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Perception and Behavioral Intention Toward MOOCs: Undergraduates in China

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Abstract

This study incorporated the technology acceptance model (TAM) and theory of planned behavior (TPB) to interpret students' perception of MOOCs. This study was based on a survey questionnaire; all 525 respondents were undergraduates in China. A five-point Likert scale was used to collect data in order to measure relationships among the constructs of perceived usefulness (PU), perceived ease of use (PEOU), attitude (ATT), subjective norms (SN), perceived behavioral control (PBC), and behavioral control (BI). The results showed that the research model that incorporated TAM and TPB provided both desirable fit and validity, and all the proposed hypotheses were positively supported. Compared with ATT and SN, PBC had a much stronger impact than did BI. This study and its findings provided educators and MOOC providers with managerial implications as well as suggestions for designing future MOC offerings.

Keywords: MOOCs, theory of planned behavior, technology acceptance model, TAM-TPB

Perception and Behavioral Intention Toward MOOCs: Undergraduates in China

Massive open online courses (MOOCs) are among the most recent e-learning initiatives to gain widespread acceptance in universities (Goel et al., 2022) with elite universities providing learners worldwide with high-quality education services beyond the constraints of temporal, physical, and geographical boundaries (Hollands & Tirthali, 2014). The functionality and usefulness of MOOCs have advanced university students' perception and awareness of this innovative educational often associated with information technology (Lung-Guang, 2019). Students can enroll themselves in a MOOC as a complement to their residential courses (Zhang, 2016) or to fulfill diverse other objectives (Sun et al., 2019).

The educational effectiveness of MOOCs has been affected by several factors, especially a persistently high dropout rate (Qiu et al., 2019). Meanwhile, numerous studies have been conducted on learning motivation regarding dropout and retention (Hossain et al., 2022; Hossain et al., 2020). Abdullatif and Velázquez-Iturbide (2020) pointed out that motivation is an essential role in explaining learners' behavior in MOOCs. However, it is not clearly known what types of factors could promote learners' motivation and further increase MOOC retention rates (Badali et al., 2022). During the COVID-19 pandemic, most residential courses were transformed into MOOCs. Viner et al. (2020) mentioned that students were forced to receive instruction and knowledge through online platforms. Raja and Kallarakal (2021) demonstrated that higher educational institutions realized the need for online education during the pandemic crisis. As the result of vigorous epidemic prevention policies, universities in China redesigned their offline programs to be offered online, and MOOCs accounted for a large proportion of these (Duan, 2021). Therefore, evaluating students' perception of MOOCs has become crucial to understanding the motivational factors that affect MOOC learners. However, little literature has focused on Chinese students' perception of MOOCs, or what factors will affect their perception and further promote their motivation to use MOOCs. In light of the scant literature available, this study set out to provide theoretical and practical insights regarding the MOOC context that would also be relevant outside China.

The main purpose of this study was to analyze Chinese students' perception and behavioral intention towards MOOCs. Data was collected from universities in China to explore their behavior regarding MOOCs. The technology acceptance model (TAM; Davis, 1989) and the theory of planned behavior (TPB; Ajzen, 1991) were used as a merged theoretical framework to explain students' general perception of MOOCs and this may affect their behavioral intention to enroll in MOOCs. TAM has been widely accepted and employed to study human behavior in terms of technology acceptance and usage (Tao et al., 2019). In the TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are two theoretical constructs connected to the construct of attitude (ATT). TPB has been associated with three conceptual determinants, namely ATT, subjective norms (SN), and perceived behavioral control (PBC; Lung-Guang, 2019). It has been adopted by numerous researchers (Lung-Guang, 2019; Si et al., 2020; Moon, 2021) for predicting and explaining the causal relationship of behavioral intention (BI). In this research, PU, PEOU, ATT, SN, and PBC were defined as independent variables and BI was identified as the dependent variable. Among all the variables, PU and

PEOU measured students' intuitive perception towards the technology of MOOCs. Since TAM and TPB were developed from the same fundamental theory of the theory of reasoned action, TPB was also selected in order to explore students' psychological perception and behavioral intention (Fishbein & Ajzen, 1980).

Literature Review

MOOCs

MOOCs are the product of the open education movement promoting high-quality education and educational resources to global learners (Zheng et al., 2015). According to Milligan et al. (2013) understanding learners' nature and their motivation to engage in a MOOC should be explored, as these are an indispensable part of a successful MOOC (Zheng et al., 2015). Raja and Kallarakal (2021) stated that relevant stakeholders should cultivate more courses free of cost to enhance students' enrollment and participation in MOOCs. Lung-Guang (2019) found that individuals who choose MOOCs usually show evidence of critical foresight that is closely related to their planned behavior. Sun et al. (2019) identified that the three basic psychological needs of autonomy, competence, and relatedness are critical to form intrinsic motivation, which can increase students' psychological engagement in MOOCs. Lu et al. (2019) found that flow and interest were critical variables that enhanced MOOC satisfaction and thus promoted learners' intention to continue using MOOCs. Hossain et al. (2020) found that learners' satisfaction, combined with cognitive need and attitude, were core conditions that enhanced continuance intention. Hossain et al. (2022) found that psychological needs and immersive experiences mediated graduates' skill gap as well as their willingness to enroll in MOOCs. Finally, Padilha et al. (2021) assessed MOOCs as an educational resource to enhance self-management intervention skills, and revealed that students were interested in participating in future MOOCs for their utilitarian value.

Merged Theoretical Framework: TAM and TPB

TAM has been widely applied in different academic contexts as a fundamental theory for predicting individual intentions to adopt a specific technology (Tao et al., 2019). Since PU and PEOU are posited as the determinants of technology usage, these two constructs are related to ATT. PU refers to an individual's perception that a particular technology that can improve ones' job performance, while PEOU refers to a belief that an individual can manage a particular technology free of effort (Davis, 1989). TPB has long been considered a pre-eminent social cognition theory for predicting human behavior, and has been associated with the three determinants of ATT, SN, and PBC (Si et al., 2020). ATT refers to an individual assessing a certain behavior positively or negatively (Moon, 2021) while SN refers to the perceived social pressure that may have an impact on an individual's behavioral intention towards a certain activity (Ru et al., 2019). PBC refers to an individual's perception of their own capacity to perform and engage in a given activity (Lung-Guang, 2019).

A number of empirical studies found TAM and TPB were able to explain an individual's acceptance and intention towards new technology-related services (Choe et al., 2021; Yang & Su, 2017). To improve the predictive power of a research model and overcome the limitation of a single theory in a particular social context, many researchers have added new variables into TAM (Jang et al., 2021; Tao et al., 2019; Unal & Uzun, 2021) and TPB (Lung-Guang, 2019; Moon, 2021; Ru et al., 2019). As well, research has integrated TAM and TPB to examine IT usage and e-service acceptance. The two theories are complementary, and findings have shown that an integrated model is better able to explore phenomena than using TAM and TPB individually (Glavee et al., 2017). Obaid (2021) used a model that incorporated TAM and TPB in an e-commerce context to offer specific recommendations on market strategies towards mobile banking. Choe et al. (2021) used a model that merged TAM and TPB to verify how to foster behavioral intention in the context of drone food delivery service. Gómez-Ramirez et al. (2019) explored the factors that influenced students' adoption of mobile learning through the model that combined TAM and TPB. Addressing MOOCs, Yang and Su (2017) proposed a merged TAM and TPB theoretical model to explain how learners responded to MOOCs with a new teaching method. Wang et al. (2020) merged TAM and TPB as a theoretical model to explore the determinants behind the performance and low completion rate of MOOCs in China.

This study focused on the psychological aspects of students; TPB has been widely adopted to predict individuals' general behavior, while TAM has been used to examine individuals' specific technology acceptance (Choe et al., 2021). It is believed that the MOOC context involves general behavior and specific technology. Therefore, we deliberately integrated TAM and TPB to explore students' perception and behavioral intention to enroll in MOOCs. Framing our work within a merged TAM and TPB theoretical model allowed us to better perceive how students respond to MOOCs while exploring the factors that influence their perception and behavioral intention towards MOOCs.

Hypothesized Relationships

PU and PEOU are the crucial variables of TAM, representing the extrinsic and utilitarian values respectively (Yang & Lee, 2022). Many consumer behavior studies have confirmed the positive impact of PU and PEOU on users' attitude. Choe et al. (2021) identified the positive impact of PU and PEOU on consumers' behavioral intention in the context of the food service industry. Yang and Lee (2022) demonstrated that PU and PEOU were two core variables positively related within sharing economy services. Addressing the MOOC context, Yang and Su (2017) explored the positive impact of PU and PEOU on learners' behavior. Wang et al. (2020) found PU and PEOU positively affected learners' attitude towards MOOCs. Therefore, this study posited the following hypotheses:

H1: Perceived usefulness has a positive impact on a learner's attitude towards using MOOCs.

H2: Perceived ease of use has a positive impact on a learner's attitude towards using MOOCs.

A number of empirical studies have confirmed, within TPB, the positive effect of ATT, SN, and PBC on consumers' behavioral intention. Moon (2021) identified that ATT, SN, and PBC positively impacted consumers' behavioral intention in the green restaurant context. Choe et al. (2021) confirmed that ATT, SN, and PBC were positively related to the formation of behavioral intention towards drone food delivery services. Si et al. (2020) revealed that ATT, SN, and PBC were critical variables for exploring sustainable use intention for bike sharing. Ru et al. (2019) found ATT, SN, and PBC influenced young people's intention to reduce fine particulate matter. Regarding the MOOC context, Luang-Guang (2019) verified the positive impact of SN and PBC on students' behavioral intention to adopt MOOCs. Wang et al. (2020) found that ATT, SN, and PBC had a positive impact on learning performance. Based on the extant literature, this study posited the following hypotheses:

H3: A learner's attitude towards using MOOCs has a positive impact on their behavioral intention.

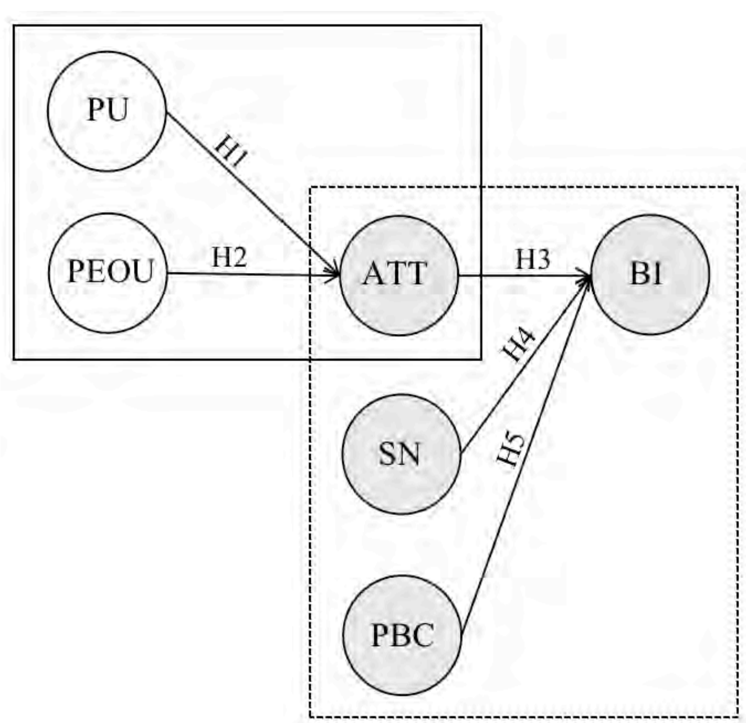
H4: A learner's subjective norm has a positive impact on their behavioral intention.

H5: A learner's perceived behavioral control has a positive impact on their behavioral intention.

Figure 1 depicts the research model for this study, including the relationships among the five hypotheses. The non-shaded constructs within the solid box represent the TAM variables. The shaded constructs within the dotted box represent the TPB variables.

Figure 1

Proposed Research Model



Methodology

Measurement Instrument and Questionnaire Development

This study used a questionnaire to collect data from undergraduates with different academic backgrounds. The questionnaire consisted of two parts—demographic information and a MOOC survey. Demographic questions addressed five aspects, namely (a) gender, (b) age, (c) number of MOOC diplomas, (d) academic background, and (e) academic year. The MOOC survey measured the variables of PU, PEOU, ATT, SN, PBC, and BI. A five-point Likert scale with 1 (*strongly disagree*) to 5 (*strongly agree*) was provided for each MOOC survey item. In total, 28 items were presented as independent and dependent variables.

To better predict students' perception and behavioral intention regarding MOOCs, all the items for measuring the constructs of PU, PEOU, ATT, SN, PBC, and BI were based on Chin et al. (2008), Venkatesh and Goyal (2010), Venkatesh et al. (2011), Zhou (2016), and Lung-Guang (2019). As well, suggestions were sought from content experts regarding how students actually perceive MOOCs. Of the 28 items on the MOOC survey (**See Appendix**), (a) five items addressed PU, (b) four items related to PEOU, (c) eight items applied to ATT, (d) three items dealt with SN, (e) five items applied to PBC, and (f) three items focused on BI.

Data Collection and Demographic Profile

Following the approach of convenience sampling (Taherdoost, 2016), 100 questionnaires were first distributed and recovered at Ningbo University as test samples to check the instrument's reliability and validity. Then, questionnaires were distributed through WJX to students at Fudan University, Zhejiang University, China University of Petroleum, and Capital Normal University. All these universities were well-known, offered courses in a variety of disciplines, and had experience producing online courses.

According to Table 1, a total of 525 students answered the questionnaire; 233 (44.38%) were males and 292 (55.62%) were females. Table 2 shows how the students' ages ranged from 17 to 30; most of the students (92.38%) were aged 18 to 22 years. Table 3 shows the 72.38% of the students did not have a MOOC certificate, 27.62% of the respondents had at least one, and the largest number of certificates by an individual was 28. Table 4 shows the academic fields the represented by the students: (a) arts and humanities (n = 249); (b) health science (n = 60); (c) science (n = 69); (d) social science and law (n = 73); and (e) technology science (n = 74). Table 5 shows that 171 were first-year students, 133 were second-year students, 138 were third-year students, and 83 were fourth-year students.

Table 1

Sample Gender

Gender	Frequency	Percent
Male	233	44.38
Female	292	55.62
Total	38	100

Table 2

Sample Age

Age	Frequency	Percent
17	2	0.38
18	59	11.24
19	112	21.33
20	136	25.90
21	117	22.29
22	61	11.62
23	24	4.57
23	8	1.52
25	3	0.57
28	2	0.38
30	1	0.19
Total	525	100

Table 3

Number of MOOC Certificates

Number of Certificates	Frequency	Percent
0	380	72.38
1	68	12.95
2	38	7.24
3	15	2.86
4	5	0.95
5	5	0.95
6	3	0.57
7	1	0.19
8	2	0.38
9	1	0.19
10	2	0.38
12	1	0.19
14	1	0.19
20	2	0.38
28	1	0.19
Total	525	100

Table 4

Academic Field

Academic Field	Frequency	Percent
Arts and humanities	249	47.43
Health science	60	11.43
Science	69	13.14

Social science and law	73	13.90
Technology science	74	14.10
Total	525	100

Table 5

Year of Study

Year of Study	Frequency	Percent
First year	171	32.57
Second year	133	25.33
Third year	138	26.29
Fourth year	83	15.81
Total	525	100

To determine possible non-response bias and generate an estimated rate of active refusals, we compared the number of questionnaires distributed with the number of responses actually received. We planned for 1,000 participants in the online questionnaire survey; after excluding the incomplete questionnaires, 525 responses were received, which represents a 52.5% rate of non-refusal, well beyond the range of 15% to 20% (Menon et al., 1996). To analyze the possible differences between early and late respondents (i.e., those who responded immediately vs. those who responded after the first or second recall), bivariate analysis was conducted. Table 6 shows there was no significant difference between the earlier and later respondents.

Table 6

Bivariate Analysis

Group	Mean	Standard deviation
Early respondents	3.7515125	0.85698319
Later respondents	3.5025641	0.95988809

Note. Probability > F: 0.0022. Bartlett's test: $chi^2 = 3.1875$. Probability > $chi^2 = 0.074$.

Data Analysis

Confirmatory factor analysis and structural equation modeling, particularly partial least square (PLS), were conducted by using SmartPLS 3.0 to analyze the convergent and discriminant validity of the measurement model. We used the bootstrapping procedure to examine the proposed theoretical research model, evaluate the proposed hypotheses, and assess the relationship among the constructs. Compared with the variance-covariance based structural equation modeling, using partial least square (PLS) for structural equation modeling has effectively evaluated exploratory theories (Henseler et al., 2009). A normal data distribution is not necessary and the approach works well with small sample sizes (Fornell & Bookstein, 1982). The Shapiro-Wilk test has been widely used to verify the normality of data (Villasenor & Estrada, 2009). The results in Table 7 show the data were abnormally distributed, since the *p* value of most variables was less than 0.05. Thus, PLS was considered the most appropriate method for this study.

Table 7

Shapiro-Wilk Test of Normality

Construct	Variable	Prob > Z
ATT	ATT 1	0.00966
	ATT 2	0.00040
	ATT 3	0.00002
	ATT 4	0.00001
	ATT 5	0.00014
	ATT 6	0.08001
	ATT 7	0.01017
	ATT 8	0.00196
SN	SN 1	0.01233
	SN 2	0.00238
	SN 3	0.05271
PU	PU 1	0.09008
	PU 2	0.07676
	PU 3	0.02023
	PU 4	0.04124
	PU 5	0.05380
PEOU	PEOU 1	0.00078
	PEOU 2	0.00069
	PEOU 3	0.00199

	PEOU 4	0.00020
PBC	PBC 1	0.04567
	PBC 2	0.02620
	PBC 3	0.00400
	PBC 4	0.00195
	PBC 5	0.02501
BI	BI 1	0.00611
	BI 2	0.00650
	BI 3	0.00269

Results

The Measurement Model: Assessing Reliability and Validity

Common method bias can occur in studies where both independent and dependent variables are measured within one survey, using the same item context and similar item characteristics (Kock et al., 2021). Following the method proposed by Alegre and Chiva (2013) the results in Table 8 show that in the MOOC context, all the inner variance inflation factor (VIF) values of PU, PEOU, ATT, SN, and PBC are 2.230, 2.230, 2.508, 2.391, and 2.287 respectively, all less than 3.3. The results indicate the research model is free of common method bias (Hair et al., 2017; Kock, 2015).

Table 8

Common Method Bias Test: Inner VIF Values

Construct	ATT	BI
ATT		2.508
BI		
PBC		2.287
PEOU	2.230	
PU	2.230	
SN		2.391

Content validity refers to how well a survey or test measures the construct that it designs to measure. To assure the validity of the measurement instrument in this study, all the scales were selected based on the extant literature (Cronbach, 1971). Boateng et al. (2018) suggested that an effective approach to assessing content validity was through the use of experts. Thus, all the scales in this survey for this study were evaluated by four experts. Two of these were specialists in educational technology and educational psychology, and two were experts in marketing and strategy. The convergent validity was verified through three aspects: (a) factor loading should be significant and higher than 0.5 as the lowest threshold; (b) composite reliability (CR) should be higher than 0.6 (Bagozzi & Yi, 1988; Fornell & Larcker, 1981); and (c) the average variance extracted (AVE) should be higher than 0.5 (Ru et al., 2019; Yang & Su, 2017). Furthermore, Cronbach's alpha is considered an indicator for measuring the reliability of the internal consistency of a scale, and the acceptable threshold should be higher than 0.6 (Cronbach, 1951). According to Table 9, the factor loading of items in this study were higher than 0.8 and the highest value was 0.929, indicating that the model was reliable. The AVE was larger than 0.7 and the highest value was 0.827, indicating that the measurement model had a good convergent effect. All the Cronbach's alpha values were higher than 0.8 and CR of the constructs were higher than 0.9, which indicated that the internal consistency among the constructs was desirable.

Table 9

Factor Loading, Cronbach's Alpha, CR, and AVE of Constructs

Construct	Item	Factor loading	Cronbach's alpha	CR	AVE
ATT	ATT 1	0.852	0.946	0.955	0.726
	ATT 2	0.862			
	ATT 3	0.829			
	ATT 4	0.848			
	ATT 5	0.868			
	ATT 6	0.860			
	ATT 7	0.855			
	ATT 8	0.843			
BI	BI 1	0.894	0.895	0.935	0.827
	BI 2	0.929			
	BI 3	0.905			
PBC	PBC 1	0.853	0.909	0.932	0.733
	PBC 2	0.858			

	PBC 3	0.843			
	PBC 4	0.849			
	PBC 5	0.877			
PEOU	PEOU 1	0.896	0.917	0.941	0.800
	PEOU 2	0.901			
	PEOU 3	0.896			
	PEOU 4	0.885			
PU	PU 1	0.829	0.914	0.936	0.745
	PU 2	0.892			
	PU 3	0.866			
	PU 4	0.887			
	PU 5	0.840			
SN	SN 1	0.882	0.864	0.917	0.786
	SN 2	0.900			
	SN 3	0.878			

Discriminant validity ensures that results are definite (Henseler et al., 2015) and that each construct is different from other constructs (Gómez-Ramirez et al., 2019). Discriminant validity also ensures that items are distinguishable from items associated with different variables. If not, then multiple variables may explain the same issue. By adopting the correlation coefficient between the square root of AVE and all possible constructs for comparison, the value of the square root of AVE must be stronger than the value of all possible constructs, in order to show that there is discriminant validity in the measurement. According to Table 10, the values of square of roots of AVE were stronger than the values of the potential constructs, thus indicating great discriminant validity in the measurement.

Table 10

Simple Correlation Matric and Discriminant Validity

Construct	ATT	BI	PBC	PEOU	PU	SN
ATT	0.852					
BI	0.629	0.909				
PBC	0.704	0.788	0.856			

PEOU	0.727	0.700	0.808	0.895		
PU	0.739	0.728	0.810	0.743	0.863	
SN	0.719	0.621	0.686	0.700	0.790	0.887

Analysis of the Structural Model

The explanatory power of the structural model can be measured through R^2, which was explained in each of the endogenous constructs. The value of each construct should be higher than 0.1 (Falk & Miller, 1992) and the values of 0.75, 0.50, and 0.25 can be viewed as the model's substantial, moderate, and weak explanatory power, respectively (Henseler et al., 2009). The Stone-Geisser test of predictive relevance (Q^2; Geisser, 1975) is a measure for estimating the PLS path model's predictive accuracy. Q^2 values higher than 0, 0.25, and 0.50 depict the PLS-path model's small, medium, and large predictive relevance, respectively (Henseler et al., 2009). The values of R^2 of this study were 0.617 and 0.635, respectively, and the values of Q^2 were 0.441 and 0.521, respectively. Clearly, the model for this study was well suited to explain the data. Figure 2 presents the results of PLS and the relationship of the variables as verified by the bootstrapping method.

Figure 2

PLS Results for the Structural Model

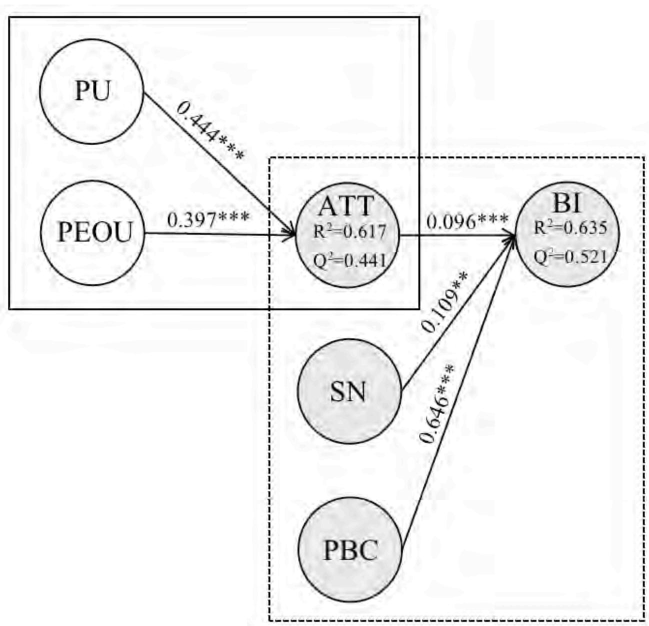


Table 11 shows that the results of the verification among the constructs and the five research hypotheses were positively supported. The path coefficients of the model were 0.444 (PU to ATT), 0.397 (PEOU to ATT), 0.096 (ATT to BI), 0.109 (SN to BI), and 0.646 (PBC to BI). As well, the R2 values of the constructs were 0.617 (ATT) and 0.521 (BI). The results also indicate that 44.4% of ATT was affected by PU, 39.7% of ATT was affected by PEOU. Furthermore; 9.6% of BI was affected by ATT, 10.9% of BI was affected by SN, and 64.6% of BI was affected by PBC.

Table 11

t-Value of Research Hypotheses and Path Coefficients

Research hypothesis	*t*	Path coefficient	*p*	Validated result
H1: PU→ATT	8.860	0.444	0.000***	Supported
H2: PEOU→ATT	7.668	0.397	0.000***	Supported
H3: ATT→BI	2.066	0.096	0.039**	Supported
H4: SN→BI	2.211	0.109	0.027**	Supported
H5: PBC→BI	13.528	0.646	0.001***	Supported

Note. $^{**}p<0.05$; $^{***}p<0.01$.

We followed the approach of Malik et al. (2021) to investigate the mediating role of ATT in the relationships among PU, PEOU, and BI. Table 12 shows the results of mediation analysis. In particular, we identified two indirect effects of PU and PEOU on BI as mediated by ATT at a 90% confidence level.

Table 12

Results of Mediation Analysis

Path	Mediator	Standard deviation	*t*	*p*	Result
PU→BI	ATT	8.860	0.444	0.056*	Supported
PEOU→BI	ATT	7.668	0.397	0.052*	Supported

Note. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Discussion

This study proposed five hypotheses to interpret the perception and behavioral intention of students towards MOOCs. Two classical theories—TAM and TPB—were integrated in a research model that was positively supported by the empirical data in this study. As PU and PEOU accounted for 44.4% and 39.7% of attitude respectively, and presented a high value of R^2 (0.617), these two essential components of TAM, as well as the antecedents of ATT in this study, were confirmed as statistically effective in explaining intrinsic attitudes towards MOOCs. The findings supported the basic assumption underling the TAM: if students are more likely to experience usefulness and ease of use in MOOCs, they are more likely to accept MOOCs. Our findings were also consistent with previous research explaining technology adoption and behavioral intention towards MOOCs (Wang et al., 2020; Yang & Su, 2017), which indicated that the extrinsic and utilitarian values of the technology could impact students' intrinsic attitude and perception. Furthermore, PU had stronger effect on ATT than did PEOU, in accord with Yang and Lee (2022).

ATT was found to have a direct positive impact on behavioral intention, a finding consistent accord with Gómez -Ramirez et al. (2019) and Wang et al. (2020), confirming that attitude was effective in explaining behavioral intention. However, this finding was in contrast with Lung-Guang (2019) wherein ATT was found to have no significant impact on behavioral intention. In addition, ATT was also confirmed to mediate the relationships among PU, PEOU, and BI. This aligned with Yang and Su (2017), suggesting that ATT played an essential mediation role between technology acceptance and behavioral intention. Additionally, SN and PBC were also positively effective in influencing students' behavioral intention towards MOOCs. This was consistent with Lung-Guang (2019), Wang et al. (2020), and Yang and Su (2017), and indicated students were easily affected by the things and people around them as well as their own positive perceptions towards MOOCs. This finding also showed that PBC took up most of the proportion among the constructs; students were more likely to construct their behavioral intention based on their actual situation regarding accepting MOOCs.

Conclusion, Implications, and Future Directions

This study helped clarify our understanding of MOOC adoption, and explored students' perception and behavioral intention towards MOOCs during the COVID-19 pandemic. This provided useful insight into the determining factors that motivate students to use MOOCs.

In terms of theoretical implications, previous studies have proven the validity of a research model that merges TAM and TPB. This study confirmed the validity of our research model in explaining technology acceptance and behavioral intention in the MOOC context, and contributed robust empirical support to the extant literature. In addition, this study collected data within China, and so informed the cultural dimensions of MOOC research. Furthermore, the mediating effect of ATT was identified, which further expanded the validity of an integrated TAM and TPB model.

Regarding managerial implications, this study offered several findings of importance to educators and MOOC providers. The utilitarian value perceived from MOOCs increased learners' intrinsic perception; the extant literature has also found that learners' intention was determined by their needs (Ossiannilsson et al., 2016). MOOCs as an innovative tool of education provide students worldwide with a new approach to enrich their educational background and develop new skills for future jobs. Blanco et al. (2016) stated that a number of students and employers engaged in MOOCs to bridge employability gaps. Hossain et al. (2022) found that awareness of psychological needs and opportunities for immersive experiences mediated the impact of skill gaps and social interaction on graduates' MOOC acceptance intention. Hence, it is critical to develop MOOC courses that increase learners' employability skills.

In this study, ATT was confirmed as a critical variable in the MOOC context. To attract and engage students in MOOCs, teachers should be aware of various learner characteristics and implement teaching that responds to their audience's attitude and perception of learning (Wang et al., 2020). Compared with ATT and SN, PBC is much more significant. Hence, we recommend that school teachers and MOOC providers explore more utilitarian and convenient approaches for students in order to overcome learning constraints. Universities should also provide students with courses related to self-learning management so students can confidently follow their own learning path.

Regarding future research directions, first, this study involved undergraduate students in China only and did not address regional and cultural differences, which may have affected the research results. Follow-up research could include learners at the master and doctorate levels to broaden the research results. Second, future research could involve regional and cultural factors as control variables or moderators on a comparative study to explore the potential differences among students in different cultural contexts. Third, this study adopted convenience sampling to collect data, which made the findings less generalizable. We suggest that follow-up research designs consider more comprehensive approaches to collect data.

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Appendix

Survey Items

Variable	Item	Main Reference
PU	1. I use MOOCs because I can get diplomas for potential future careers 2. I use MOOCs because I can communicate with other learners during the MOOC learning process 3. I use MOOCs because I can share knowledge among learners during the MOOC learning process 4. I use MOOCs because I can communicate with the instructor or teaching assistant during the MOOC learning process 5. I use MOOCs because I spend less time and gain more than in a traditional class	Chin et al. (2008); Davis (1989); Venkatesh & Goyal (2010)
PEOU	1. I think I can set learning goals according to my own situation 2. I think I have free choice of study path according to my own wishes 3. I think I can manage my learning progress according to my own learning situation 4. I think I can learn specific sections of the course according to my personal needs	Chin et al. (2008); Davis (1989)
ATT	1. MOOCs have multidisciplinary and interesting course content 2. MOOCs have multiple functional modules which allow me to choose what I prefer	Ajzen (1991); Venkatesh & Goyal (2010); Venkatesh et al. (2011)

	3. MOOCs have many types of advanced technical channels (e.g., PC side, mobile side, different browsers)	
	4. MOOCs have many types of teaching methods which make me enjoy the study (e.g., video, ppt, cases, literature)	
	5. I think MOOC study is useful	
	6. I think MOOCs study is enjoyable	
	7. I think MOOCs study is sensible	
	8. I think MOOCs study is interesting	
SN	1. I use MOOCs because many social media has reported the benefits and advantages of using MOOCs	Ajzen (1991); Luang-Guang (2019)
	2. I use MOOCs because many schools are promoting the use of MOOCs	
	3. I use MOOCs because people around me are using MOOCs (e.g., friends, classmates, teachers)	
PBC	1. I think I have enough time and energy to use MOOCs	Ajzen (1991); Luang-Guang (2019); Zhou (2016)
	2. I think I have enough capital to bear the cost of using MOOCs	
	3. I think I have multiple ways to obtain specific knowledge to master course content	
	4. I think I have necessary e-mail as well as network and computer capacity to use MOOCs	
	5. I think I can pass the MOOC-designed courses easily.	
BI	1. In the future, I will use MOOCs as an additional	Ajzen (1991); Luang-

study course	Guang (2019); Zhou
2. In the future, I will recommend MOOCs to my friends	(2016)
3. In the future, I will share my own MOOC learning experience with my friends.	