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Antecedents of Adult Students' Behavioral Intention and Usage Behavior of Massive Open Online Courses in Chongqing, China

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Abstract

Purpose: This study aims to investigate the factors influencing the behavioral intention and usage behavior of Massive Open Online Courses (MOOCs) among adult students in higher education. The proposed conceptual framework includes variables such as perceived usefulness, perceived ease of use, subjective norms, performance expectation, intrinsic motivation, behavioral intention, and usage behavior. **Research design, data, and methodology:** The researcher employed a quantitative method, distributing questionnaires to a sample of 500 adult students in higher education in Chongqing. The study utilized purposive, stratified random, and convenience sampling techniques for both online and offline data collection. The collected data were analyzed using structural equation modeling and confirmatory factor analysis to derive meaningful insights. **Results:** The findings indicate that perceived usefulness, perceived ease of use, subjective norms, performance expectation, and intrinsic motivation significantly influence behavioral intention, with performance expectation having the strongest impact and perceived ease of use having the weakest impact. Furthermore, behavioral intention was found to significantly impact usage behavior. **Conclusions:** The study confirmed six hypotheses aligned with the research objectives. As a result, it is recommended that colleges and universities focus on enhancing adult students' performance expectations in MOOC teaching to achieve better educational outcomes.

Keywords : Massive Open Online Courses, Performance Expectation, Perceived Usefulness, Behavioral intention, Usage behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The research on MOOC usage intentions of higher education students is still in its infancy. Reviewing the literature, it is found that in the research on the behavioral intention of MOOC, people mainly focus on college students and pay less attention to students of higher continuing education. However, the MOOC learning of higher continuing education students has certain particularity. It is challenging to apply the current MOOC model's influencing elements for college students' behavioral intentions to higher continuing education for adults (Yi et al., 2018). Therefore, this study takes adult higher continuing education students as the research object, discusses their behavioral intention of using MOOC and the influencing factors of their usage behavior, it suggests improvements in order to encourage the extensive use of MOOC in adult higher continuing education and serve as a resource for the information-building process in adult higher continuing education (Zhang, 2018).

The study of usage intention is an important hotspot at home and abroad. Many types of research exist on learners' usage intention or behavior of online learning platforms. However, most existing research focuses on students' usage intention in higher education or basic education, while there are few types of research on adult higher education (Davis et al., 2014). Based on existing studies, this study summarizes the key variables that affect adult higher education students' intention to use MOOC platforms and verifies them; students' intentions to utilize the MOOC platform and their understanding of how to use it will be used to build a theoretical model of adult higher education. This study is useful for enhancing the research findings of the use of

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MOOC in the field of adult higher education, filling in the gaps in the model of influencing factors of adult higher education students' willingness to use MOOC, and offering some theoretical references for future research.

2. Literature Review

2.1 Perceived Usefulness

When examining how users adopt computer technology, Davis et al. (1989) defined perceived usefulness as the extent to which individuals believe that adopting a certain system may improve their ability to execute their jobs. When Davis et al. (1989) researched this occurrence, they proposed this theory. The definition of perceived usefulness has started to shift as it is used more often in marketing. Currently, browsing reviewers' perceived utility to online reviews is where "perceived usefulness" is most often used. According to studies by Aitken et al. (2008), perceived utility is the degree to which readers of online product evaluations can understand the message the reviewer is trying to convey. This definition is based on the notion of advertising effectiveness. How much do these details influence readers' attitudes, emotions, and desire to support the product or service?

Perceived usefulness was brought into the context of websites. As a result, variable by Venkatesh and Davis (2003). They also looked at how customer evaluations affected perceived usefulness and concluded that perceived usefulness is the most crucial variable from the viewpoint of the system. Kempf and Smith (1998) connect perceived usability and perceived diagnosticity, contending that "the utility of the website experience in determining product quality and product performance" may be used to quantify overall diagnosticity at the product level. Yi et al. (2018) performed research on the low completion rate of users in the MOOC learning process to demonstrate that elements like satisfaction, perceived utility, and MOOCs all influence learners' desire to continue using MOOCs to various degrees. Additionally, they developed and validated the research model.

Yeung and Jordan (2007) investigated how eager workers were to utilize online learning platforms in Hong Kong businesses. They discovered that perception is helpful, perception and usability, system quality, information quality, and service quality improve customer satisfaction. Mitzner et al. (2016) examined the relationship between PU and PEU of a computer interface designed for older users and demographic, technology experience, cognitive abilities, and personality. The strongest correlates of PU and PEU were technology experience, personality dimensions of agreeableness, and openness to experience and attitudes. Koutromanos et al. (2015) examined factors affecting students' and in-service teachers' intention to use a spatial hypermedia application, the HyperSea. PU was the most important predictor linking ATTs and intentions to use these applications. Hence, a hypothesis is set:

H1: Perceived usefulness has a significant influence on behavioral intention.

2.2 Perceived Ease of Use

According to Davis et al. (1989), the technology acceptance model defines perceived usability as the difficulty consumers experience while utilizing a particular system. Perceived usability refers to the ease of users using the platform, such as the active form of the platform (login, registration, course selection), whether it is very convenient, and whether the program is simple. Secondly, because it is intended for students, the interface's language, style, and pattern, as well as the variety of resources (courses, material, and assignments), will impact how user-friendly they perceive it to be (Wang & Emurian, 2005).

The comfortable experience of interface design will increase the user's favorable impression, thus influencing the choice behavior of users. In the same type of service, the platform with a strong favorable impression will be preferred (Wang & Emurian, 2005). Faria et al. (2017) evaluated users' adoption rate and acceptability in e-learning systems by including significant external elements in the technology acceptance model. It is determined via empirical study that there is some relationship between platform features and users' perceived ease of use and self-efficacy. Additionally, platform attributes are excellent indicators of perceived usefulness.

Perceived usefulness and satisfaction substantially influence perceived usefulness, and perceived usefulness and ease of use have a large impact on continuing use intention (Cho et al., 2009). Troshani et al. (2011) used the UTAUT model to study students' intentions to use online learning. They discovered that system accessibility significantly impacts those intentions, perceived ease of use has no impact on those intentions, and teacher influence and technical support have no impact on students' attitudes toward use. Thus, a hypothesis is proposed:

H2: Perceived ease of use has a significant influence on behavioral intention.

2.3 Subjective Norm

Gabbiadini (2019). According to the idea of planned behavior, the monitoring data shows that people's sustained use of fitness APPs for exercise positively influences people's health behavior (TPB). Planned behavior theory (TPB) may predict health-related behavioral intentions in various health-related areas. Several theoretical models explain the link between attitudes and certain actions. According to this theoretical paradigm, the behavior-determining component is influenced by attitude, subjective norm, and perceived behavior control.

Subjective norms also influence behavioral intention. The association between subjective norms and behavioral intention is moderated by experience and volition, while the relationship between subjective norms and perceived usefulness is moderated by experience (Venkatesh & Davis, 2000). Zhang (2014) developed a model of teachers' online teaching behaviors based on the theory of planned behavior (TPB) and TAM. According to this model, perceived usefulness and ease-of-use influence behavioral intention through behavioral attitudes in TPB, and the research findings support the notion that behavioral attitudes and subjective norms are the primary influences on teachers' online teaching behaviors. Accordingly, this study aims to investigate the relationship per stated below:

H3: Subjective norm has a significant influence on behavioral intention.

2.4 Performance Expectations

The UTAUT model by Venkatesh and Davis refers to performance expectation as the extent to which users believe technology may help them do their tasks more effectively. In his study, Zhang (2018) suggested that performance expectations indicate that MOOC platforms may provide users with features and services tailored to their learning requirements, enhancing users' learning effects and capabilities.

Venkatesh and Davis (2000) measured performance expectations with four questions: improving performance, improving efficiency, improving effect, and technology usefulness. Hew et al. discovered that learners often enroll in MOOCs to acquire new information. According to Wang and Yan (2016), performance expectation is the most important factor affecting college students' adoption of MOOCs. According to Li et al. (2016), when students are under pressure to do well on tests, instructors' primary reason for using technology is to raise students' test results.

Liu et al. (2011). Performance expectation positively affects the perceived usefulness of mobile search. When users use mobile visual search, they have expectations due to their demand for information acquisition. Therefore, mobile visual search is perceptually useful.

In his research on public acceptance of automated traffic roads using UTAUT, Madigan et al. (2016) concluded that performance expectations, effort expectations, social influence, promotion circumstances, and hedonic motivation influence the public's desire to utilize automated traffic roads. The beneficial impacts of perceived interest, individual innovation, social influence, and performance expectation on the usage of mobile learning by open learners were confirmed and evaluated by Bao (2017) based on the UTAUT model. Therefore, a hypothesis is put forward:

H4: Performance expectation has a significant influence on behavioral intention.

2.5 Intrinsic Motivation

According to Ryan and Deci (2000), many distinct types of human motivation exist, including intrinsic and extrinsic drives. Different types of motivation will affect learning, performance, enjoyment, and other aspects of life. Different motivational factors will also affect how well a person can regulate their processes. The self-determination hypothesis states that human actions may be classified into two groups: self-determined and non-self-determined, each controlled by one of the two motivational styles known as extrinsic or intrinsic motivation. People build intrinsic motivation, a drive based on their interests and well-being, from the bottom up. (Xu & Liu, 2017). Roca and Gagne (2008) interpret intrinsic motivation as the beginning of a certain behavioral activity due to an individual's interest or belief in it. Dysvik and Kuvaas (2011) assert that intrinsic motivation moderates the relationship between perceived work autonomy and performance on the job. They also find that autonomy has varying effects on job performance depending on the intrinsic motivation level. Locke and Latham (2006) A high level of intrinsic motivation mean that users have a strong desire and need to achieve health goals. In this case, after setting a health goal, intrinsic motivation strongly urges users to consciously self-manage to achieve the goal, thus enhancing the health goal. Dysvik and Kuvaas (2011), who separately validated that intrinsic motivation had a moderating influence on the relationship between perceived work autonomy and job performance, claim that depending on the level of intrinsic motivation, job autonomy has different consequences on job performance.

Deci and Ryan (2000) proposed the concept of "basic psychological needs," which they defined as three basic psychological needs: autonomy, competence, and belonging. They did this by integrating and ending other psychological needs like intrinsic motivation and encouraging the internalization of extrinsic motivation. The author thinks that extrinsic and intrinsic motivation are not opposed to each other, and the key to motivating motivation lies in the continuous internalization of extrinsic motivation.

Lee (2010) studied e-learning and concluded through empirical research that there was an obvious correlation between intrinsic motivation and the willingness to continue using the Internet. Davis et al. (2014) found that the main motivations for college students to use MOOCs are free, interesting, and updating knowledge. Participation with peers is the main motivation for learners to use MOOCs, and this incentive significantly influences the perceived happiness of the learners. (Fisser et al., 2015). Yang (2016) built a research model based on self-determination and sustainable use theories, proving that intrinsic motivation benefits learners' willingness to continue using. So, it can be hypothesized that:

H5: Intrinsic motivation has a significant influence on behavioral intention.

2.6 Behavioral intention

While behavioral expectation relates to a person's assessment of the difficulty of putting a behavior into practice by carefully considering such aspects as intention, aptitude, and environment, behavioral intention refers to whether or not a person declares their plans to accomplish something (Sun, 2021). Bagozzi et al. (2000) distinguished the emphasis of behavioral intention and behavioral expectation through empirical means. A person's desire to carry out a certain activity when fully awake represents their behavioral intention, which expresses how strongly they have an individual subjective intention. People's hopes, wants, desires, and other feelings may all be manifestations of behavioral purpose (Min et al., 2022).

Fishbein and Ajzen (1975) divided behavioral intention into repurchase, word-of-mouth, and premium purchase intention from the consumer field. Specifically in online learning, behavioral intentions can be expressed as intended use, re-use, and recommended use. Intended use refers to the willingness to use in the future, re-use refers to the possibility of re-use or choice, and recommended use refers to the user's recommendation to others. In conclusion, the behavioral intention of this research refers to the learners' arbitrary readiness to utilize online learning in the future, to use it again, or to suggest it to others. Delone and Mclean (2003) improved the original D&M model, in which "net income" replaced "personal impact" and "organizational impact." In the causal relationship, positive "use" will improve "user satisfaction," and enhanced "user satisfaction" will have a direct impact on "use intention," which in turn will have an impact on the system's continuing "usage."Damberg (2022) used the UTAUT2 theoretical model to reveal the driving factors of fitness APP users' intention to use and investigated the intention to continue using and increase health awareness as driving factors. The survey showed that habits, game perception, health awareness, performance perception, and price value impacted usage intention.

Davis et al. (2014) found that the main motivations for college students to use MOOCs are free, interesting, and updating knowledge. Participation with peers is the main motivation for learners to use MOOCs, and this incentive significantly influences the perceived happiness of the learners. (Fisser et al., 2015). Based on the value expectation theory, Piret and Boivin (2019) developed a tool to measure MOOCs registration motivation. They verified the influence of three expectation factors, three value factors, and one social influence factor on users' MOOCs enrollment rate. The results showed that interest and expectation of the course, personal adaptability of distance learning, and adaptability of family and work were the highest motivation factors for the evaluation of the enrollment rate of MOOCs. One of the foundations for addressing continuous use behavior is a desire to use constantly, and the intention to use continuously may foretell continuous use behavior (Yang, 2016). Consequently, a hypothesis is developed:

H6: Behavioral intention has a significant influence on usage behavior.

2.7 Usage Behavior

According to Davis et al. (1989), user behavior related to people's real use activities is consistent with the technological acceptance paradigm. Use behavior refers to the specific behavior of an individual in the present or future. The intention to use is an important factor affecting user behavior. When the individual use intention is strong, the probability of user adoption behavior is higher. Therefore, a relationship exists between the willingness to use and user behavior. Chen (2019) believes that

user behavior can be understood as the specific content that people do when using certain objects; In the use of MOOCs, the use of behavior means that users can be familiar with the learning process of MOOCs, conscientiously complete the course tasks, and use MOOCs to learn according to the course requirements, to improve their knowledge and skills. Lewis et al. (2013) utilized UTAUT to develop a set of instructional technology usage models for teachers, and the findings of the study demonstrated that instructors' desire to use IT was affected by societal pressure, performance expectations, and effort expectations. Social motivation and values are significant elements affecting users' use behavior of mobile short video, according to research by Hara et al. (2007), who researched the factors influencing users. This research was based on logging technology.

3. Research Methods and Materials

3.1 Research Framework

A framework is a cognitive tool used to simplify the processing and storage of information (Wolfsfeld, 1993). Timothy and Maitreesh (2018) believes that frame is things' outline, scope, and main structure. The conceptual framework of this study is a previous research framework developed from the research. It is adapted from the following theoretical models.

First, Davis et al. (1992) conducted research based on users' intrinsic motivation, believing that users would be subject to intrinsic and extrinsic motivation when accepting technology. Davis et al. put forward the Motivation Model (MM).

Second, Davis et al. (1989) illustrates how important it is for this model's predictive power that variables' behavioral intentions be considered. The central tenet of the rational behavior theory is that the generation of behavior is based on the information accumulated prior to the behavior and the thinking and analysis of the information, meaning that the majority of human behavior is produced under the control of reason and will.

Third, the UTAUT model is one of the basic models to study all kinds of behavioral intention and usage behavior. Based on UTAUT, some scholars have built a model of factors influencing students' ICT learning effect (Idorenyin & Donyaprueth, 2019).

Moreover, finally, Guriting and Ndubisi (2006), based on the technology acceptance model, combined with perceived ease of use, perceived usefulness, and other variables, constructed a model about users' behavioral intention in online banking. This study uses computer self-efficacy, computer experience, perceived usefulness, and perceived ease of use as variables. Based on the technology acceptance model, it explores the influencing factors of customers' behavioral intention for online banking. The results show that perceived ease of use and usefulness constitute customers' main behavioral intention for online banking.

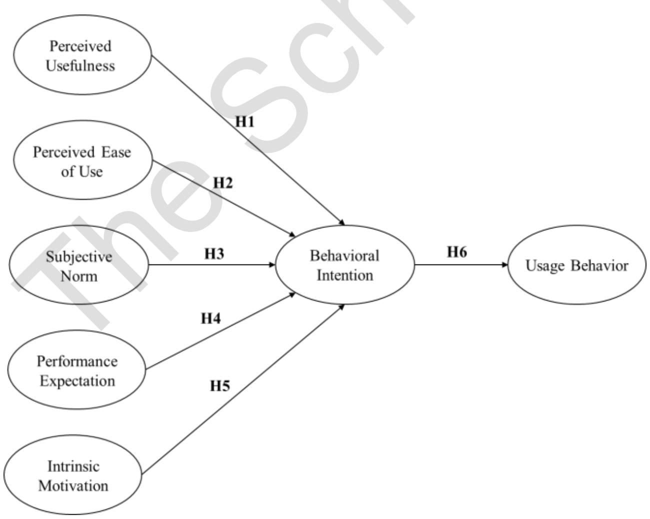

Figure 1: Conceptual Framework

H1: Perceived usefulness has a significant influence on behavioral intention.
H2: Perceived ease of use has a significant influence on behavioral intention.
H3: Subjective norm has a significant influence on behavioral intention.
H4: Performance expectation has a significant influence on behavioral intention.
H5: Intrinsic motivation has a significant influence on behavioral intention.
H6: Behavioral intention has a significant influence on usage behavior.

3.2 Research Methodology

Gathering data is the first step. This study developed a questionnaire on the influencing elements of MOOC use intention and usage behavior of adult higher education students to meet the study's goals and objectives. The objective consistency project (IOC) assessment of the questionnaire was carried out by this study's consecutive invitations of three experts in adult education and online education, and it was completed. On this basis, the Likert scale was used to assign scores to the seven-variable scale test questions, and based on this, the usage intention and usage behavior of the MOOC samples surveyed in CHONGQING were predicted. From September to October 2022, 35 eligible subjects were invited to complete the questionnaire. This research conducted a screening questionnaire to weed out ineligible candidates and confirm that the responses were from the target group seeking adult higher education in Chongqing.

Secondly, data processing. Due to the impact of the novel coronavirus outbreak and control policies, it is unrealistic to conduct large-scale questionnaire distribution and collection on the spot. Therefore, this study adopts a questionnaire star to conduct a questionnaire survey and collect data. Prior to data collection, the content validity of the study was assessed using the Item-Objective Congruence (IOC) index. All scale items received a rating of 0.6 or higher from three expert evaluators. Furthermore, a pilot test involving 50 participants was conducted, and the results of the Cronbach alpha coefficient reliability test indicated strong internal consistency, with all items scoring at or above 0.6 (Hair et al., 1998).

Finally, the data is analyzed and processed. After large-scale questionnaire collection, this study will use SEM analysis to verify all previous research hypotheses based on CFA analysis and try to establish a structural model. Regarding research tools, the software was used in this study for SEM analysis.

3.3 Population and Sample Size

The target population is adult students in higher education students from Chongqing City. According to Latunde (2016), sample sizes should be manageable to get reliable findings. The size of overall size, the makeup of the entire internal sampling error, the sampling technique, the budget, etc., are the primary variables influencing the sample size (Chen & Fang, 2019). Williams et al. (2010), at least 500 samples are needed to explore complex models.

The sample size of the research has been determined to be at least 500 people in combination with the requirements of the above scholars on the sample size and the actual needs of the research. In this study, 500 valid samples were selected in Chongqing.

3.4 Sampling Technique

The researcher used three sampling techniques. This study adopts the method of purposive sampling to select adult higher education students from three counties (cities and districts) in Chongqing. In order to meet the requirements of stratified random sampling, 3 districts were selected from the municipal districts and counties under the jurisdiction of Chongqing for questionnaire distribution. The study is based roughly on the number of students using MOOCs for adult higher continuing education in each county and region. According to Table 1, among the 500 samples collected in Chongqing, 149, 228, and 123 were provided to Shapingba District, Yubei District, and Nanan District, respectively. Finally, a convenient sample was selected to reach the target respondents by online and offline questionnaire distribution.

Table 1: Sample Units and Sample Size

Area	Population Size	Proportional Size
Chongqing	Shapingba District	149
	Yubei District	228
	Nan 'an District	123
Total		**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

The demographic characteristics of Chongqing sample respondents are summarized as follows: In terms of gender, most respondents are female, accounting for 63.4%, while male respondents account for 36.6%. From the perspective of age, most respondents were concentrated in the age group of 26-35, with 284 people in this age group, accounting for 56.8%. The proportion of people aged 36 and above is 30.6%, and the proportion of people aged 18-25 is 12.6%. In terms of students' majors, the sample of Chongqing is mainly liberal arts students, with 196 students, accounting for 39.2%; The second is science students, whose number is 155, accounting for 31.0%; Engineering students accounted for 14.6 percent of the total, while other majors accounted for 15.2 percent. In terms of the occupations of the respondents, 148 people were working in enterprises, accounting for 29.6%; The number of people working for the government or public institutions was 148, accounting for 29.6%; 90 people were self-employed, accounting for 18.0%; In addition, the number of freelancers in this survey reached 58, accounting for 11.6%; The remaining staff accounted for 11.2%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	183	36.6%
	Female	317	63.4%
Academic Year	18-25 years old	63	12.6%
	26-35 years old	284	56.8%
	Age 36 and older	153	30.6%
Professional category	Liberal arts	196	39.2%
	Science type	155	31.0%
	Engineering type	73	14.6%
	other	76	15.2%
Occupational type	Enterprise personnel	148	29.6%
	Government or public institution	148	29.6%
	Individual trader	90	18.0%
	freelancer	58	11.6%
	other	56	11.2%
Monthly income	Less than 3000 yuan	102	20.4%
	3000 yuan - 8000 yuan	243	48.6%
	Over 8000 yuan	155	31.0%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

In this study, confirmatory factor analysis (CFA) was performed, and Cronbach α (CA), factor load, and mean-variance extraction (AVE) combined reliability (CR) were used to evaluate convergence effectiveness. The results are shown in Table 3. Combination reliability or structural reliability (CR) and mean-variance extraction (AVE) are other ways to measure the reliability and consistency of scale items (Peterson & Kim, 2013). According to Fornell and Larcker (1981), a CR of 0.7 and above is acceptable. The acceptable threshold for factor load is 0.5 or higher (Hair et al., 1998). In this study, both CR and AVE values exceeded the threshold. Regarding composite reliability, the best architecture for internal consistency is the attitude of use. In this study, the factor load of all individual items is greater than 0.50, indicating that the factor load of this study is at an ideal level.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived usefulness (PU)	Davis et al. (1989)	4	0.819	0.649-0.797	0.823	0.539
Perceived ease of use (PEOU)	Nielsen (1993)	3	0.781	0.727-0.760	0.783	0.545
Subjective Norm (SN)	Fishbein and Ajzen (1975)	4	0.799	0.635-0.840	0.805	0.510
Intrinsic Motivation (IM)	Ryan and Deci (2000)	3	0.821	0.800-0.868	0.819	0.602
Performance Expectations (PE)	Venkatesh and Davis (2000)	4	0.818	0.708-0.821	0.821	0.535
Behavioral intention (BI)	Lee (2010)	3	0.751	0.597-0.792	0.754	0.509
Usage Behavior (UB)	Davis et al. (1989)	4	0.802	0.648-0.742	0.804	0.506

As shown in Table 4, comparing the goodness-of-fit index and its acceptance range of Chongqing samples found that each index could meet the model fitting conditions and did not need to be fitted again. Specifically, in this sample, CMIN/DF=1.716, GFI=0.935, AGFI=0.917, NFI=0.920, CFI=0.965, TLI=0.958, RMSEA=0.038. Therefore, the model of this study does not need to be revised again, and this model is the final model.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.716
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.935
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.917
NFI	≥ 0.80 (Wu & Wang, 2006)	0.920
CFI	≥ 0.80 (Bentler, 1990)	0.965
TLI	≥ 0.80 (Sharma et al., 2005)	0.958
RMSEA	< 0.08 (Pedroso et al., 2016)	0.038
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index and RMSEA = Root mean square error of approximation.

Fornell and Larcker (1981) proposed that the validity of the discrimination is confirmed when the square root of AVE is greater than the coefficient of any related structure. As shown in Table 5., the AVE square roots of all structures on the diagonal are 0.734, 0.738, 0.714, 0.776, 0.731 and 0.711, respectively, greater than the inter-scale correlation. Therefore, the validity of discrimination is guaranteed.

Table 5: Discriminant Validity

	PU	PEOU	SN	IM	PE	BI	UB
PU	**0.734**						
PEOU	0.440	**0.738**					
SN	0.286	0.111	**0.714**				
IM	0.486	0.319	0.286	**0.776**			
PE	0.624	0.350	0.200	0.360	**0.731**		
BI	0.619	0.378	0.281	0.423	0.632	**0.713**	
UB	0.494	0.346	0.169	0.397	0.402	0.346	**0.711**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

A structural equation model is a statistical model that combines multiple variables into a causal network designed to reveal a complex theoretical structure by measuring the relationship between an indicator and an underlying concept. After building a structural equation model, evaluating the model's fit is important because it can tell us whether the model can be used to predict unknown data (Hooper et al., 2008).

Kline (2015) argued that the structural equation model provides an important method for testing models, revealing causality, and predicting future trends, which has a wide range of applications in research analysis and theoretical construction.

According to the modified structural model, the goodness of fit index was recalculated, as shown in Table 6. The statistical results were CMIN/DF=3.622, GFI=0.852, AGFI=0.815, NFI=0.828, CFI=0.868, TLI=0.848, RMSEA=0.072. The adjusted model has good goodness of fit.

Table 6: Goodness of Fit for Structural Model

	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shams uddin, 2015; Awang, 2012)	3.622
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.852
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.815
NFI	≥ 0.80 (Wu & Wang, 2006)	0.828
CFI	≥ 0.80 (Bentler, 1990)	0.868
TLI	≥ 0.80 (Sharma et al., 2005)	0.848
RMSEA	< 0.08 (Pedroso et al., 2016)	0.072
Model Summary		**In harmony with empirical data**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = Goodness-of-fit index, AGFI = Adjusted goodness-of-fit index, NFI = Normed fit index, CFI = Comparative fit index, TLI = Tucker–Lewis index and RMSEA = Root mean square error of approximation.

4.4 Research Hypothesis Testing Result

Table 7 provides the significance of each variable based on its standardized path coefficient (ß) and t-value. which shows the relationships between the constructs, wherein a p-value of <0.05 is required to support each hypothesis. A solid line depicts the validity of the premise, while a dashed line proves otherwise

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-Value	Result
H1: PU→ BI	0.548	7.214*	Supported
H2: PEOU→BI	0.146	2.906*	Supported
H3: SN→BI	0.141	2.872*	Supported
H4: PE→ BI	0.601	7.946*	Supported
H5: IM→BI	0.200	3.963*	Supported
H6: BI→ UB	0.510	6.907*	Supported

Note: * p<0.05
Source: Created by the author

This study uses regression or standardized path coefficients to measure the correlation between the independent and dependent variables in the hypothesis.

All six hypotheses proposed in this study have been verified in the Chongqing sample. The standardization coefficient of **H1** is 0.548, and the t value is 7.214. The standardization coefficient of **H2** is 0.146, and the t value is 2.906. The standardization coefficient of **H3** is 0.141, and the t value is 2.872. The standardization coefficient of **H4** is 0.601, and the t value is 7.946. The standardization coefficient of **H5** is 0.200, and the t value is 3.963. The standardization coefficient of **H6** is 0.510, and the t value is 6.907.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study looks at the elements influencing consumers' happiness with and propensity to utilize e-commerce platforms in Chongqing. This study investigates the factors that influence the behavioral intention and usage of MOOCs by adult higher continuing education students in Chongqing. The research objects are people with experience using MOOCs from three different regions of Chongqing, respectively. In order to draw research conclusions more scientifically, this study builds its research framework based on summarizing previous research achievements. The technological acceptance model (TAM) proposed by Venkatesh and Davis (2003), the motivation model (DM) proposed by Davis et al. (1992), and the technology acceptance model (TAM) proposed by Davis et al. (1989) are a few of the theoretical underpinnings that have greatly influenced this work. Idorenyin and Donyaprueth (2019) model of the elements impacting the success of ICT-based learning and Guriting and Ndubisi (2006) updated expanded TAM of online banking.

This study uses quantitative research methods to sample adult higher education students with MOOC experience in Chongqing City. This study employs confirmatory factor analysis and structural equation modeling to conduct factor analysis and correlation regression analysis on the collected data based on reliability analysis and multiple linear tests to investigate the behavioral intention of adult higher education students in MOOCs and the influencing factors of their usage behavior. The findings demonstrate that subjective norms, intrinsic motivation, performance expectations, perceived utility, perceived ease of use, and behavioral intention may all affect how people utilize MOOCs.

5.2 Recommendation

In addition to impacting the frequency of online learning activity, learner acceptability of online learning is a crucial precondition for online learning platforms to achieve their educational, social, and economic potential. Under the influence of the epidemic, the popularity of online learning has been greatly improved, and its importance is also increasing. The degree to which subjective norms, intrinsic motivation, performance expectations, behavioral intent, and use behavior influenced perceived utility, perceived ease of use, and other factors was examined in this study. This can assist teachers, colleges, and universities in better comprehending the factors that influence students' use of online learning, allowing them to create programs that will improve students' behavioral intentions and use behaviors, which will be crucial in addressing the shortcomings of traditional classroom instruction, promoting the transformation of students' learning styles, raising teaching standards, and encouraging the use of vocational education information technology.

This study concludes that perceived ease of use, perceived usefulness, subjective norms, intrinsic motivation, performance expectation, and behavioral intention are the influencing factors of behavioral intention and usage behavior of MOOCs based on the analysis of three survey samples in Chongqing. Further research and utilization of the above factors can help MOOCs to be promoted and applied more quickly. In this study, performance expectation is the strongest predictor of MOOCs' behavior intention and usage behavior. Therefore, emphasis must be placed on improving learners' performance expectations.

5.3 Limitation and Further Study

Due to the limitations of capacity, time, space, and epidemic situation, there are still some things that could be improved in this study. First, the samples in this study are only from three areas of Chongqing City, which is not widely representative, including Shanghai, Beijing, Guangzhou, and other important cities are not included in the study. Second, there are a few dimensions involved in this study. Only perceived usefulness, perceived ease of use, subjective norms, intrinsic motivation, and performance expectation are used to study the influencing factors of MOOCs' behavior intention and usage behavior. Some factors that may impact MOOC's behavior intention and usage behavior are not included. In the following research, the scope of the research can be further expanded to include Shanghai, Beijing, Guangzhou, and other cities in the research sample. In addition, the research can be conducted on groups other than adult college students, such as ordinary college students and college teachers, to study their behavioral intention of MOOCs and the influencing factors of their usage behavior.

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