the field of online education user behavior, but also provide suggestions for development strategies for online education platforms and educational content producers.

From the perspective of user experience, this paper adopts quantitative and qualitative research methods, and through interviews, summarizes the relevant influencing factors of continuing intention in online learning, and puts forward corresponding research hypotheses. The questionnaire was developed according to the research variables. Pilot study is carried out on the initially formed questionnaire, and the questionnaire is revised again according to the data results, and finally a questionnaire of factors affecting learning behavior of online education learners with good reliability and validity is formed. Descriptive statistics, reliability analysis, validity analysis and hypothesis testing were carried out on the recovered 423 valid questionnaire data, and finally get the results. System quality and course quality have a positive impact on user experience, user experience will affect users' willingness to continue using online education platforms by affecting perceived value.

Keywords: Online education, User experience, Continuing intention, Perceived value

Introduction

The popularity of online education has enabled more and more people to enjoy the convenience brought by the Internet, which also makes it easier for people to get lost in the ocean of the internet. How to improve the service quality of online courses, strengthen the depth of online education, and improve learning effects have gradually become the focus of the online education industry. The realization of deep learning depends on improving the user experience. Online education user experience reflects learners' feelings about using online courses. The quality of user experience may affect learners' attitudes and status. For online education, whether the learning needs themselves can be effectively met and whether the learning effect is manifested are the "motivating factors" that can make learners feel satisfied. This study extracts perceived usefulness and perceived ease of use constructs from perceived value theory. User experience is divided into three categories: functional experience, emotional experience and social experience.

Consumer usage behavior can be divided into initial use and continuous use according to the number of uses. Intention to use for the first time refers to the psychological activity of whether consumers have the desire to use or purchase a product or service, and intention to continue to use refers to the user's continued willingness to use it for a long period of time in the future after the initial adoption. In this paper, the willingness to continue to use refers to the subjective willingness of users to continue to use the platform in the future after using the online education platform. It is a more intuitive solution to explore the problem of online education learners' willingness to continue learning, so as to take corresponding countermeasures. The main issue to be studied in this paper is how to combine the theories of Technology Acceptance Model (TAM), Information System Success Model (ISS), Value-based Adoption Model (VAM), and Information System Expectation Confirmation Model (IS-ECM) from the perspective of user experience, to explain and analyze the formation mechanism of online learners' continuing intention.

Research Objectives

1. To find out the factors that affect the user experience of online education platforms.
2. To find out the factors that affect the use›s continuing intention of online education platform.
3. To find out how online education platforms can improve user experience and users› continuing intention.

Literature Reviews

Influencing factors of online course user experience: Judging from the existing literature, the related research on user experience is very rich, and there are many factors affecting user experience. Chen Zhihua (2014) proposed to design the usefulness and usability evaluation index of online courses from the perspective of user experience, and believed that educational usefulness includes "meeting the needs of learners, supporting the organization of learning, supporting the learning process, aiding in achieving the accomplishment of learning goals, the improvement of learners' autonomy in learning, and the support of learners' interaction with the curriculum" are six dimensions. Xiaqun (2014) outlined the elements that influence the experience of online courses and built a user experience model based on a summary of the user experience status and influencing factors of online courses. There are mainly sensory factors, emotional factors, value-added experience factors, technical function factors and course content factors. Hu Ying (2015) referred to the six factors affecting information systems in the D&M model proposed by Delone et al.: “Quality of information, systems, and services; usability; user happiness; and net income”, and analyzed network cognition through structural equation model. The relationship between usefulness, usage behavior, learning achievement, emotional feedback, and user experience satisfaction. Based on the model of user experience design elements proposed by Jesse James Garrett, Zhao Jianbao et al. (2016) divided the factors that affect the user experience of online courses into five categories: learner needs, learning content and organizational model, interface and interaction design, emotional design, and functionality. In terms of content experience, function experience and interface experience, an evaluation model of user experience for online courses is established. Chen Meifen analyzed the relationship between user experience and learning motivation of large-scale online courses (Chen Meifen, 2017), and pointed out that the visual features, usability and support services of online courses are the main factors affecting user experience.

Influencing factors of online education users' continuing intention: In the research on online education users' continuing intention, user information Satisfaction and Expectancy Disinformation Theory launched a study on users' continuous use of online learning behavioral intention research, through the empirical analysis of the collected sample data, found that the user's online learning continuous intention is mainly composed of information quality, system quality, service quality, perceived usefulness, expectation confirmation, satisfaction and factors such as computer self-efficacy. TAM and ECM are the theoretical models typically employed by researchers in current research on the influencing variables of users' continuous use intention of online learning. Scholars frequently extend or expand the aforementioned models by including variables from other relevant research theories and models in order to construct a research model of user continuous use behavior in various learning scenarios. The relevant results have important reference significance for the development of this study. Through the above research, the conceptual research framework is obtained.

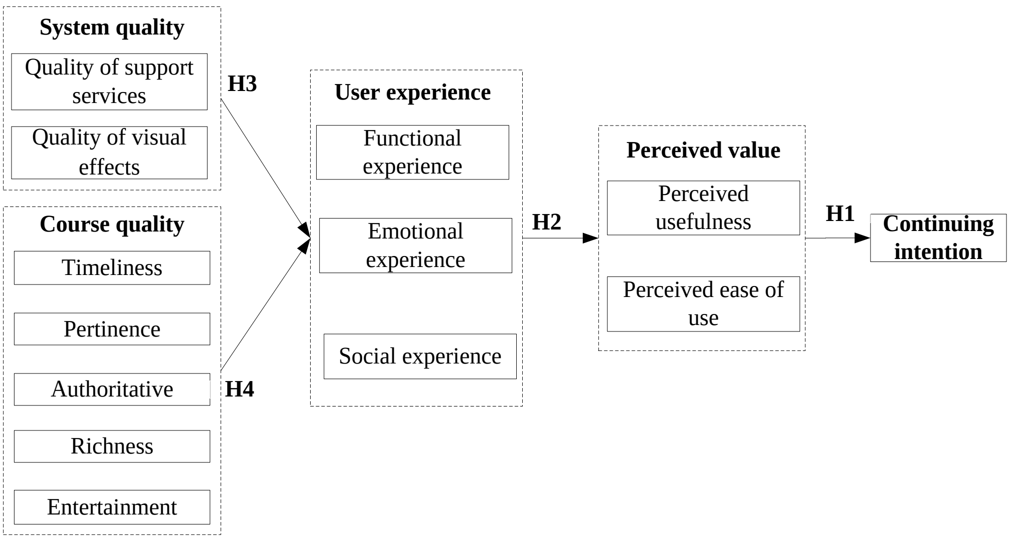

Figure 1: Conceptual Framework from Original Research

The Relationship Between Perceived Value and Continuing Intention

The continuing intention in this research specifically includes the user's willingness to continue learning a course on the platform and the willingness to continue learning on the platform after the end of the course. In the Expectation Confirmation Model (Bhattacheijee, 2010). H1: Perceived value has a positive impact on the Continuing Intention of online education platform users.

The Relationship Between User Experience and Perceived Value

In this study, user experience specifically refers to all the experiences that users get during the interaction with the online education platform. Based on previous research, user experience in this study is divided into three categories: functional experience, emotional experience and social experience. Functional experience refers to the practicability of the online education platform itself, and whether it meets the learning needs of users; emotional experience refers to the mood or emotion of users during the learning process; social experience refers to whether users have established relationships with classmates and teachers during the learning process of the platform. The following hypotheses is proposed: H2: User experience is positively related to the Perceived value of online education platform users.

The Relationship Between System Quality and User Experience

In online education platforms, system quality may have an impact on user experience. First, whether the functions and function quality provided by the platform can meet the learning needs of users will affect the user's functional experience; secondly, in the process of using the functions, the functions Richness, responsiveness, etc. may affect the user's mood; finally, the communication, discussion area and other functions in the online education platform are the basis for the user to establish contact with teachers and other students, and the quality of the function will affect the user's social experience. Therefore, the following hypotheses are proposed: H3: The system quality is positively related to the user experience of online education platform users.

The Relationship Between Course Quality and User Experience

In the online education environment, the course content is the main way for users to acquire knowledge, and is the key to satisfying user's learning needs, which will affect the user's functional experience; emotional experience. Therefore, the following hypotheses are proposed: H4: The course quality is positively related to the user experience of online education platform users.

Research Methodology

First, systematically collect and sort out the current status of online education development, understand a large number of literature related to learners in online education, such as technology acceptance model, information system success model, perceived value acceptance model, information system expectation confirmation model, combined with expert interview methods, According to the existing research results and interview results, research questions are put forward, the description of related concepts, variables and relationships is clarified, and a specific research framework model is constructed. Furthermore, aiming at the two empirical studies on the influencing factors of user experience and the influencing factors of learners' continuing intention in online education, the research hypotheses and conceptual models are tested through empirical research methods such as questionnaire design, questionnaire survey, reliability and validity testing, and correlation analysis. Finally, apply the research conclusions and countermeasures obtained in the above research. The research objects must be people with experience in using online education to achieve the purpose of the research. Since the author works in Taiyuan Institute of Technology, the target population of this research is all the people who use online education platform of Taiyuan Institute of Technology, more than 16,000.

The interviewers in this study cover users of different ages, and their majors cover computer science and technology, electronics Information, economic management, design art, etc. If the number of interviews exceeds 20, there will be information saturation, so 20 professors of Taiyuan Institute of Technology were selected for interviews. The sample size of the questionnaire is derived from Taro Yamane formula (1967) for calculating sample size. The Cochran's formula is shown below:

$$n = \frac{N}{1+Ne^2} \quad (1)$$

n = corrected sample size; N = population size; e = Margin of error (Moe)

Based on this study, with a population of 16,000 and an error level of 0.05, the required sample size is calculated as follows:

$$n = \frac{N}{1+Ne^2} = \frac{16000}{1+16000*0.05^2} = 390 \quad (2)$$

This paper adopts the method of random sampling, and the effective sample size is 423. This paper first adopts qualitative data analysis method and obtains first-hand information by participating in in-depth interviews. Through interviews with 20 professors involved in online teaching. Summarize the real thoughts of the interviewees, and then transcribe, code, and analyze the collected interview data to extract the influencing factors of user experience and continuing intention in online education, and form an initial model.

Questionnaire survey and personal interview data collection procedures, in order to ensure the reliability and validity of the sample, the researchers randomly searched for students based on their majors and collected questionnaires. In this study, the questionnaires were distributed through online and offline channels. Online is mainly produced through the questionnaire star website, and then sent to the respondents through WeChat, QQ, Weibo, etc. During the three semesters (spring semester 2021 to spring semester 2022), a total of 486 questionnaires were returned. The questionnaire is deleted according to the following principles: The time to complete the questions is too short (less than 2 minutes) ; The selection results of such questions are obviously inconsistent; Fourth, the questionnaire options are all consistent. By eliminating invalid questionnaires, 423 questionnaires were finally recovered, and the effective rate of questionnaires was 87.0%.

After the questionnaire design is completed, use the computer software SPSS and AMOS to input, process and analyze the pilot test data and formal data collection. We employed the following data analysis procedures. First, use SPSS for reliability analysis, validity analysis and exploratory factor analysis (EFA) of sample data quality; then use AMOS for confirmatory factor analysis (CFA) and structural equation modeling (SEM), and test research hypotheses.

Results

Description of valid sample data, including gender, grade, major, used online education platform and other indicators. Descriptive statistical analysis was carried out on the questionnaire data by SPSS software, and the specific results are shown in table 1.

Personal Data	**Item**	**Frequency**	**Percentage (%)**	**Cumulative Percent (%)**
Gender	Male	288	68.09	68.09
	Female	135	31.91	100.00
Grade	Freshman	72	17.02	17.02
	Sophomore	144	34.04	51.06
	Junior	162	38.30	89.36
	Senior	45	10.64	100.00
Professional category	Science and engineering	225	53.19	53.19
	Humanities and Social Sciences	117	27.66	80.85
	Arts and sports	81	19.15	100.00
Internet usage years	2 years and below	18	4.26	4.26
	3-5 years	171	40.42	44.68
	5+ years	234	55.32	100.00
Total of each item		**423**	**100.0**	**100.0**

It can be seen from Table 1 that the ratio of males to females in the sample is close to 2:1. Since Taiyuan Institute of Technology is a college that is partial to science and engineering, the ratio of males to females is somewhat unbalanced. In terms of grades, the sample grades are mainly distributed between sophomores and juniors, accounting for more than 70%. From the perspective of majors, science and engineering samples accounted for more than 50%, and humanities and social sciences and arts and sports accounted for 27.66% and 19.15%, respectively. More than 50% of the respondents have used the Internet for more than 5 years.

This paper uses the “reliability analysis” function of the SPSS tool to detect the Cronbach's α reliability coefficient of the internal consistency of the questionnaire data. Nunnally (1967) believed that when the Cronbach's α coefficient is above 0.7, it indicates that the questionnaire has good internal consistency. Usually, when the reliability coefficient is above 0.8, it can be considered that the internal consistency is high. Generally, when the factor loading is greater than 0.7 and Cronbach's α coefficient is greater than 0.7, the reliability of the data can be accepted. The test results show that there are 48 effective measurement items in the 13 latent variables in the influencing factor model of users' continuing intention of online education platform users, the factor loads are all greater than 0.7, and the overall Cronbach's α coefficient value is 0.929, which is much greater than 0.7. The result has an ideal level of reliability. And the Cronbach's α of the 13 measurement scales of potential influencing factors of users' continuous use intention are all > 0.8, indicating that the measurement reliability of each latent variable in the model measurement questionnaire was relatively good.

This article first uses the exploratory factor analysis method (EFA) to test the characteristic validity of the survey questionnaire. Before the factor analysis, the questionnaire data needs to be checked in Bartlett spherical, and the value of KMO (Kaiser-Meyer-Olkin) is measured. The larger the value of KMO, the more suitable for factor analysis. If KMO> 0.7, it indicates that the data is suitable for factor analysis.

Table 2 KMO and Bartlett's test results

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.887
Barlett's Test of Sphericity	Approx.Chi-Square	10786.628
	Df	1128
	Sig	0.000

This paper uses SPSS to conduct exploratory factor analysis on 48 test items of the questionnaire. The KMO and Bartlett sphericity test results in Table 3 show that KMO = 0.887 (>0.7), and the degree of significance (Sig.) = 0.000 (very significant), indicating that the assumption that each variable is independent does not hold, the data concentration measured by the questionnaire is good, and it is suitable for factor analysis.

Then use the "factor analysis" function of SPSS to conduct exploratory factor analysis on the obtained 48 item data. The analysis parameters are set as follows: the extraction method is “principal component” (the eigenvalue is greater than 1), and the rotation method is “Maximum variance method”, the output coefficient display format is “sort by size”, “cancel small coefficient” (absolute value < 0.50). The matrix components after orthogonal rotation show that 13 common factors with eigenvalues greater than 1 are extracted from the 48 measurement indicators of the questionnaire data, and the cumulative explained variance reaches 70.703%, indicating that these 13 factors can reflect 70.703% of the 48 items. The information contained in the overall questionnaire data can be better explained by the extracted 13 common factors. After analyzing and calculating the measurement model of the initial model, the standardized factor loadings of 48 measurement items are all above 0.7 (between 0.708 and 0.862), and have passed the significance test, indicating that each measurement item has a strong explanatory power for the latent variable to which it belongs. The combined.

Table 3 Comparison of Correlation Coefficient Matrix and Square Root of AVE

	QOSS	QVE	CT	CP	CA	CR	CE	FE	EE	SE	PU	PEOU	CI
QOSS	**0.782**												
QVE	0.284	**0.799**											
CT	0.195	0.303	**0.823**										
CP	0.200	0.310	0.328	**0.784**									
CA	0.230	0.180	0.186	0.272	**0.821**								
CR	0.149	0.271	0.286	0.226	0.254	**0.808**							
CE	0.177	0.238	0.308	0.344	0.321	0.297	**0.863**						
FE	0.487	0.414	0.412	0.429	0.404	0.446	0.404	**0.780**					
EE	0.378	0.529	0.451	0.466	0.500	0.418	0.458	0.535	**0.773**				
SE	0.233	0.142	0.066	0.067	0.063	0.054	0.057	0.136	0.123	**0.837**			
PU	0.279	0.279	0.246	0.255	0.255	0.246	0.244	0.455	0.428	0.243	**0.761**		
PEOU	0.213	0.219	0.192	0.199	0.201	0.190	0.190	0.341	0.344	0.183	0.472	**0.799**	
CI	0.182	0.184	0.161	0.167	0.168	0.161	0.160	0.294	0.284	0.157	0.557	0.514	**0.747**

Note: The square root value of AVE of latent variables is marked in bold, and the others are the correlation coefficients between latent variables

reliability of the variables was also higher than the suggested value of 0.7 (between 0.817 and 0.893), indicating a high internal consistency across groups of measures. The AVE of the variables (between 0.558 and 0.700) all satisfy the criterion of greater than 0.5, indicating that the measure can reflect the characteristics of the latent variable. Therefore, the overall measurement model has good convergent validity.

Discriminant validity is used to test that the measurement item is only related to the construct to which it belongs and not related to other constructs. The square root of the average extraction variance of the latent variable is compared with the correlation coefficient between the latent variable and other latent variables. If the former is larger, it means that the scale has good discriminant validity. The results are shown in Table 3.

The parameter matrix of the correlation coefficients of the 13 latent variables and the AVE square root value of the latent variables shows that the AVE square root value between latent variables is greater than the absolute value of the correlation coefficient between the two variables, indicating that the measurement model of the influencing factors of user continuation willingness has a good quality. Discriminant validity means that the characteristics of each latent variable are significantly different from other latent variables.

In order to test whether the relevant assumptions of the theoretical model of the online education user platform's continuous use of intentional factors are valid, the path analysis function of AMOS will be used to verify the adaptability of the model's theoretical structure model, and the relevant parameters will be estimated to analyze the research model. The simulation path and explanatory power of the model finally determine the causal path relationship and influence size of the 13 latent variables in the model. The model and sample data of the " continuing intention" are standardized, and the output model diagram after verification factors is analyzed as shown in **Figure 2**.

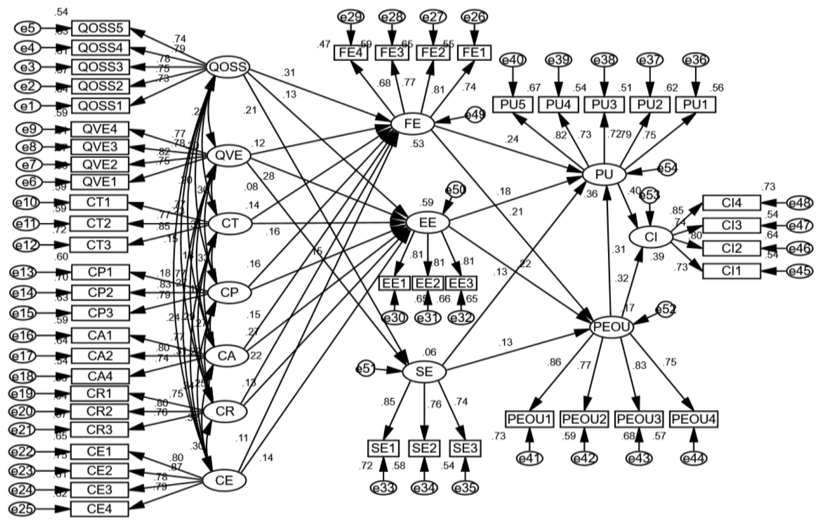

Table 4 Fitting Index Analysis Results

	χ2/df	RMSEA	TLI	AGFI	GFI	CFI
Adaptation standard	<5	<0.08	>0.9	>0.8	>0.8	>0.9
Results	1.282	0.026	0.968	0.875	0.890	0.971

On the basis of structural model analysis, according to the theoretical assumptions put forward in the model of influencing factors of user's continuing intention, the author tested whether the hypothesis of the relationship between latent variables is true from the two aspects of path coefficient sensitivity and validity. The test results are shown in Table 5.

Discussions

According to the conclusion of data theoretical analysis, the conceptual framework of the study was adjusted and revised accordingly, and a model of the influence of user experience on continuous use intention was obtained. Figure 3 clearly shows the path and degree of correlation between user experience and continued use intention. Dashed lines indicate no effect, bold lines indicate maximum effect.

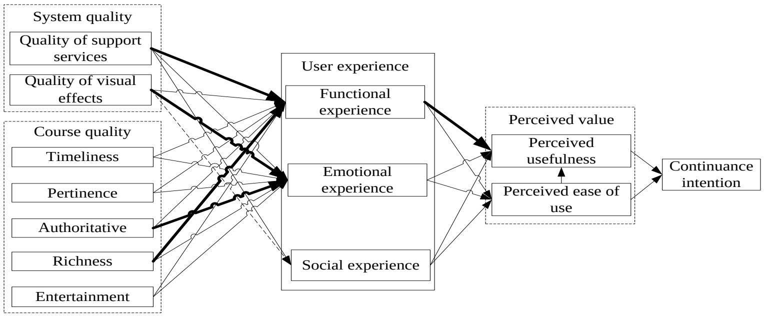

Figure 3 Conceptual framework of users' Continuing Intention

Conclusions

Firstly, the online education platform should allow users to perceive the improved learning effect brought about by the platform. According to the data analysis results, the path coefficient of functional experience to perceived usefulness is 0.24, which is greater than the path coefficients of emotional experience and social experience to perceived usefulness; it shows that functional experience is the core factor affecting perceived usefulness and users' willingness to continue using. In the current online courses, the learning process is mixed with multiple assignments and assessment opportunities, so that users can perceive their professional learning effects. **Secondly,** the online platform should design as simple and easy-to-use functions as possible to ensure that the platform has perfect functions and quick response. For example, when watching a learning video, provide a note function, the video will automatically pause when taking notes, and the note also indicates the time of the video, so you can check it next time. This saves the user the energy of opening documents and taking notes while studying. Functions such as these can effectively improve user perception of ease of use and facilitate user retention. **Thirdly,** online education platforms should encourage interactive behaviors that are helpful to learning. This study finds that users' social experience will increase users' perceived usefulness. Therefore, the online education platform should correctly treat the social activities of users on the platform and encourage the interactive behavior of learning. The platform side can establish an interactive point mechanism to encourage teachers and users to participate in the discussion.

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