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Studying user satisfaction and intention to use in MOOC Platform: The case of Universities in Shanghai

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Abstract
Online education is the direction of the future development of higher education in China. How to improve the initiative of college students in online learning and research the satisfaction of MOOC platform will provide useful reference for the development of online education. Based on the ACSI model and the characteristics of the online learning platform, this study studied five latent variables, learning expectation, service quality, learning satisfaction and continuous learning intention, a set of online learning satisfaction evaluation system including 21 measurement variables was designed. In order to find out the key factors affecting the satisfaction of online learning service, this paper uses PLS-SEM to analyze the loading of each index, and on this basis, makes an empirical analysis of college students in Shanghai in the form of questionnaire survey. The results show that the factors affecting the satisfaction of online learning platform are learning expectation, service quality and perceived value.

Keywords: MOOC platform, Learning satisfaction, online education, Structural Equation Modeling

1. Introduction

Since the introduction of "MOOC" in 2008, online education is connecting the world's various regional educational resources and learner based on the application of Internet technology and artificial intelligence. As a new form of modern education, online education has been widely used worldwide. In China, online education uses high-quality online resources to fill up the shortcomings in the quality of regional and intercollegiate talent training, and realize the basic value orientation of higher quality higher education equity. In 2012, China's online education began to take off under the vigorous promotion of the Ministry of Education of China. The Ministry of Education identified the first batch of 490 national quality online open courses in 2017, the number had increased to 1,291 by 2019, a 2.6-fold increase in just two years [1]. The number of online courses and learners show a high growth trend. During the Covid-19, the Ministry of Education proposed that all universities implement online education and have been offered 7.133 million online courses. The frequency of online learners reached 1.18 billion [2]. Online education played an emergency role and realized “classes suspended but learning continues” during the Covid-19. Not only that, large-scale practice will provide valuable experience for global online education.

Students are direct users of MOOC platforms, and their degree of satisfaction with online learning will directly affect learning effects and the choice of MOOC platforms. Therefore, after the Covid-19, how to win the satisfaction of learners and improve the quality of online course will be an important topic for online education construction. Based on the structural equation model, this paper constructs the satisfaction model of MOOC platform for college students, forming the interaction path of learners' expectation, perceptual quality, perceptual value, learners' satisfaction and their willingness to use, in order to provide useful reference for the construction and development of online learning platform.

2. Theoretical basis and model

2.1 Model Construction

After Cardozo first proposed the concept of "customer satisfaction" in 1965 [3], as an important indicator of the quality of an organization or service, it has been widely used in research in various fields such as marketing and economics, and has constructed a large number of theories model. The most representative one is the American Customer Satisfaction Index model (ACSI) built on the basis of the Swedish Customer Satisfaction Barometer (SCSB) in 1990. The model has 6 implicit parameters. Variables: customer expectations, perceived quality, perceived value, customer satisfaction, customer complaints, and customer loyalty [4-7]. At present, ACSI model has mature theoretical support and high academic authority in customer satisfaction assessment, and is one of the most widely used customer satisfaction assessment models.

In the field of education, satisfaction level is an important observation point affecting learning effect, and is increasingly valued by researchers. In the study of the satisfaction of learners of MOOC platform, Dai Xin-lai defined the learner's satisfaction as a kind of subjective emotional response resulting from the learner's comparison of the actual experience perception of the platform course with the individual's expectations [8]. Shen Zhonghua found that knowledge construction, teacher-student interaction and information processing had significant positive effects on the effectiveness and satisfaction of the university students [9]. Li Yingying set up a theoretical model of college students' satisfaction in network learning based on the quality of teaching, students' sense of task value, network self-efficacy, network use ability, learning motivation, network interaction and social support [10]. In existing research, more start points are related to online curriculum quality and teacher-student interaction. As an important vehicle for online instruction, the user effect and experience of the platform have been neglected for a long time. In practice, we have found that whether the platform can support a large number of learners online at the same time and maintain smoothness is also an important factor in satisfaction. Furthermore, a large number of learners, without receiving any pre-training, encounter troubles during the operation of the MOOC platform, and whether they can provide even customer service and solutions is also an important issue.

This study uses the ACSI model as the framework to retain the four variables of perceived expectation, perceived quality and perceived value, and customer satisfaction, and adds measurement variables related to platform technical support and customer service to the perceived quality. Meanwhile, referring to the China Customer Satisfaction Index (CCSI) model constructed by Tsinghua University [11], it combines customer complaints and customer loyalty variables. Finally, a satisfaction model of college students' MOOC platform is formed with five variables: customer expectations (CE), perceived quality (PQ), perceived value (Perceived Value: PV), customer satisfaction (CS) and continuance using (CU), as shown in Figure 1.

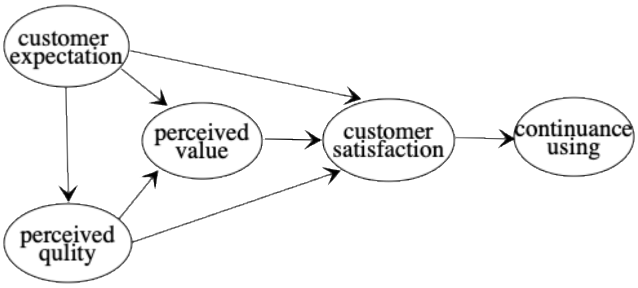

Fig 1: Satisfaction Influencing Factor Model

2.2 Research methods

At present, most of the customer satisfaction evaluation models are established using the methods of Partial Least Squares (PLS) and Linear Structural Relationship (LISREL) [12].

PLS is called "Soft Modeling" (Soft Modeling), the second-generation structural equation modeling method developed by Wold, which is suitable for structural equation models that include latent variables and a series of causal relationships [13]. Different from the traditional structural equation model based on the covariance matrix, each aspect requires at least 4 questions, and PLS can be measured by a single question; Secondly, PLS uses a non-parametric inference method, the data does not need to completely obey the multivariate normal distribution and strict assumptions, and it is more suitable for the research of biased distribution and small sample satisfaction [14]. Therefore, this paper chooses to use the PLS structural equation model for corresponding research.

Structural equation model consists of two parts: measurement model and structural model. The measurement model is used to illustrate the relationship between the observed variable and the latent variable, and the structural model is used to illustrate the relationship between the latent variables. Basic equations of structural model and measurement model:

$$\eta = B\eta + \Gamma\xi + \varsigma \tag{1}$$

$$y = \Lambda_x \eta + \mathcal{E}y \tag{2}$$

$$x = \Lambda_x \xi + \mathcal{E}x \tag{3}$$

Among them, η is endogenous potential variable, ξ is exogenous potential variable, y is endogenous measurement variable, x is exogenous measurement variable, $\mathcal{E}y$ and $\mathcal{E}x$ are incomplete measurement residuals interpreted by potential variables, ς is endogenous potential variable cannot be interpreted as estimate error. B is the regression matrix associated with the endogenous potential variable and Γ is the regression matrix associated with the external potential variable. Based on a large number of relevant research documents and the ACSI measurement system, this study designed 23 observational variables around 5 latent variables such as customer expectations, service quality, perceived value, learning satisfaction, and continuous learning willingness (Table 1).

Table 1: MOOC Platform Satisfaction Measurement Indicator System

Latent variable		Measured variable
CE (ξ_1)	x	Course content expectations (CE1); Technology expectations (CE2); Customer service expectations (CE3);
PQ (ξ_2)	x	Website page (PQ1); Course Resources (PQ2); update rate (PQ3); course information (PQ4); data acquisition (PQ5); Matching of course to learning objectives (PQ6); platform suitability PQ7); Customer Service (PQ8);
PV (ξ_3)	x	improve efficiency (PV1); achieve goals (PV2); Meet demand (PV3) Increase interest (PV4); Help learning (PV5);
CS (η_1)	y	Content satisfaction (CS1); Technical satisfaction (CS2); Customer service satisfaction (CS3); Overall satisfaction (CS4);
CU (η_2)	y	willingness to use (CU1); long-term use (CU2); recommended use (CU3);

3. Data analysis and research results

Designed a network survey questionnaire powered by www.wjx.cn, and pushed it to the students using the online learning platform through the teachers of universities in Shanghai. The questionnaire survey lasted for a week from December 23 to December 31 and received a total of 688 valid questionnaires. According to the pre-survey, it was found that the sample data quality of respondents whose response time was obviously too short (less than 60 seconds) was relatively unsatisfactory. Questionnaires deemed invalid and removed. Finally, 380 valid data samples for empirical analysis were obtained. This study uses SmartPLS3.0 statistical software to estimate the path coefficients of the model, and on this basis, the significance of the path coefficients is tested. As shown in Table 2, the T values are all greater than 1.96 and the path coefficients are all significant. On this basis, the model information Validity analysis and model testing.

3.1. Reliability and validity of the measuring model

According to the structural equation model testing guidelines of Straub and Lewis, the measurement model needs to be tested through internal consistency and convergence validity [15-16]. In this study, internal consistency was tested by Cronbach's Alpha (α) coefficient and Composite Reliability (CR) value. As shown in Table 2, the CA value of the model is higher than the standard level of 0.8, and the CR value of the model is higher than the standard. Level 0.8, meets the requirements [17]. The average variation extraction amount (AVE) was used to evaluate its convergence validity. The AVE in the model was all greater than the benchmark value of 0.5, indicating that the measurement model is credible and the latent variable can explain at least 50% of the variation, and all variable loads are higher than 0.7. The better the convergence validity of the measurement model [18].

Table 2: Index system of PLS path analysis model

Latent variable	CA	CR	AVE	Factor loading	t-test	Measured variable
CE	0.994	0.964	0.900	0.941	86.338	CE1
				0.953	132.647	CE2
				0.951	129.610	CE3
CS	0.956	0.968	0.884	0.932	75.468	CS1
				0.935	103.246	CS2
				0.938	115.221	CS3
				0.956	145.496	CS4
CU	0.949	0.967	0.908	0.948	120.292	CU1
				0.966	214.959	CU2
				0.945	74.383	CU3
PQ	0.941	0.952	0.711	0.843	42.570	PQ1
				0.872	51.119	PQ2
				0.890	66.643	PQ3
				0.875	46.655	PQ4
				0.830	43.454	PQ5
				0.867	46.458	PQ6
				0.743	20.698	PQ7
				0.817	31.257	PQ8
PV	0.957	0.967	0.855	0.931	100.604	PV1
				0.937	108.124	PV2
				0.928	88.956	PV3
				0.902	54.895	PV4
				0.924	94.087	PV5

In addition, as shown in Table 3, the AVE square roots of the five latent variables are all greater than the correlation coefficient between the latent variables, indicating that the model has good discriminative validity19.

Table 2: AVE square and potential coefficient of correlation

	CE	CS	CU	PQ	PV
CE	**0.948**				
CS	0.851	**0.940**			
CU	0.824	0.847	**0.953**		
PQ	0.807	0.830	0.765	**0.843**	
PV	0.823	0.819	0.852	0.783	**0.925**

3.2 Evaluation of Structural Models

The predictive ability of the structural model in this study is evaluated by the multiple decision coefficient R^2 of the structural model. The larger the value of R^2, the stronger the explanatory ability of the measured variable to the latent variable. In this study, the degree of interpretation of learning satisfaction to the model was 80.0%, and the degree of interpretation of the model by continuous learning willingness was 71.7%, both of which were higher than the 0.5 criterion, indicating that the model's interpretative ability basically met the requirements [20]. From the perspective of the model fit index, the model SRMR in this study is 0.033, and the NFI is 0.908. When the SRMR is lower than 0.05 and the NFI is higher than 0.9, the model fits better [21]. Therefore, the theoretical model of MOOC Platform satisfaction constructed by this research is more reasonable.

The path coefficients of learning expectation confirmation to perceived usefulness and satisfaction are 0.549 and 0.385, respectively, indicating that the degree of satisfaction of MOOC platforms to students' learning expectations has a greater impact on perceived usefulness, and directly affects the satisfaction of MOOC platforms. The path coefficients of perceived quality to perceived value and satisfaction are 0.340 and 0.326, respectively, indicating that the services provided by the MOOC platform have a certain impact on perceived value, which is beneficial to improve satisfaction. The path coefficient of perceived value to satisfaction is 0.247, indicating that perceived value has a certain influence on satisfaction of online learning platforms. The path coefficient of satisfaction to continuous use is 0.847, indicating that satisfaction has a significant impact on whether students continue to choose this platform for learning.

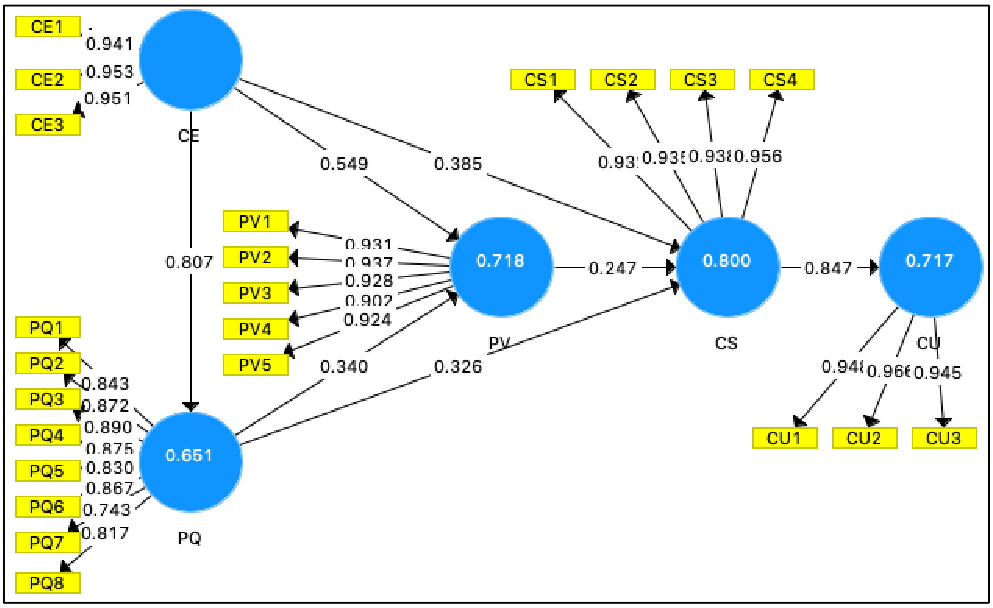

Fig 2: Structural equation model calculation results and path coefficients

4. Conclusion

The results of this research show that learning expectations, perceived quality, and perceived value all have significant effects on the behavior of college students using MOOC platforms for course learning. Among them, learning expectations are the most obvious, followed by perceived quality and perceived value. Therefore, in the post-Covid-19 era, MOOC platforms can improve their competitiveness and attract students to use them for a long time. The following aspects should be started first.

First of all, it is necessary to accurately grasp the demands of students and position them as the main body of online education. Students' main learning expectations are the key factor for MOOC platform satisfaction. The higher the degree of confirmation that students expect, the higher their online learning satisfaction. MOOC platforms can change the traditional classroom model based on teacher lectures, establish a student-centered, teacher-guided, platform-based teaching model that provides technology and services, and focus on cultivating and guiding students' willingness to learn actively to get better Learning effect.

Second, improve the perceived quality of MOOC platforms. The direct effect of MOOC platform perceived quality on satisfaction is 0.326, the indirect effect is 0.084, and the total effect is 0.410. Course content, platform technology and platform services have a significant impact on the perceived quality of MOOC platforms. In the investigation, it was found that during the Covid-19, all universities in Shanghai provided a large amount of online teaching training in order to smoothly carry out online education. In order to better teach and supplement the lack of online teaching resources, most teachers have adopted an MOOC platform plus a social platform like wechat to supplement the lack of resources and services of the online learning platform. Even so, in the survey, there are still students who are less satisfied with platform interaction and after-class services, and reflect that online learning does not enhance their interest in learning. While the online learning platform continues to introduce and build high-quality education resources, it also increases investment in platform technology construction, on the basis of satisfying simple video teaching, improving the interaction between teaching and learning, timely discussion platforms, homework feedback platforms, and feedback on learning effects will all be important factors for future online learning platforms to attract students and improve learning satisfaction.

Finally, improve the level of perceived value. Research results show that students subjectively perceive that MOOC platforms are useful for knowledge acquisition and can improve learning efficiency to varying degrees, which will benefit the improvement of MOOC platform satisfaction. In the design of MOOC platform, the perceived value should be strengthened. In the course designer, the content of the course should be designed according to the acceptance level of the students, and the learners should be given certain incentives, the course scores should be refined, and the interesting classroom design should be integrated into the online teaching course. With the help of the platform's technical advantages, a mixture of likes and mutual evaluations, online discussions and peacetime score awards are adopted to give students external driving force, promote students to use online learning platforms to complete learning tasks, and improve platform satisfaction. The platform provides technical support for teaching, improves the design of platform functions, simplifies function operations, and tries to avoid students' interest in online learning due to the unsmooth learning process.

Online education that integrates "Internet +" and "AI +" technologies is an important development direction for China's education. During the Covid-19, a large number of online education has provided us with a lot of data and experience. After the Covid-19, MOOC platforms should speed up the improvement of the perceived quality of online learning platforms to better meet students' learning expectations, so as to enhance students' willingness to learn online, and to feel the value of learning in the learning process and improve learning efficiency. This research model does not involve variable factors such as student characteristics (gender, major, grade, etc.). In subsequent research, different moderating variables will be introduced to construct a more detailed research model to analyze the impact of different groups on the satisfaction of online learning platforms path analysis provides reference for the development and promotion of online education.

5. References

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