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A Study on The Influencing Factors of Students' Behavioral Intention and Usage Behavior of Massive Open Online Courses in Dazhou, China

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Abstract

Purpose: Massive Open Online Courses (MOOCs) play an important role in adult higher education. This study aims to explore the factors that influence the students' behavior intention and usage behavior of Massive Open Online Courses (MOOCs). The proposed conceptual framework includes perceived usefulness, perceived ease of use, subjective norms, performance expectation, intrinsic motivation, behavioral intention, and user behavior. **Research design, data, and methodology:** Using a quantitative method (n=500), questionnaires were distributed to adult students in higher education in Dazhou City. The study employed purposive, stratified random and convenience sampling to distribute online and offline questionnaire for the data collection. Structural equation modeling and confirmatory factor analysis were used for to analyze the data and interpret the results. **Results:** The results show that perceived usefulness, perceived ease of use, subjective norm, performance expectation, and intrinsic motivation have significant influence on behavioral intention, in which performance expectation has the strongest impact and perceived ease of use has the weakest impact. Additionally, behavioral intention significantly influences usage behavior. **Conclusions:** Six hypotheses were proved to be consistent with the research objectives. Therefore, it is suggested that colleges and universities enhance the performance expectation of adult students in MOOCs teaching to obtain better teaching results.

Keywords: Massive Open Online Courses, Performance Expectation, Perceived Usefulness, Behavioral Intention, Usage Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

Massive Open Online Courses (MOOCs) play an important role in adult higher education. With the continuous development of technology and the popularization of the Internet, MOOCs (massive open online courses) provide a more flexible and convenient way of learning for adult higher education. First, MOOCs have the advantage of flexibility. MOOCs allow students to learn in their own time and place. Adult students often have work, family, or other obligations that result in time constraints. MOOCs offer flexibility through an online learning platform, enabling students to study autonomously at their own pace and avoid traditional classroom time and location constraints. Secondly, MOOCs facilitate students to study independently. MOOCs encourage students to participate actively in the learning

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process. Students can choose learning materials according to their learning pace and needs, replay, and repeat learning content, and participate in discussions and interactions independently. This mode of autonomous learning is conducive to the cultivation of individual learning and self-management ability of adult learners. MOOCs are an emerging form of online education. In 2008, MOOCs grew out of Siemens and Downes' online courses on connectionism (Downes, 2008). In 2013, five Coursera courses were accredited by the American Education Council, which means that the certificate of MOOC has the same validity as the certificate of traditional education (Kolowich, 2013). That same year, MOOCs entered China. MOOC stands for Massive Open Online Course, and MOOCs are the mainland transliteration of MOOCs.

The first letter, "M," stands for Massive, either the number of people studying the Course or the range of activities involved. The second letter, "O," stands for "Open." It means that learners, regardless of nationality, can register for the courses they are interested in with just one email address. The learning atmosphere is rich. The third letter, "O," stands for "Online," which means to complete the Course on the Internet. You only need to have access to the Internet conditions and equipment. You can use the online learning system anytime and anywhere to self-manage your learning progress and participate in learning activities. The fourth letter, "C," stands for Course, meaning the Course (Lindsey et al., 2014).

At present, MOOC's application trend in adult higher education has become increasingly obvious. More and more adult universities, colleges of continuing education, Radio and television universities, and Open universities have opened MOOC courses, registered students have flooded in, and MOOC has become one of the means to improve the influence of schools (Luo, 2018). The arrival of the MOOC era has brought challenges and great opportunities to the education sector. With the aid of MOOCs, China's adult education sector should seize this chance to grow adult education in-depth more quickly (Shang & Fu, 2015).

However, 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. 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.

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.

Perceived usefulness is a measure of how much users feel utilizing an information system will improve their talents and whether they think using it would benefit them, according to the technology adoption paradigm put forward by Venkatesh and Davis (2000). The key driver for user satisfaction and ongoing use of information systems, according to Bhattacherjee and Premkumar (2004), is perceived usefulness. This notion is a crucial determinant of consumer acceptability and technological adoption and plays a significant role in other models. According to Hu et al. (2007), the perception of perceived usefulness means that when a user operates an information technology product, he or she views whether the product can benefit him or herself based on his or her feelings.

Davis (1986) found via empirical study that perceived usefulness significantly influenced people’s behavioral intentions, accounting for more than 50% of the variation in behavioral intentions. Despite having little effect on real ease of use, perceived ease of use greatly influenced behavioral intention. The influence of outside circumstances on behavioral intention can only be mitigated by attitude.

Perceived usefulness was brought into the context of websites. As a result, variable by Venkatesh et al. (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 diagnostic, contending that “the utility of the website experience in determining product quality and product performance” may be used to quantify overall diagnostic at the product level.

Sarkar and Khare (2017) examined the impact of consumers’ personality traits, such as value consciousness and coupon proneness, on ATT toward online shopping. A self-administered questionnaire was used to collect data, and structural equation modeling was used to analyze the data. The results indicate that PU and perceived risk influenced ATT toward online shopping. Value consciousness and coupon proneness significantly moderate the impact of PU and perceived risk on ATT toward online shopping. 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

Nielsen (1993) asserts that a user's capacity to utilize technology is directly connected to how much effort they put into using it. He claims that perceived ease of use relates to how little effort is needed to utilize a system.

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.

Gefen and Straub (2000) categorized information technology and goods according to their intended uses once the acceptance model was implemented. The ease of use of information technology or products might significantly improve their utilization only when the technology or product is used for the purpose for which it was designed. They made the observation, however, that the simplicity of use of such things is less significant when such products, such as information technology or commodities, are used as a tool to accomplish other aims (such as online shopping, where the primary purpose is to save time).

Hsieh and Wang (2007) have shown that prolonged use depends on perceived ease of use. Additionally, several articles based on the TAM theory propose perceived ease of use to examine the influence on use intention or behavior (Chen, 2019). 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). By including significant external elements in the technology acceptance model, Faria et al. (2017) evaluated users' adoption rate and acceptability in e-learning systems. It is determined via empirical study that there is some relationship between platform features and users' perceived ease of use and self-efficacy.

The propensity to utilize online learning platforms was significantly influenced by compatibility, self-utility, perceived usefulness, and satisfaction (Hung & Cho, 2010). According to Chen (2019), perceived usefulness and satisfaction substantially influence perceived usefulness, and perceived usefulness and perceived ease of use have a large impact on continuing use intention (Cho et al., 2009). Thus, a hypothesis is proposed:

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

2.3 Subjective Norm

Fishbein and Ajzen (1975) defined "subjective norms" as individuals forming their norms through the perception of behavioral norms and expectations of the surrounding environment. They verified their positive influence on individual behavioral intention through empirical research. Subjective norms refer to external pressure on individuals to perform behaviors (Venkatesh & Davis, 2000).

The four components of the theory of planned behavior are the desire to utilize actual conduct, attitude, subjective norm, and behavior (Fishbein & Ajzen, 1975). The technological acceptance model (TAM) was expanded by Venkatesh and Davis (2000), who suggested the TAM2, in which external factors were divided into two categories: cognitive instrumental process and social impact, with subjective norms included in the latter.

According to social identity theory, people hope to adjust their behaviors according to group norms (Kitcharoen & Vongurai, 2021). When their peers choose to reduce or even give up using a certain short video platform, users will be driven by subjective norms to adjust their behaviors in order to make them feel more "fit in." (Osatuyi & Turel, 2020)

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 (2015) investigated the elements affecting teachers' adoption of the flipped classroom using the Rational Behavior Theory (TRA). He did more than show how behavioral attitudes, arbitrary standards, and perceived actions affect usage intention. 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 (2000) refers to performance expectation as the extent to which users believe technology may help them do their tasks more effectively. As defined by Pedersen (2005), performance expectations pertain to the notion that people may enhance other elements of their lives in addition to their professional performance when using information systems or technology.

According to Davis and Venkatesh (1996), performance expectation is the degree to which users consider a particular technology to assist them in achieving improved job performance. This perception includes concepts like perceived utility, the expectation of outcomes, and task applicability.

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. Wang et al. (2020), based on the COVID-19 outbreak, empirical research on how people utilize short government films during public crises.

In his research on public acceptance of automated traffic roads using UTAUT, Merat et al. (2016) they concluded that performance expectations, effort expectations, social influence, promotion circumstances, and hedonic motivation influence the public's desire to utilize automated traffic roads. 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 need for novelty, challenge, expanding one's capacity, exploration, and learning is known as intrinsic motivation. The pursuit and accomplishment of intrinsic wants and objectives may be sparked by intrinsic motivation, which can encourage individuals to engage in engaging activities and advance their ongoing development. According to the self-determination theory, intrinsic motivation is a person's innate inclination to pursue certain behaviors to satisfy their intrinsic wants, as Ryan and Deci (2000) noted in another research. Self-consciousness, which plays a significant part in behavior self-management, is intrinsic motivation. However, owing to individual variations, people have varying levels of innate drive and intrinsic needs, which may moderate how people behave.

Perceived pleasure is the innate drive for people to use information technology; Davis et al. (1989) defined it as "the level of enjoyment provided by the use of certain information technology in addition to the work effect" in the TAM model.

Latham and Locke (1991) pointed out that A goal is a desire consciously set by people through thinking. Set goals that stimulate people's intrinsic motivation to take action to achieve their wants or needs; In the case of high levels of intrinsic motivation, a strong sense of self-management motivates users to think positively and choose useful ways to achieve their goals.

Locke and Latham (2006). A high level of intrinsic motivation means 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.

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). 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. So, it can be hypothesized that:

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

2.6 Behavioral Intention

Fishbein and Ajzen (1975) operationalized behavioral intention into the possibility of individual action, believing that behavioral intention is people's expectation of their behavior in a given environment. However, other researchers believe there is a difference between what one intends and expects to do. 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).

Fishbein and Ajzen (1975) divided behavioral intention into repurchase int, word-of-mouth 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."

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

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 user 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.

Scholars mainly build models to study the effects of inherent variables in models and various external variables introduced on user behavior. Fishbein and Ajzen (1975) believed that perceived behavioral control would affect individuals' use of behavioral intention, expanded the original rational behavior theory, added perceived behavioral control variables, he put out the behavior planning hypothesis, which claimed that a person's behavioral intention was influenced by their behavioral attitude, subjective norms, and perceived behavioral control. The critical function of behavior control in behavior is outlined, along with three internal psychological components of the model that are clearly stated as modulating the effect of external conditions on user behavior.

Based on the notion of rational conduct, Davis et al. (1989) suggested a technology acceptance model for information system users. Additionally, he evaluated the impact of external factors, perceived utility and reported ease of use on attitudes, behavioral intentions, and actions. He also looked at how attitudes influence intentions and behaviors.

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.

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) believe that frame is the 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).

Secondly, Davis et al. (1989) illustrates how important it is for this model's predictive power that variables' behavioral intentions be taken into account. 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.

Once more, 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).

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.

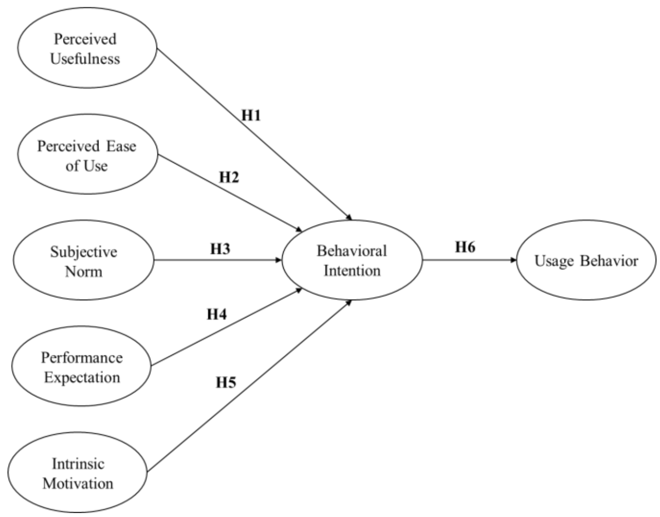

Figure 1: Conceptual Framework

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 behavioral.

3.2 Research Methodology

Gathering data is the first step. This study developed a questionnaire on the influencing elements of MOOCs 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 MOOCs samples surveyed in Dazhou 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 DAzhou.

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. The collected data can be analyzed online by SPSS or SPSSAU in the questionnaire star or generated. After the SAV file or Excel file, use the appropriate data analysis software on your computer for analysis. In this research, the reliability and validity of the statistical samples were examined using SPSS software. The analysis showed that the scale test question's KMO value was more than 0.7. The questionnaire was scientific and effective and could be distributed on a large scale.

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, AMOS 22.0 or SPSSAU software will be used in this study for SEM analysis.

3.3 Population and Sample Size

The target population is adult students in higher education students from Dazhou 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. This study selected 500 valid samples in Dazhou City, Sichuan Province.

3.4 Sampling Technique

In order to investigate the usage intention of adult higher education students, three methods of purposive, stratified random, and convenience sampling, were selected. In this study, 500 adult students in higher education students were selected from Dazhou City by judgment sampling. For purposive sampling, at least 500 samples were collected from the above areas. In order to meet the requirements of stratified sampling, three counties were selected from the municipal districts and counties under the city's jurisdiction 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, of the 500 samples collected in Dazhou, at least 153, 220, and 127 were from the corresponding areas of Tongchuan District, Dachuan District, and Kaijiang County. Finally, a convenience sampling was to distribute online and offline questionnaire the target respondents who were available and willing to answer.

Table 1: Sample Units and Sample Size

Area	Population Size	Proportional Size
Dazhou	Tongchuan District	153
	Dachuan District	220
	Kaijiang County	127
Total	**3**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

This study distributed questionnaires to respondents with MOOCs experience from three areas in Dazhou City. During the survey, demographic information such as gender, age, and occupation of the respondents was aggregated. Five hundred valid questionnaires were collected in Dazhou City for the following research.

This section provides a statistical description of the basic personal information of 500 respondents in Dazhou City. The demographic characteristics of the respondents are summarized as follows: In the Dazhou sample, in terms of gender, most respondents were female, accounting for 66.8%, while male respondents accounted for 33.2%. From the perspective of age, most respondents were concentrated in the age group of 26-35, with 288 people in this age group, accounting for 57.6%. People aged 36 and above accounted for 26.6%, and those aged 18-25 accounted for 15.8%. In terms of student majors, the sample of Dazhou is mainly liberal arts students, the number of students is 219, accounting for 43.8%; The second is science students, whose number is 146, accounting for 29.2%; There were 55 engineering students, accounting for 11.0%, and 80 other majors, accounting for 16.0%. From the occupation of the respondents, nearly half of the respondents are enterprise staff, whose number is 169, accounting for 33.8%; The number of people working for the government or public institutions was 152, accounting for 30.4%; 86 people were self-employed, accounting for 17.2%; In addition, the number of freelancers in this survey reached 47, accounting for 9.4%; The remaining staff accounted for 9.2%. From the perspective of income level, the monthly income level of the surveyed group is mostly between 3000-8000 yuan, and a total of 252 people's monthly income level is concentrated in this range, accounting for 50.4%. In addition, 112 people with a monthly income of less than 3,000 yuan were surveyed, accounting for 22.4%; The monthly income level of more than 8,000 yuan accounted for 136 people, accounting for 27.2%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	166	33.2%
	Female	334	66.8%
Academic Year	18-25 years old	79	15.8%
	26-35 years old	288	57.6%
	Age 36 and older	133	26.6%
Professional category	Liberal arts	219	43.8%
	Science type	146	29.2%
	Engineering type	55	11.0%
	other	80	16.0%
Occupational type	Enterprise personnel	169	33.8%
	Government or public institution	152	30.4%
	Individual trader	86	17.2%
	freelancer	47	9.4%
	other	46	9.2%
Monthly income	Less than 3000 yuan	112	22.4%
	3000 yuan - 8000 yuan	252	50.4%
	Over 8000 yuan	136	27.2%

Source: Constructed by author

4.2 Confirmatory Factor Analysis (CFA)

In this study, confirmatory factor analysis (CFA) was performed, and Cronbachα (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	0.836	0.701-0.784	0.839	0.566
Perceived ease of use (PEOU)	Nielsen (1993)	3	0.814	0.772-0.772	0.816	0.596
Subjective Norm (SN)	Fishbein and Ajzen (1975)	4	0.818	0.662-0.854	0.826	0.546
Intrinsic Motivation (IM)	Ryan and Deci (2000)	3	0.869	0.800-0.868	0.869	0.690
Performance Expectations (PE)	Venkatesh and Davis (2000)	4	0.839	0.731-0.779	0.839	0.566
Behavioral intention (BI)	Lee (2010)	3	0.775	0.632-0.798	0.774	0.535
Usage Behavior (UB)	Davis et al. (1989)	4	0.800	0.641-0.737	0.803	0.505

As shown in Table 4 above, comparing the goodness-of-fit index of the Dazhou sample and its acceptance range found that each index could meet the model fitting conditions and did not need to be fitted again. Specifically, in this sample, CMIN/DF=2.105, GFI=0.923, AGFI=0.901, NFI=0.918, CFI=0.955, TLI=0.947, RMSEA=0.047. Therefore, this study has passed the CFA test.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.105
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.923
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.901
NFI	≥ 0.80 (Wu & Wang, 2006)	0.918
CFI	≥ 0.80 (Bentler, 1990)	0.955
TLI	≥ 0.80 (Sharma et al., 2005)	0.947
RMSEA	< 0.08 (Pedroso et al., 2016)	0.047
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 of sample 1 are 0.752, 0.772, 0.739, 0.831, 0.752, 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	**0.752**						
PEOU	0.434	**0.772**					
SN	0.692	0.343	**0.739**				
IM	0.521	0.335	0.500	**0.831**			
PE	0.628	0.345	0.351	0.406	**0.752**		
BI	0.634	0.361	0.490	0.502	0.637	**0.731**	
UB	0.497	0.343	0.385	0.426	0.394	0.428	**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. Table 6 confirms the acceptable fit of structural model.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/df	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	3.988
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.859
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.814
NFI	≥ 0.80 (Wu & Wang, 2006)	0.850
CFI	≥ 0.80 (Bentler, 1990)	0.882
TLI	≥ 0.80 (Sharma et al., 2005)	0.856
RMSEA	< 0.08 (Pedroso et al., 2016)	0.077
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	0.445	7.628*	Supported
H2: PEOU→BI	0.094	2.073*	Supported
H3: SN→BI	0.403	6.598*	Supported
H4: PE→ BI	0.636	8.998*	Supported
H5: IM→BI	0.308	6.129*	Supported
H6: BI→ UB	0.515	7.275*	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. In sample 1, all six hypotheses proposed in this study have been verified. The standardization coefficient of **H1** was 0.445, and the t value was 7.628. The standardization coefficient of **H2** is 0.094, and the t value is 2.073. The standardization coefficient of **H3** is 0.403, and the t value is 6.598. The standardization coefficient of **H4** is 0.636, and the t value is 8.998. The standardization coefficient of **H5** is 0.308, and the t value is 6.129*. The standardization coefficient of **H6** is 0.515, and the t value is 7.275.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

This study aims to analyze the important factors that affect the behavioral intention and use behavior of adult higher education students in Dazhou. MOOCs have changed people's learning methods and greatly facilitated learning activities. Under the epidemic's influence, MOOCs' importance and popularity have further increased. Therefore, to stimulate students' use behavior, it is necessary to study the influencing factors of MOOC behavior intention and use behavior. Based on previous studies, this study constructed a research framework. It proposed six research hypotheses to investigate whether perceived usefulness, perceived ease of use, subjective norms, performance expectations, and intrinsic motivation have direct or indirect effects on MOOCs' behavioral intention and usage behavior. The determinants of this study are derived from the technical model proposed by Davis et al. (1989). The proposed motivation model and the UTAUT model proposed by Venkatesh et al. (2003).

The objects of this study are adult higher education students with MOOCs experience in three different regions of Dazhou, China. In order to ensure the accuracy and scientificity of the study, the purpose sampling and stratified sampling were carried out. This study included adult higher education students in 3 counties (cities, districts) of Dazhou City and proportionally allocated the sample number to each region. In order to ensure the effectiveness of the questionnaire and facilitate the analysis, this study adopted the Likert scale to set the questionnaire and passed the goal consistency (IOC) test. After data recovery, this study analyzed the data using Cronbachα reliability, kurtosis skewness test, multiple linear analysis, etc., to ensure the reliability of the questionnaire samples. On this basis, CFA and SEM are used to analyze and discuss the influencing factors of adult higher education students' MOOCs behavior intention and usage behavior and verify the validity of the framework model. The analysis results show that all six hypotheses proposed in this study have been verified. It can be concluded that performance expectation is the strongest predictor of MOOCs' behavior intention and usage behavior. Therefore, helping users establish performance expectations is the key to stimulating MOOCs' intention and usage behavior.

5.2 Recommendation

Based on the analysis of three survey samples in Dazhou City, this study believes that perceived ease of use, perceived usefulness, subjective norms, intrinsic motivation, performance expectation, and behavioral intention influence behavioral intention and usage behavior of MOOC platforms. Gao (2011) used the UTAUT model to study the influencing factors of teachers' continuous use in online teaching and believed that performance expectations significantly impacted the intention of continuous use. Zhang (2015) also believe that performance expectation positively impacts the behavioral intention of mobile learning. 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, institutions of higher learning must focus on improving learners' performance expectations in adult MOOCs.

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 Dazhou 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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