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A Study on Intention and Behavior of Undergraduates to Use Massive Open Online Courses in Sichuan, China

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Abstract

Purpose: Based on COVID-19's effect in China, this paper explores the influence of behavioral intention and behavior of undergraduates in their use of Massive Open Online Courses (MOOCs) learning in China. 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. **Research design, data, and methodology:** The target population includes 500 undergraduates using MOOCs. This study was conducted using a quantitative method, using a questionnaire. 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 ease of use. Perceived usefulness and perceived ease of use significantly impact attitude. Attitude and subjective norms significantly impact behavioral intention toward behavior. Nevertheless, this study found a non-supported relationship between self-efficacy, perceived usefulness, and perceived ease of use. **Conclusions:** The findings recognize that most learners are concerned with MOOCs' efficiency, costless, convenience, and openness, and this has also attracted special attention from educational theorists and academics.

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

JEL Classification Code: E44, F31, F37, G15

1. Introduction

The rise of the Internet has revolutionized the development of human society. A new model with obvious network branding has emerged from clothing, food, housing, and transport, closely related to people, work, education, health, and other fields (Pew Research Center, 2019). The advent of the "Internet +" era has brought new opportunities and challenges to many traditional industries, and the Internet has also brought new ways of teaching in the field of education, one of which is the Massive Open Online Courses or MOOCs learning in recent years. MOOC is a modern teaching model based on the Internet, telecommunication technology, cloud storage, cloud computing, and other advanced technologies. It has gained the recognition of most learners quickly due to its efficiency, freedom, convenience, and openness. It has also attracted special attention from educational theorists and academics (Schiano di Pepe, 2021).

The absolute dominance of the traditional education model is beginning to falter in today's highly developed Internet. Online education has gained great success based on the development of technology, especially network technology. In particular, the remote sharing of international quality educational resources and the global pandemic of the new crown virus has highlighted the positive effects of online education (Basar et al., 2021).

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Over the past ten years, China's MOOC has adhered to the development approach of the main university body, government support, and social participation, built an online open course platform suitable for China's national conditions by gathering advantageous strengths and high-quality resources, and supported universities with advantages in disciplines and modern teaching techniques to open and share high-quality courses, and achieved fruitful results (ICEE, 2022).

Because of the problems of learning effects in the rapid development of online education due to the COVID-19 pandemic, this paper explores the influence of behavioral intention and behavior of undergraduates in their use of Massive Open Online Courses (MOOCs) learning in China. 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

People's judgments about organizational execution concern what one can do with whatever skills one possesses. They include self-efficacy, which is personal belief based on actions. The beliefs can offer competence to impact people's behavior and cognition and change the environment (Feng et al., 2022). Self-efficacy affects how much effort and time people will take to overcome obstacles. It is also a belief that greatly influences people's motivation and the outcome (Gao et al., 2008). What is important is how the mindset influences consumer efficacy (White et al., 2011). Self-efficacy affects an individual's system anxiety which in turn affects the perceived usefulness of the system. Prior research in the context of information systems suggests a direct relationship between self-efficacy and perceived usefulness (Wang et al., 2003). The ease-of-use consideration is important for potential adopters due to their self-efficacy in learning to use the technology (Davis, 1989). Some scholars support the role of an individual's self-efficacy as an antecedent and determinant of ease-of-use of new technology (Feng et al., 2022). 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) is a term to represents the degree that innovation is perceived to be easy to understand, learn, or operate. PEOU is an individual's perception of using new technology without effort (Davis, 1989). The degree of PEOU was more positive when users perceived that the system was easier to learn (Frey & Osborne, 2017). PEOU is consistently demonstrated as directly impacting post-adoption use (Choi et al., 2011; Taylor & Strutton, 2010) or as joint with perceived usefulness (Achenreiner et al., 2019). Users who find the system easy to use are more likely to believe in its usefulness. Some scholars found that perceived usefulness had a greater impact on continuous use intention than perceived use time.

Moreover, the perceived range of use positively affects perceived usefulness (Achenreiner et al., 2019; Choi et al., 2011; Taylor & Strutton, 2010). By summarizing previous research, perceived ease of use positively affects the perceived usefulness of e-learning systems (Shao, 2018). The ease of use of new technology can predict users' attitudes towards that technology; researchers believe that attitudes are influenced by perceived ease of use (Huang et al., 2007). Based on this, we propose 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

Perceived usefulness (PU) is individuals' perception that using new technology will enhance or improve their performance. Individuals believe that the PU of a system is the extent how which the new technology will enhance their task performance. In the technology acceptance model (TAM), PU is how innovation will increase job performance (Davis, 1989). Potential adopters will see a particular information system as helping them to improve their job performance (Moes & Vliet, 2017). PU is used to investigate its impact on behavioral intention, and it helps to raise either favorable or unfavorable experiences of users in a particular technology (Venkatesh & Bala, 2008). In the TAM model, perceived usefulness influences users' attitudes toward using the technology, which in turn influences the willingness to use the technology (Davis, 1989). Through the study of TAM, some scholars have proposed that perceived usefulness directly impacts attitudes toward using new technologies (Arteaga Sánchez et al., 2013; Tom Dieck et al., 2017). Based on the above discussions, a hypothesis is demonstrated:

H4: Perceived usefulness has a significant impact on attitude.

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2.4 Attitude

The attitude was an important predictor of behaviors (Golnaz et al., 2010). It was a stable psychological tendency of an individual towards a specific object (Ajzen, 1991). It 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). Multiple studies have shown a correlation between attitude and purchase intention (Amos et al., 2008). It was believed that the influence of attitudes on consumers' purchase intention is worth evaluating. This would directly affect people's purchasing behavior in the future (Reed et al., 2012). Numerous studies have also pointed to a positive relationship between IT consumer attitudes and behavioral intentions to use this information technology. Attitude is a cognitive element that conditions behavioral intention and is a valid component (Davis, 1989). 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 the perceived social pressure to perform or not to perform the behavior (Ajzen, 1991). It covers an individual's opinion regarding the influence received from some people we often see (Hee, 2000). It refers to the influence of other people's and the organization's opinions when deciding what to do (Lin, 2008). A person's subjective norm is decided by her perception that salient societal referents think about whether he or she should behave certainly or not (Fishbein & Ajzen, 1975). There was a strong link between subjective norms and behavioral intentions (Ajzen, 1991). When studying the influence of electronic brokerage systems on users' behavioral intention, researchers found that subjective norms impact users' behavioral intention to use electronic brokerage systems (Bhattacherjee, 2000). Therefore, this research can make the following assumption:
H7: Subjective norm has a significant impact on behavioral intention.

2.6 Behavioral Intention

The behavioral intention will provide the most exact behavior prediction if an appropriate measurement is gained. It can perceive a person's intention to use services (Yang et al., 2016) and predict real usage behavior (Kijsanayotin et al., 2009). Behavioral intention is like self-instruction that makes people behave certainly. It is the most effective behavior prediction (Teo & Beng Lee, 2010). Researchers have found that "behavioral intention" is important for potential consumers to use or buy IT (producing actual behavior) systems. Through research, researchers have shown that blockchain technology's behavioral intention and behavior in the logistics industry are positively related, especially regarding product information tracking details (Jain et al., 2020). Thus, a proposed hypothesis is indicated:
H8: Behavioral intention has a significant impact on behavior.

2.7 Behavior

Behavior is the way a person conducts himself/herself toward situations and others (Maity et al., 2019). 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). Behaviorism, broadly defined, postulates that an individual develops all aspects of behavior through experiences related to the connection between environmental stimuli and responses to those stimuli (Tomporowski, 2003). In the study of consumer relations, actual consumption behavior is influenced by the stimuli brought about by the surrounding environment and the behavioral intentions of the consumer (Lin, 2008).

3. Research Methods and Materials

3.1 Research Framework

The theoretical framework is explored to develop an essential conceptual framework for this research, including Fatima et al. (2017), Arteaga Sánchez et al. (2013), Hsiao and Tang (2014), and Lee (2006). These theoretical frameworks are the sources of all variables in the conceptual framework, such as self-efficacy, perceived usefulness, perceived ease of use, attitude, behavioral intention, subjective norm, and behavior. There are four major previous research frameworks to support and develop the conceptual framework. This study established a conceptual framework, as shown in Figure 1.

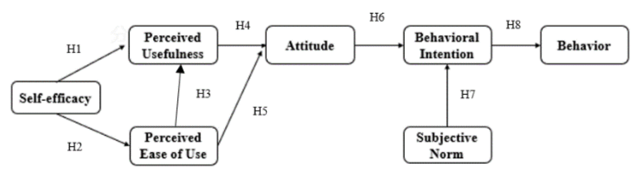

Figure 1: Conceptual Framework

H1: Self-efficacy has a significant impact on perceived usefulness.
H2: Self-efficacy has a significant impact on perceived ease of use.

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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

Questionnaires are one of the most common methods to collect data from samples. The questionnaire consists of three main sections. The first part consists of screening questions. The second part contains the statistical data of the population surveyed for this study. The third part aims to measure the study's variables with a five-point Likert scale. A questionnaire was distributed to 500 undergraduate students at Sichuan University using MOOCs for their studies. The questionnaires were assessed in advance by the item-objective congruence (IOC) index, with all scale items passed at a score rating from three experts equal to or above 0.6. The examination of a pilot test (n=50) by the Cronbach alpha coefficient reliability test showed that all items have strong internal consistency equal to or above 0.6 (Bland & Altman, 1997). After collecting the data, we will apply structural (convergent and discriminant validity) and structural equation modeling (measurement and structural models) to the data collected above. The analysis results will be used to test this study's model and all hypotheses.

3.3 Population and Sample Size

The target population of this study is undergraduate students studying at Sichuan University in China who use MOOCs for learning. The calculator measured a minimum sample size of 425, the minimum sample size for the model structure was equal to 162, and the recommended minimum sample size was equal to 425 samples. In conjunction with the study itself, the researchers decided to select 500 as the sample size for the study (Soper, n.d.).

3.4 Sampling Technique

The sampling procedure for this study has three steps: judgmental, convenience, and snowball sampling. First, judgmental sampling was to select undergraduate students studying at Sichuan University in China who use MOOCs for learning. Second, the researcher used convenience sampling to distribute online and paper questionnaire at the campus as it is a more active and structured location for undergraduate students. The above method will address the low accuracy rate by focusing on people who are willing to answer the survey questions and are easily accessible. Third, snowball sampling was used to distribute the questionnaire by phone and email from colleagues working at Sichuan University, who are frontline teachers teaching undergraduate students, and each colleague can help reach their students.

4. Results and Discussion

4.1 Demographic Information

According to Table 1, the demographic results of 500 respondents show that 229 were males and 271 were females, accounting for 45.8 percent and 54.2 percent, respectively. Most respondents are second-year students of 37 percent, followed by first-year of 26.4 percent, third-year of 23.6 percent, and fourth-year of 13 percent. The majority group of students uses MOOCs more than 8 hours per week.

Table 1: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	229	45.8%
	Female	271	54.2%
Undergraduate Year	First Year	132	26.4%
	Second Year	185	37%
	Third Year	118	23.6%
	Fourth Year	65	13%
Frequency use of MOOCs	3 hours or below/ week	66	13.2%
	4-6 hours/week	104	20.8%
	7-8 hours/week	129	25.8%
	Over 8 hours/ week	201	40.2%

4.2 Confirmatory Factor Analysis (CFA)

The measurement model in Table 2 employed Confirmatory Factor Analysis (CFA) within a Structural Equation Model (SEM). The measurement model was initially subjected to Confirmatory Factor Analysis (CFA) within a Structural Equation Model (SEM). The outcome of the CFA affirmed the significance of all items within each variable and demonstrated factor loadings that established discriminant validity. Cronbach alpha coefficient reliability test showed that all items have strong internal consistency equal to or above 0.6 (Bland & Altman, 1997). Following Stevens (1992), item loadings greater than 0.40 with a p-value below 0.05 were considered satisfactory for Confirmatory Factor Analysis. Additionally, adhering to the recommendations of Fornell and Larcker (1981), if the Average Variance Extracted (AVE) falls below 0.5 but the Composite Reliability (CR) exceeds 0.6, the convergent validity of the construct remains adequate.

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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	0.730	0.629-0.722	0.732	0.477
Perceived Usefulness (PU)	Arteaga Sánchez et al. (2013)	4	0.808	0.677 -0.784	0.808	0.514
Perceived Ease of Use (PEOU)	Arteaga Sánchez et al. (2013)	3	0.785	0.707-0.766	0.787	0.552
Attitude (ATT)	Arteaga Sánchez et al. (2013)	4	0.777	0.650-0.725	0.780	0.471
Behavioral Intention (BI)	Hsiao and Tang (2014)	3	0.717	0.586 -0.740	0.726	0.471
Subjective Norm (SN)	Hsiao and Tang (2014)	3	0.775	0.697 -0.755	0.777	0.537
Behavior (BEH)	Hsiao and Tang (2014)	2	0.822	0.828 -0.844	0.823	0.699

The measurement model is confirmatory factor analysis (CFA), which describes the relationship between observed and latent variables. The measurement model is the basis of the structural equation model. When the fitting results of the whole structural equation model are poor, the modification of the model should also be adjusted from each confirmatory factor analysis result (Siriphat, 2016). In Table 3, the measurement model fit was tested in statistical software. The model ensures acceptable fit without adjustment, including CMIN/DF=1.497, GFI= 0.953, AGFI = 0.936, NFI=0.931, CFI=0.976, TLI =0.970, IFI=0.976, and RMSEA = 0.032.

Table 3: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	281.434/188 = 1.497
GFI	≥ 0.90 (Hair et al., 2006)	0.953
AGFI	≥ 0.90 (Hair et al., 2006)	0.936
NFI	≥ 0.85 (Kline, 2011)	0.931
CFI	≥ 0.85 (Kline, 2011)	0.976
TLI	≥ 0.85 (Kline, 2011)	0.970
IFI	≥ 0.85 (Kline, 2011)	0.976
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.032
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	**0.686**						
SE	0.670	**0.691**					
PU	0.295	0.196	**0.717**				
PEOU	0.642	0.515	0.206	**0.743**			
SN	0.249	0.130	0.060	0.337	**0.733**		
BEH	0.680	0.539	0.301	0.451	0.258	**0.836**	
BI	0.675	0.520	0.267	0.641	0.422	0.671	**0.686**

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 goodness-of-fit indices were calculated based on the structural model. The statistical results were acceptable, including CMIN/DF =2.152, GFI = 0.928, AGFI = 0.909, NFI=0.895, CFI = 0.940, TLI = 0.931, IFI=0.941, and RMSEA = 0.048.

Table 5: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	432.562/201 = 2.152
GFI	≥ 0.90 (Hair et al., 2006)	0.928
AGFI	≥ 0.90 (Hair et al., 2006)	0.909
NFI	≥ 0.85 (Kline, 2011)	0.895
CFI	≥ 0.85 (Kline, 2011)	0.940
TLI	≥ 0.85 (Kline, 2011)	0.931
IFI	≥ 0.85 (Kline, 2011)	0.941
RMSEA	≤ 0.08 (Pedroso et al., 2016)	0.048
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

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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, H2, H4, H5, H6, H7, and H8 were found to be supported, while H1 and H3 did not show support.

Table 6: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: SE→PU	0.138	1.717	Not Supported
H2: SE →PEOU	0.597	9.049*	Supported
H3: PEOU →PU	0.123	1.573	Not Supported
H4: PU→ATT	0.182	3.818*	Supported
H5: PEOU→ATT	0.690	10.609*	Supported
H6: ATT→BI	0.795	11.285*	Supported
H7: SN→BI	0.242	5.124*	Supported
H8: BI→ BEH	0.752	11.413*	Supported

Note: *=p-value<0.05

From Table 6, the results are summarized as follows:

H1: Self-efficacy has no significant impact on perceived usefulness with standardized path coefficient of 0.138 and t-value of 1.717.

H2: Self-efficacy has a significant impact on perceived ease of use with standardized path coefficient of 0.597 and t-value of 9.049.

H3: Perceived ease of use has no significant impact on perceived usefulness with standardized path coefficient of 0.123 and t-value of 1.573.

H4: Perceived usefulness has a significant impact on attitude with standardized path coefficient of 0.182 and t-value of 3.818.

H5: Perceived ease of use has a significant impact on attitude with standardized path coefficient of 0.690 and t-value of 10.609.

H6: Attitude has a significant impact on behavioral intention with standardized path coefficient of 0.795 and t-value of 11.285.

H7: Subjective norm has a significant impact on behavioral intention with standardized path coefficient of 0.242 and t-value of 5.124.

H8: Behavioral intention has a significant impact on behavior with standardized path coefficient of 0.752 and t-value of 11.413.

5. Conclusion, Recommendation & Limitation

5.1 Conclusion and Discussion

This research aims to explore the influence of behavioral intention and behavior of undergraduates in their use of Massive Open Online Courses (MOOCs) learning in China. The results show that self-efficacy significantly impacts perceived ease of use. Perceived usefulness and perceived ease of use significantly impact attitude. Attitude and subjective norms significantly impact behavioral intention toward behavior. Nevertheless, this study found a non-supported relationship between self-efficacy, perceived usefulness, and perceived ease of use.

Self-efficacy significantly impacts the perceived ease of use of MOOCs, as aligned with the topic of e-learning adoption by Feng et al. (2022). Venkatesh and Davis (2000) proposed the Technology Acceptance Model (TAM), which suggests that perceived usefulness and ease of use significantly impact attitude. Many scholars also support that attitude and subjective norms significantly impact behavioral intention toward behavior (Ajzen, 1991; Al-Debei et al., 2013; Ozgen & Kurt, 2013).

The impact of self-efficacy on the perceived usefulness of Massive Open Online Courses (MOOCs) was examined, and the results revealed no significant relationship between the two variables. Previous research studies in the field support this finding. One study conducted by Smith et al. (2003) explored the factors influencing the perceived usefulness of online learning platforms and found that while self-efficacy positively impacted other outcome variables, such as learner satisfaction and engagement, it did not significantly affect perceived usefulness.

A study by Liaw et al. (2007) explored the factors influencing learners' perceptions of usefulness and ease of use in web-based learning environments. The results indicated that perceived ease of use did not have a significant direct effect on perceived usefulness. Instead, other factors such as system quality, information quality, and learner characteristics played a more significant role in determining perceived usefulness.

5.2 Recommendation

Based on the context of undergraduate students studying at Sichuan University in China, the following recommendations can be made to enhance self-efficacy, perceived usefulness, perceived ease of use, attitude, behavioral intention, subjective norm, and behavior. The findings can contribute to academic practitioners and future researchers. The university should consider providing opportunities for students to engage in experiential learning activities to apply their knowledge and skills in real-world

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scenarios. This can help boost self-efficacy by providing evidence of their competence. To address perceived usefulness, the college should incorporate real-world examples, case studies, and industry professionals' guest lectures to highlight the subject's practical utility and value.

The educator should provide students with clear instructions, guidelines, and technical support to help them overcome any potential barriers or challenges they may face when using technology for learning purposes. Furthermore, the university should encourage open discussions and debates, allowing students to express their opinions and perspectives and facilitating opportunities to connect their learning to real-life issues and challenges.

The behavioral intention can be driven by offering incentives or rewards for active participation and completion of course requirements to reinforce positive behavioral intentions. This involves encouraging peer-to-peer collaboration and teamwork and opportunities for mentoring and guidance from faculty members or seniors. The school administrators suggested implementing academic support services, such as tutoring or study groups, to assist students in overcoming challenges and improving their academic performance.

5.3 Limitation and Further Study

The study on the intention and behavior of undergraduates to use Massive Open Online Courses (MOOCs) in Sichuan, China, may have certain limitations that could be addressed in further research. These limitations include sample size and representativeness, contextual factors, and qualitative approach. Future studies could aim for a larger and more diverse sample of undergraduate students from different universities or regions in China to enhance the representativeness of the results. Additionally, Factors such as the availability of internet access, institutional support, and cultural attitudes toward online learning could play a significant role. Further research could incorporate these contextual factors to gain a more comprehensive understanding of the subject. Finally, the study might have extended qualitative data, such as interviews or focus groups, to assess intention and behavior.

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