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Explaining Postgraduates' Behavior on the Use of Massive Open Online Courses in Sichuan, China

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Abstract

Purpose: Massive Open Online Courses (MOOC) learning has been remarkably adopted due to COVID-19 in China. Thus, this study aims to examine the factor impacting behavioral intention and behavior of postgraduates in their use of MOOCs in Sichuan. The key constructs are self-efficacy, perceived usefulness, perceived ease of use, attitude, behavioral intention, subjective norm, and behavior. **Research design, data, and methodology:** This study applied a quantitative approach to distributing questionnaires to 500 postgraduates using MOOCs at Sichuan University. The sampling techniques are judgmental, convenience, and snowball sampling. The content validity was verified by the item-objective congruence (IOC) index, and the reliability test was employed by Cronbach alpha through a pilot test (n=50). In addition, confirmatory factor analysis (CFA) and structural equation modeling (SEM) were analyzed. **Results:** Self-efficacy has a significant impact on perceived usefulness and perceived ease of use. Perceived usefulness and perceived ease of use significantly impact attitude. Attitude and subjective norms significantly impact behavioral intention toward behavior. On the contrary, this study found a non-supported relationship between perceived usefulness and perceived ease of use. **Conclusions:** Educators should seek ways to improve students' motivations and MOOCs' system to be more efficient, considering key factors impacting the use behavior.

Keywords : MOOCs, Attitude, Behavioral Intention, Subjective Norm, Behavior

JEL Classification Code: E44, F31, F37, G15

1. Introduction

MOOC stands for Massive Open Online Course, a massive open online course. This model mainly uses the classroom videos of major universities as the access to content and puts these videos, course materials, and reference materials on the Internet for everyone to learn (Shaari et al., 2018). As most of the content comes from the classrooms of famous universities, such as Stanford University, MIT, Harvard, etc., the number of users learning through the MOOC platform initially showed explosive growth. However, as the learning effect of the MOOC model was tracked and studied in depth, it was found that the learning effect of MOOC was far from the expectation of classroom teaching, mainly in the aspects of application and lack of comprehensive ability. Typical representatives of this model include Coursera, founded by a professor from Stanford University, and edX, a web-based online teaching platform launched by MIT and Harvard University (Guri-Rosenblit, 2006).

In terms of user scale, the size of China's online education users reached 269 million in 2019, up 33.83% from 201 million in 2018. In this regard, Chen Liteng, an analyst of life service e-commerce at the e-commerce research Centre of the Net Economic Society, pointed out that the penetration rate of online education is about 10%, and there is a very broad upside in the future. Furthermore, from the perspective of the industry's rigid demand and development prospects,

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this will be a market with a trillion-dollar scale (Textor, 2021).

Overall, the development of online education is closely related to the level of technological development, changes in educational philosophy, and the upgrading of users' educational needs and lifestyle changes. As the scale of Internet education continues to expand. The business model becomes more stable, the learning needs of education users deepen, consumer awareness awakens, and consumer power upgrades, China's online education has now entered an era of intelligent education with vertical segmentation of learning fields, rich and diverse learning methods, open sharing of resources and realization of educational content (Stoian et al., 2022).

Although online education has great prospects for development, many things could still be improved in the current development process. The pain points of the online education industry are focused on the direct user experience and platform services for users at both the teacher and student ends. How to protect the copyright interests of the original course content of the online teachers, how to improve the audit specification of the courses and online teachers, how to better protect the user experience from the platform product and service level, how to better match the content with the users quickly and accurately, and how to attract the retention of the student users in the long term are all points that need further improvement or breakthrough in the industry at this stage. In addition, the new education ecosystem needs to address the plight of learners' learning ability and physical and mental health, the plight of education quality due to the contradiction between supply and demand of high-quality online education, and the plight of management under the explosive development of online education (Basar et al., 2021).

Based on learners' massive learning behavior data on MOOC online learning platforms, most researchers' research perspectives focus on analyzing learners' learning behavior characteristics but need to be more comprehensive empirical research on the factors influencing MOOC online learning behavior. In order to fully explore the learning behavior data of MOOC online groups and investigate the relevant factors affecting learners' MOOC online learning, provide a basis for the subsequent improvement of MOOC online learning behavior, and guarantee the learning effectiveness of learners, this study takes undergraduate students in Sichuan as the research object and analyses and marquises the relationship between MOOC learners' behavioral intention and actual behavior. Therefore, the research model is built upon the key constructs, including self-efficacy, perceived usefulness, perceived ease of use, attitude, behavioral intention, subjective norm, and behavior.

2. Literature Review

2.1 Self-Efficacy

Self-efficacy is viewed as an individual conviction that can mobilize capabilities in organization and execution. Self-efficacy characterizes a person’s observed capability to accomplish an expected level of performance (Feng et al., 2022). Self-efficacy plays a vital role in influencing what people will do and the degree of effort of the people. Self-efficacy is indispensable to students in overcoming difficulties (Achenreiner et al., 2019). Some scholars say computer self-efficacy directly relates to perceived usefulness (Holden & Rada, 2011). In the context of adopting high-technology innovations, self-efficacy is particularly related. The more individuals have confidence in their abilities to master or use technological innovation, the more they anticipate reaping the benefits from such technology. Individuals generally perceive a technology to require less effort to use as they gain more knowledge and confidence through direct experience with the technology (Kulviwat et al., 2014). Given the strong empirical support for the relationship between self-efficacy, perceived usefulness, and perceived ease of use, the following hypotheses are proposed:

H1: Self-efficacy has a significant impact on perceived usefulness.

H2: Self-efficacy has a significant impact on perceived ease of use.

2.2 Perceived Ease of Use

Perceived ease of use (PEOU) refers to the ease of dictating the learning and navigating the system's usage among users (Davis, 1989). Furthermore, it represents the individuals' intrinsic motivation to act or perform at some level of behavior (Gumussoy et al., 2008). Perceived ease of use is an important antecedent of TAM. It shows individuals' effortless intentions towards using new technology and the ease it will take to human life (Davis, 1989). We can see that if users find the system easy to use, they will see the usefulness of the learning platform and be willing to participate in the technology (Arteaga Sánchez et al., 2013). By summarizing previous research, perceived ease of use positively affects the perceived usefulness of e-learning systems (Shao, 2018). Many researchers have used the TAM model in their learning studies to discuss the relationship that perceived ease of use has a significant effect on individuals' behavioral intentions to use learning systems and have found that attitude is an important bridge to this relationship, meaning that perceived ease of use has a clear role in attitude (Liu et al., 2009; Ong et al., 2004; Sheng et al., 2008). Based on these assumptions, this study proposes the following hypotheses:

H3: Perceived ease of use has a significant impact on perceived usefulness.
H5: Perceived ease of use has a significant impact on attitude.

2.3 Perceived Usefulness

In the technology acceptance model (TAM), perceived usefulness (PU) is the extent how which innovation will increase job performance (Davis, 1989). PU is a particular system to improve their role quality (Mathwick et al., 2001). PU signals the level of beliefs when individuals use the systems to perform work (Saade & Bahli, 2005). In addition, PU is the confidence level of users to apply the technology to their work and assist them to work more efficiently (López-Nicolás et al., 2008). TAM is a main variable that can lead to the intention to use the system and indicates about 40% of the construct in one's behavioral intention of using new technology (Jaradat & Al-Mashaqba, 2014). PU is argued to be a factor in a user's intention to accept innovation (Venkatesh & Davis, 2000). A belief influences the attitude toward using a new system in the perceived usefulness of a person's use of technology (Letchumanan & Tarmizi, 2011). The researcher also explored the behavioral intentions of FIFA instructors using multimedia materials for educational purposes. This study found that perceived usefulness had a significant effect on users' attitudes (Gallardo et al., 2013). Based on the above discussions, a hypothesis is demonstrated:
H4: Perceived usefulness has a significant impact on attitude.

2.4 Attitude

Attitude reveals the feeling of the individuals no matter whether they accept the behavior (Al-Debei et al., 2013) and accounts for a person's preference for an action or a product (Ozgen & Kurt, 2013). Attitude is a personal view of an object, like or dislike. People were much easier to adopt a behavior they approved of (Armitage & Conner, 2001). However, that attitude was the most convincing predictor of purchase desire (Khan & Azam, 2016). It was still noticed that consumers' attitudes toward products were directly relevant to their willingness to consume (Afendi et al., 2014). It has also been confirmed that attitudes also play a significant role in consumers' decisions to purchase. (Abd Rahman et al., 2015). The behavioral intention to use the system is influenced by attitudes toward using the system (Letchumanan & Tarmizi, 2011). A causal relationship between attitudes and behavioral intentions has been demonstrated through a study of membership organizations (Ki & Hon, 2012). The study of external indicators in the TAM model determines that when individuals use new technologies, the user's attitude impacts behavioral intentions (Jain et al., 2020). Hence, the current research focuses on the following hypothesis:
H6: Attitude has a significant impact on behavioral intention.

2.5 Subjective Norm

Subjective norm is somebody's perception of if people significant to the person think the behavior should be executed (Teo & Beng Lee, 2010). Furthermore, it means a person's perception that most people who are related to him or she think whether he should behave in a certain way (Fishbein & Ajzen, 1975). It is based on the normal conviction about people's expectations (Cheon et al., 2012). Studies reveal that student's views of the professor changed related to using computers when the instructor is schooling (Bellone & Czerniak, 2001). There is enough research revealing that people are affected by the behavior of others, which can cause everyone to abide by the rule the group is abiding by (Li & Kitcharoen, 2022). The relationship between Subjective norms and behavioral intentions was demonstrated in a study examining the behavior of Muslim consumers who patronize retail shops (Mohd Suki & Abang Salleh, 2018). In a study of parental behavior toward anti-junk food consumption, researchers found that subjective norms influenced behavioral intentions (Yarimoglu et al., 2019). While exploring consumers' intentions to use smart libraries, researchers concluded that subjective norms positively and directly impact behavioral intentions (Yu & Huang, 2020). Therefore, this research can make the following assumption:
H7: Subjective norm has a significant impact on behavioral intention.

2.6 Behavioral Intention

Behavioral intention can perceive a person's intention to use services (Yang et al., 2016) and predict real usage behavior (Kijsanayotin et al., 2009). Behavioral intentions reflect the degree to which people work hard (Ajzen, 1991). That means the possibility of people performing in a certain way (Fishbein & Ajzen, 1975). It is the crucial prerequisite of an individual's real action (Zhang et al., 2012), but there is a difference between behavioral intention and actual behavior (Yeh, 2019). People who prefer the service will likely be adopters (Leong et al., 2013). In the TAM model, it has been shown that behavioral intention is one of the determinants of behavior (Davis, 1989). The strong link between behavioral intentions and behavior is supported in the context of entrepreneurship research (Kautonen et al., 2013). We can also learn from studying the TPB model that behavioral intention directly triggers behavior (Ajzen, 1991). Thus, a proposed hypothesis is indicated:
H8: Behavioral intention has a significant impact on behavior.

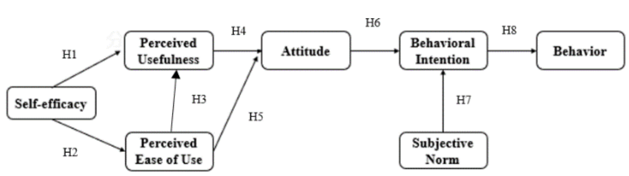
2.7 Behavior

Behavior is something a person does that can be observed, measured, and repeated and is how a person conducts himself/herself toward situations and others. (Fishbein & Ajzen, 1975).The theory of rational activity argues that behavior is a controllable factor under personal willpower (Ajzen, 1991). Behavior is not simply movement but must be defined by its function. Also, our understanding of behavior must agree with evolutionary theory (Baum, 2013). Behavior is the internally coordinated response (action or inaction) of an entire organism (individual or group) to internal and external stimuli, excluding responses that are more easily understood as developmental changes (Levitis et al., 2009). Behavior does not refer only to physical activity but rather represents a complex intermingling of affective and cognitive processes that guide decisions in the short- and long-term (Heimlich & Ardoin, 2008).

3. Research Methods and Materials

3.1 Research Framework

In this research, we delve into the theoretical framework to construct a fundamental conceptual framework. Our exploration draws upon the works of Fatima et al. (2017), Arteaga Sánchez et al. (2013), Hsiao and Tang (2014), and Lee (2006). These notable theoretical frameworks serve as the foundation for all variables encompassed within the conceptual framework. These variables include self-efficacy, perceived usefulness, perceived ease of use, attitude, behavioral intention, subjective norm, and behavior. Notably, four significant previous research frameworks have been instrumental in supporting and enhancing the development of the conceptual framework. As illustrated in Figure 1, this study establishes a robust conceptual framework.



Fiqure 1: Conceptual Framework

H1: Self-efficacy has a significant impact on perceived usefulness.
H2: Self-efficacy has a significant impact on perceived ease of use.
H3: Perceived ease of use has a significant impact on perceived usefulness.
H4: Perceived usefulness has a significant impact on attitude.
H5: Perceived ease of use has a significant impact on attitude.
H6: Attitude has a significant impact on behavioral intention.
H7: Subjective norm has a significant impact on behavioral intention.
H8: Behavioral intention has a significant impact on behavior.

3.2 Research Methodology

Data collection from samples often involves the utilization of questionnaires, which stand as one of the most prevalent methods. Our questionnaire comprises three primary sections. The initial segment encompasses screening questions, ensuring suitability for participation. The subsequent section encompasses statistical data pertaining to the population under study. Finally, the third section employs a five-point Likert scale to measure the study's variables. To gather data, we distributed questionnaires to 500 postgraduate students at Sichuan University who utilized MOOCs for their studies.

Prior to distribution, the questionnaires underwent evaluation using the index of item-objective congruence (IOC), wherein all scale items scored above 0.6 as rated by three experts. Additionally, a pilot test was conducted with a sample size of 50, employing the Cronbach alpha coefficient reliability test. The results indicated a strong internal consistency of all items, surpassing a threshold of 0.6 (Bland & Altman, 1997).

Once the data collection is complete, we will subject it to analyses of structural validity, including convergent validity and discriminant validity. Furthermore, structural equation modeling will be applied to the collected data, encompassing both measurement and structural models. The outcomes of these analyses will serve to test the model and all hypotheses proposed in this study.

3.3 Population and Sample Size

This study focuses on undergraduate students at Sichuan University in China who utilize MOOCs for their educational pursuits. To determine an appropriate sample size, calculations were performed using a calculator, resulting in a minimum sample size of 425. Furthermore, for the model structure, the minimum sample size was determined to be 162. However, it was recommended to have a minimum sample size of 425 (Soper, n.d.). In consideration of these factors and the study's requirements, the researchers opted to select a sample size of 500 for this investigation.

3.4 Sampling Technique

The sampling procedure employed in this study encompasses three distinct steps: judgmental sampling, convenience sampling, and snowball sampling. Initially, judgmental sampling was utilized to select postgraduate students studying at Sichuan University in China who actively engage with MOOCs for their learning endeavors. This method allowed for a targeted selection based on specific criteria.

Subsequently, convenience sampling was employed to distribute both online and paper questionnaires at the university campus. This approach was chosen due to its practicality and structured nature, as it provided a more accessible and active location for undergraduate students. By focusing on individuals who were willing to respond to the survey questions and readily available, this method aimed to mitigate potential accuracy issues associated with low response rates.

Furthermore, snowball sampling was utilized to disseminate the questionnaires via phone and email through colleagues working at Sichuan University. These colleagues, who were frontline teachers responsible for instructing undergraduate students, played a pivotal role in reaching out to their respective students and facilitating the distribution of the questionnaires.

By combining these three sampling methods, the study aimed to attain a diverse and representative sample of participants from the target population.

4. Results and Discussion

4.1 Demographic Information

According to Table 1, the demographic results of 500 respondents show that 298 were males and 202 were females, accounting for 59.6 percent and 40.4 percent, respectively. Most respondents are Master's Degree students of 83 percent, and Doctorate students of 17 percent. The majority group of students use MOOCs more than 6-8 hours per week at 44.6 percent.

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	298	59.6%
	Female	202	40.4%
Program of Study	Master's	415	83.0%
	Doctorate	85	17.0%
Frequency use of MOOCs	3 hours or below/ week	28	5.6%
	4-6 hours/week	121	24.2%
	6-8 hours/week	223	44.6%
	Over 8 hours/ week	128	25.6%

4.2 Confirmatory Factor Analysis (CFA)

The measurement model presented in Table 2 employed Confirmatory Factor Analysis (CFA) as part of a Structural Equation Model (SEM). The initial step involved subjecting the measurement model to CFA within the SEM framework. The results of the CFA demonstrated the significance of all items within each variable and revealed factor loadings that confirmed the presence of discriminant validity. To assess the internal consistency of the items, a Cronbach alpha coefficient reliability test was conducted, indicating strong internal consistency with values equal to or above 0.6 (Bland & Altman, 1997). Following the guidelines outlined by Stevens (1992), item loadings above 0.40 with a p-value below 0.05 were deemed satisfactory for Confirmatory Factor Analysis. Furthermore, in line with the recommendations of Fornell and Larcker (1981), the convergent validity of the construct was considered adequate if the Average Variance Extracted (AVE) exceeded 0.5 and the Composite Reliability (CR) surpassed 0.6. By utilizing these approaches and adhering to established criteria, the measurement model was rigorously evaluated to ensure its robustness and validity.

Table 2: 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
Self-efficacy (SE)	Fatima et al. (2017)	3	0.773	0.713-0.747	0.774	0.533
Perceived Usefulness (PU)	Arteaga Sánchez et al. (2013)	4	0.768	0.642 -0.712	0.769	0.455
Perceived Ease of Use (PEOU)	Arteaga Sánchez et al. (2013)	3	0.885	0.774-0.853	0.857	0.666
Attitude (ATT)	Arteaga Sánchez et al. (2013)	4	0.776	0.647-0.710	0.777	0.466
Behavioral Intention (BI)	Hsiao and Tang (2014)	3	0.881	0.810 -0.883	0.881	0.712
Subjective Norm (SN)	Hsiao and Tang (2014)	3	0.884	0.819 -0.891	0.883	0.716
Behavior (BEH)	Hsiao and Tang (2014)	2	0.790	0.785 -0.832	0.791	0.654

The measurement model is confirmatory factor analysis (CFA), which describes the relationship between observed variables and latent variables. In Table 3, the measurement model fit was tested in a statistical software.

The model ensures acceptable fit without adjustement, including CMIN/DF=1.391, GFI= 0.955, AGFI = 0.939, NFI=0.950, CFI = 0.985, TLI =0.982, IFI=0.986, and RMSEA = 0.028.

Table 3: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	261.592/188 = 1.391
GFI	≥ 0.90 (Hair et al., 2006)	0.955
AGFI	≥ 0.90 (Hair et al., 2006)	0.939
NFI	≥ 0.85 (Kline, 2011)	0.950
CFI	≥ 0.85 (Kline, 2011)	0.985
TLI	≥ 0.85 (Kline, 2011)	0.982
IFI	≥ 0.85 (Kline, 2011)	0.986
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.028
Model summary		**Acceptable Model Fit**

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 = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

As per the guidelines outlined by Fornell and Larcker (1981), the assessment of discriminant validity involved calculating the square root of each Average Variance Extracted (AVE). The findings of this study as of Table 4 indicated that the value of discriminant validity surpassed all inter-construct/factor correlations, thus providing supportive evidence. With the establishment of both convergent and discriminant validity, there is sufficient evidence to establish construct validity.

Table 4: Discriminant Validity

	ATT	SE	PU	PEOU	SN	BEH	BI
ATT	**0.683**						
SE	0.483	**0.730**					
PU	0.569	0.536	**0.675**				
PEOU	0.230	0.220	0.186	**0.816**			
SN	0.638	0.539	0.590	0.281	**0.846**		
BEH	0.425	0.105	0.293	0.179	0.296	**0.809**	
BI	0.623	0.553	0.540	0.243	0.749	0.311	**0.844**

Note: The diagonally listed value is the AVE square roots of the variables

4.3 Structural Equation Model (SEM)

The structural equation model determines the causal relationship between variables. As shown in Table 5, the statistical results were acceptable, including CMIN/DF =2.911, GFI = 0.914, AGFI = 0.901, NFI=0.889, CFI = 0.924, TLI = 0.912, RMSEA = 0.062.

Table 5: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	585.080/201 = 2.911
GFI	≥ 0.90 (Hair et al., 2006)	0.914
AGFI	≥ 0.90 (Hair et al., 2006)	0.901
NFI	≥ 0.85 (Kline, 2011)	0.889
CFI	≥ 0.85 (Kline, 2011)	0.924
TLI	≥ 0.85 (Kline, 2011)	0.912
IFI	≥ 0.85 (Kline, 2011)	0.924
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.062
Model summary		**Acceptable Model Fit**

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 = normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, IFI = Incremental Fit Index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

This study assessed the correlation between the independent and dependent variables proposed in the hypotheses by examining standardized path coefficients and t-values. The analysis presented in Table 6 considered p-values below 0.05 as statistically significant. As a result, H1, H2, H4, H5, H6, H7, and H8 were found to be supported, while H3 did not show support.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SE→PU	0.553	8.504*	Supported
H2: SE →PEOU	0.223	4.013*	Supported
H3: PEOU →PU	0.065	1.251	Not Supported
H4: PU→ATT	0.581	8.461*	Supported
H5: PEOU→ATT	0.124	2.464*	Supported
H6: ATT→BI	0.249	6.113*	Supported
H7: SN→BI	0.793	17.337*	Supported
H8: BI→ BEH	0.302	4.721*	Supported

Note: *=p-value<0.05

From Table 6, the results are summarized as follows:

H1: Self-efficacy has a significant impact on perceived usefulness with standardized path coefficient of 0.553 and t-value of 8.504.

H2: Self-efficacy has a significant impact on perceived ease of use with standardized path coefficient of 0.223 and t-value of 4.013.

H3: Perceived ease of use has no significant impact on perceived usefulness with standardized path coefficient of 0.065 and t-value of 1.251.

H4: Perceived usefulness has a significant impact on attitude with standardized path coefficient of 0.581 and t-value of 8.461.

H5: Perceived ease of use has a significant impact on attitude with standardized path coefficient of 0.124 and t-value of 2.464.

H6: Attitude has a significant impact on behavioral intention with standardized path coefficient of 0.249 and t-value of 6.113.

H7: Subjective norm has a significant impact on behavioral intention with standardized path coefficient of 0.793 and t-value of 17.337.

H8: Behavioral intention has a significant impact on behavior with standardized path coefficient of 0.302 and t-value of 4.721.

5. Conclusion, Recommendation & Limitation

5.1 Conclusion and Discussion

This research achieves its objective to explores the influence of behavioral intention and behavior of postgraduates in their use of Massive Open Online Courses (MOOCs) learning in China. The results show that self-efficacy has a significant impact on perceived usefulness and perceived ease of use. Perceived usefulness and perceived ease of use significantly impact attitude. Attitude and subjective norms significantly impact behavioral intention toward behavior. On the contrary, this study found a non-supported relationship between perceived usefulness and perceived ease of use.

Several studies have explored the relationship between perceived ease of use and perceived usefulness in the context of technology acceptance. However, when focusing specifically on MOOCs and postgraduate students, the results suggest that perceived ease of use may not have a significant impact on perceived usefulness. For instance, a study conducted by Fatima et al. (2017) examined the factors influencing the adoption of MOOCs among postgraduate students. Their findings revealed that while perceived ease of use was positively associated with the intention to use MOOCs, it did not have a significant impact on perceived usefulness.

The impact of various factors on the adoption and usage of Massive Open Online Courses (MOOCs) among postgraduates in China has garnered significant attention in research. This discussion focuses on the relationships between self-efficacy, perceived usefulness, perceived ease of use, attitude, subjective norms, and behavioral intention in this context.

Numerous studies have established that self-efficacy plays a crucial role in shaping individuals' attitudes and behaviors towards technology adoption. In the context of MOOCs among postgraduates, research suggests that self-efficacy has a significant impact on both perceived usefulness and perceived ease of use.

For example, Hsiao and Tang (2014) examined the factors influencing the acceptance and use of e-learning systems among postgraduate students. Their findings revealed that higher levels of self-efficacy were positively associated with perceived usefulness and perceived ease of use of the e-learning system.

Moreover, perceived usefulness and perceived ease of use have been found to significantly influence attitude toward using MOOCs among postgraduates. Lee (2006) conducted a study exploring the factors affecting the adoption of e-learning systems, including MOOCs, among postgraduate students. The results indicated that perceived usefulness and perceived ease of use had a positive impact on attitude toward using the e-learning system.

Furthermore, both attitude and subjective norms have been identified as significant predictors of behavioral intention toward using MOOCs among postgraduates. Attitude refers to an individual's overall evaluation or favorable/unfavorable assessment of using MOOCs, while subjective norms represent the influence of social and normative pressures.

Empirical evidence supports the impact of attitude and subjective norms on behavioral intention in the context of MOOC adoption. For instance, Fatima et al. (2017) conducted a study investigating the factors influencing the adoption of MOOCs among postgraduate students. Their findings revealed that both attitude and subjective norms significantly influenced behavioral intention to use MOOCs.

These findings suggest that fostering positive attitudes and social support, in addition to building self-efficacy, are important in promoting the adoption and usage of MOOCs among postgraduates in China. Institutions and educators should emphasize the benefits and ease of use of MOOCs, provide support mechanisms, and create a supportive social environment to enhance behavioral intention and actual usage.

In conclusion, self-efficacy significantly impacts perceived usefulness and perceived ease of use, which, in turn, influence attitude. Both attitude and subjective norms significantly impact behavioral intention toward using MOOCs among postgraduates in China. Understanding these relationships is vital for developing effective strategies to promote the adoption and usage of MOOCs in higher education.

5.2 Recommendation

Based on the findings discussed, here are some recommendations that can be derived for promoting the adoption and usage of Massive Open Online Courses (MOOCs) among postgraduates in China. By implementing these recommendations, institutions can create an environment conducive to the adoption and utilization of MOOCs among postgraduates, enhancing the accessibility and quality of online education resources and opportunities. Since self-efficacy has been found to significantly impact perceived usefulness and perceived ease of use, it is essential to focus on building postgraduates' self-confidence in utilizing MOOCs. This can be achieved through targeted interventions such as training programs, workshops, and supportive resources that help students develop the necessary skills and competencies to navigate and engage effectively with MOOC platforms.

Given the influence of perceived usefulness on attitude, it is crucial to highlight the benefits and relevance of MOOCs for postgraduates. Institutions and educators should clearly communicate the potential advantages of utilizing MOOCs, such as access to high-quality content, flexibility in learning, and opportunities for self-paced education. Recognizing the impact of perceived ease of use on attitude, efforts should be made to enhance the user experience and usability of MOOC platforms. User-friendly interfaces, clear navigation, and intuitive features can contribute to a positive perception of ease of use. Regular feedback collection and incorporating user suggestions for improvement can help identify and address usability issues, ensuring a smoother and more seamless learning experience.

Given the influence of subjective norms on behavioral intention, it is important to create a supportive social environment that encourages MOOC adoption among postgraduates. Institutions can organize events, workshops, or discussion forums where students can share their experiences and provide peer support. Faculty members and instructors can actively promote MOOC usage and highlight its value, acting as positive role models and influencers for postgraduates.

To facilitate the adoption of MOOCs, institutions should offer comprehensive guidance and support services to postgraduates. This may include orientation sessions, tutorials on using MOOC platforms, technical assistance, and access to resources such as online libraries and discussion forums. Clear communication channels should be established to address any queries or concerns postgraduates may have, ensuring a smooth and positive learning experience. It is essential to continually monitor and evaluate the effectiveness of interventions aimed at promoting MOOC adoption. Feedback from postgraduates should be collected regularly to identify areas for improvement and refine strategies accordingly. Ongoing assessment of the impact of interventions on self-efficacy, perceived usefulness, attitude, subjective norms, and behavioral intention can help guide future initiatives and ensure their effectiveness.

5.3 Limitation and Further Study

The study examining the intention and behavior of undergraduates in Sichuan, China regarding the use of Massive Open Online Courses (MOOCs) has certain limitations that could be addressed in future research. These limitations pertain to sample size and representativeness, contextual factors, and the absence of a qualitative approach. By addressing these limitations in future research, a more comprehensive and accurate understanding of undergraduates' intention and behavior toward MOOCs can be achieved. This would contribute to the development of effective strategies and interventions to promote the adoption and utilization of MOOCs among undergraduates in Sichuan, China, and beyond.

First, future studies could aim for a larger and more diverse sample of undergraduate students, not only from Sichuan but also from various universities and regions across China. By including a more extensive and varied participant pool, the representativeness of the study's findings can be enhanced, leading to more robust conclusions.

Furthermore, it is crucial to acknowledge that factors such as internet access, institutional support for MOOCs, and cultural attitudes toward online learning can significantly influence students' intention and behavior. To gain a more comprehensive understanding, future research should incorporate these contextual factors into the study design. This could involve assessing the impact of these factors on the adoption and usage of MOOCs among undergraduates in Sichuan, China.

Finally, the current study primarily focused on quantitative data collection, which might limit the depth of understanding regarding students' intention and behavior. To complement the quantitative findings, future research could include qualitative methods, such as interviews or focus groups, to delve into the underlying motivations, barriers, and experiences related to MOOC usage. This would provide richer insights and a more nuanced understanding of the topic.

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