Factors Affecting Undergraduate Students' Adoption of Massive Open Online Courses (MOOCs)

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Abstract: The present study does have a great contribution to Vietnamese higher education institutions that adopted blended learning using Coursera MOOCs, especially blending the courses with offline mentors in brick-and-mortar classrooms. In the current study, the perceived value of constructs of the extended UTAUT2 model with additional variables of language competence and teacher influence was used to examine undergraduate students' MOOC adoption at a private Vietnamese higher education institution. This study was conducted via an online survey with 322 students who participated in at least one Coursera MOOC. The quantitative instrument consisting of a 36 items questionnaire was adapted from the UTAUT2 model Venkatesh (2003) and Venkatesh (2012); Barak et al., (2016), and Sebastianelli et al., (2015). The findings revealed that there was a correlation between performance expectancy, effort expectation, social influence, facilitating condition, hedonic motivation, price value, habit, language competence, teacher influence, and students' behavioral intention for continued use of MOOCs. More importantly, while social influence, hedonic motivation, price value, and habits had a strong impact on MOOC adoption, the variables of performance expectancy, facilitating condition, language competency, and teacher influence unexpectedly did not have any effects on the behavioral intention of undergraduate students towards MOOC adoption. Interestingly, effort expectation had an inverse impact on students' adoption of MOOCs. From the findings, implications and future suggestions of the research have been presented.

Keywords: Coursera MOOC, UTAUT2, Behavioral Intention, Language Competency, and Teacher Influence.

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Introduction

The internet has dramatically impacted every aspect of human life. Education is no exception. In the other words, it has transformed the way knowledge is conveyed from traditional classrooms to scalable modern classrooms called MOOCS (Massive open online courses) that are regarded as a tool for "innovative disruption" which will be the promise for education (Tirthali, 2016). Besides, one of the main goals of the Sustainable Development Goals (SDG4) for Quality Education, which are to be attained by all of the member countries by 2030, is to promote lifelong learning, and MOOCs are thought to be a great medium for doing it. Additionally, MOOCs have been "a game changer" in the education domain because of their ability to grant users instant access to varying forms of education at any time and place, often as a free or affordable service. In other words, students who cannot fully commit to significant commitments such as traveling abroad to seek education from prestigious foreign higher education can now participate anywhere and at any time (Barak, Watted & Haik, 2016).

Among MOOC providers, Coursera is known as the largest MOOC provider across the globe with over 2.700 courses. Moreover, according to Class Central, a top MOOC aggregator, there are approximately 78 million users of MOOC (Shah, 2018). It is the soaring penetration of MOOCS that has attracted numerous researchers and scholars, who have studied plenty of various aspects of MOOCs to contribute to the existing body of knowledge of the prevailing MOOCs in the world. According to Meet and Kala (2021), 102 MOOC-related articles were published from 2013 to 2020. Though lots of researchers examined MOOC adoption, the current study targets Asian undergraduate students in a non-native English-speaking country, particularly in Viet Nam.

Although Vietnam is currently still in the early stages of implementing MOOCs into its educational system when considering readjustments and following the global model, MOOCS have been adopted by many universities (https://vietnamnews.vn, 2021). However, Vietnam is still facing obstacles that prevent it from reaching the true potential of MOOCs as time constraints, and the limited interaction between instructors and students. Prof. Giap Van Duong, founder of the first MOOC in Vietnam, during an interview with vnExpress, has even suggested that the lack of emotional expression from the teachers which is a common occurrence in MOOCs has led to a detachment between teacher and student which hinders the potential of MOOCs even further (htkh.hou.edu.vn, 2019). Thus, the current study was carried out at a selected private Vietnamese university by using the extended UTAUT2 with two additional variables of language proficiency and teacher influence to explore MOOC adoption by undergraduate students. The reasons for adding two more constructs to the model are explained as follows. First, language proficiency plays an integral part in MOOC enrolment and students only participate in MOOCs that are available in their language (Aldahdouh & Osório, 2016; Connolly, 2016). Likewise, Mendoza et al. (2017) noted in highlighting the necessity to investigate the impact of language proficiency on MOOC adoption. In addition to the significant role of language proficiency, teachers' or instructors' influence on the learning process of MOOC users is needed to be evaluated (Littlejohn et al., 2020). The term "teacher's influence" is regarded as a teacher's involvement in inspiring and guiding a student to use MOOCs for his or her improved comprehension and knowledge of the subject. It could be said that a teacher positively impacts a student's activities in a brick-and-mortar classroom or a virtual setting. Along with encouraging a positive attitude toward MOOC learning, a teacher's prior experience with MOOC as a learner, their familiarity and ease with educational technology, and their teaching expertise could all be potential influences (Tseng et al., 2019; Jung & Lee, 2020).

In light of the aforesaid, more studies are needed to explore MOOC adoption by students at higher education institutions. In particular, the application of MOOCs combined with offline mentors and learners' language proficiency in these courses (Ho et al., 2022). As a result, the aims of our research are to explore factors impacting students' behavioral intention of using MOOCs via the UTAUT2 model. Additionally, we undertake the study with undergraduate students as the core subjects of the research and language competency and teacher influence in offline sessions as additional variables positively affecting MOOC adoption. For such purposes, it leads to our research with the following questions:

RQ1: To what extent does students' behavioral intention toward the adoption of MOOCs through UTAUT2?

RQ2: To what extent does language competency affect students' behavioral intention toward the adoption of MOOCs?

RQ3: To what extent does teacher influence affect students' behavioral intention toward the adoption of MOOCs?

Literature review

Definition of MOOCs

MOOCs are defined as "a MOOC integrates the connectivity of social networking, the facilitation of an acknowledged expert in a field of study, and a collection of freely accessible online resources" (McAuley et al., 2010). Another definition of MOOC is an online course that provides instruction in virtual settings, which are known as a website that contains online courses in video format, lectures formatted as short videos combined with formative quizzes, automated assessments, and peer and self–assessment, and an online forum for peer support and discussion (Glance, 2013). It is also considered an online course that can gain significant participant numbers to learn for about 4-10 weeks and is subject to a certain rule. The first week is for participants to learn content via videos, and the last week is used to submit assignments and presentations for assessment (Taneja and Goel, 2014).

The Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT's theoretical model of the use of technology in learning is defined by actual behaviors. The UTAUT model shows that the adoption of technology in learning MOOCs will be directly influenced by four main constructs, namely performance expectations, effort expectations, social influence, facilitating conditions, and other moderators viz. gender, age, and experience (Venkatesh et al., 2003). In addition, the UTAUT model will synthesize existing theories about how people use technology to learn (Venkatesh and Davis, 2000; Venkatesh et al., 2003).

The Extended Unified Theory of Acceptance and Use of Technology (UTAUT 2 Model)

According to Venkatesh et al., 2012, "consumer effect, automaticity, and monetary costs" were later added to the UTAUT2 model in addition to the four primary constructs of the UTAUT. The extended UTAUT2 model was used in the current study because of the following reasons. First, the UTAUT2 model can be said to have overcome the incompleteness of the previous TRA (Ajzen & Fishbein, 1975), TAM (Davis, 1989), TPB (Ajzen, 1991), and UTAUT1 models and has also been applied by many researchers in new technology acceptance models in general and MOOC in particular (Venkatesh & Davis, 2000). Second, plenty of researchers have used and verified the UTAUT2 model on a variety of technologies, but little research has been done to support UTAUT 2 in the context of education (Mittal et al., 2021; Tseng et al., 2019). Third, the extended model is widely used as it can address the limitations of the UTAUT model (Venkatesh et al., 2012).It is significantly noted that moderators of the original UTAUT model are not used in the current study because these moderators may not impact the adoption context. (Dwivedi et al., 2019).

Performance expectancy (PE)

It is defined as the extent to which individuals believe that the use of technology can support them to improve their performance and fulfill plenty of tasks. (Venkatesh et al., 2003).

Effort expectancy (EE)

Students are willing to accept the application of technology in learning if they feel that using MOOC technology is very easy called the effort expectancy by Dečman, (2015) and Fianu et al., (2018). Likewise, the phrase "degree of ease associated with utilizing the system" is used to characterize effort expectation. (Venkatesh et al., 2012; Zhou et al., 2010).

Social influence (SI)

Social influence (SI) is also a significant factor that leads students to use MOOCs as people such as family members, and friends, whom students believe that their use of the new system will help their studies (Venkatesh et al., 2003).

Facilitating condition (FC)

Facilitating conditions define the extent individuals believe the organizational and technical infrastructure is in place to support their use of the system (Venkatesh et al. 2003). In other words, students can use phones, laptops, and compatible electronic devices that can easily study with supporting students anywhere and anytime (Brown and Venkatesh 2005; Venkatesh et al., 2003).

Hedonic motivation (HM)

Hedonic motivation (HM) has been included as a crucial predictor in the study of each student's behavior, pleasure from using MOOCs in learning, and level of interest in MOOCs is essential to students' interest in the use of MOOCs in education (Holbrook and Hirschman, 1982).

Price value (PV)

Price value (PV) is described as an individual user's cognitive trade-off between the benefits they receive from using technology and the amount of money they spend on it (Venkatesh, 2012). In the institutional context of research, even though students do not have to pay any cost to study MOOCs on Coursera, tuition and fee payment for courses on the platform are truly included in the school's tuition fee.

Habit (H)

Habit is defined as the degree to which a person tends to act automatically as a result of learning (Limayem et al.2007). Venkatesh et al., (2012) argue that the use of previous experience is a prerequisite for the habit of using technology and that habit is a key factor in the future adoption of that technology.

Language competency (LC)

Language competency (LC) refers to a student's knowledge and ability in the language in virtual classrooms. Research in information systems has found that language influences the acceptance of technology (Deng et al., 2019). MOOCs have a lot of reading materials, lectures, and videos for users to refer to, all in English. If a person is fluent in the language, it is possible to understand all the content of the MOOC lecture. In developing countries, language strongly affects students' MOOC adoption (Aldahdouh & Osório, 2016; Anand Shankar Raja and Kallarakal, 2020).

Teacher influence (TI)

The term "teacher's influence" (TI) refers to a teacher's involvement in inspiring and encouraging a student to use online learning resources for his or her increased comprehension and topic knowledge. According to Safri & Hanafiah, (2020), certain MOOCs do not provide mentors, or coaches, for students, which prevents them from connecting with MOOC instructors and creating opportunities for participation. Therefore, offline mentors are crucial for students to handle MOOCs.

Previous Studies and hypotheses development

The considerable impact of performance expectations on behavioral intention to use e-learning has been noted in existing research on technology adoption (Dečman, 2015; Fianu et al., 2018; Jambulingam, 2013; Persada et al., 2019). Performance expectations were discovered to be a key factor in the adoption of online teaching and learning during the Pandemic due to its utility (Kala & Chaubey, 2022; Mittal et al., 2021). It is in the same vein, Šumak et al., (2010) discovered that performance expectation was a significant predictor of student attitude toward e-learning. Similarly, performance expectancy influenced behavioral intention in a number of online contexts, such as the acceptance of blended learning (Azizi et al., 2020), the adoption of e-learning (Tarhini et al., 2017), the adoption of MOOCs (Tseng et al., 2019), adoption of emerging information technology in higher education classrooms (Lewis et al., 2013), use of learning management systems (Ain et al., 2016). These findings agree with the finding by Venkatesh et al., (2012) who postulated that behavioral

intention is directly influenced by performance expectation. As a result, we propose the hypothesis:
H1. Performance expectancy impacts undergraduate students' behavioral intention to adopt MOOCs.

Effort Expectancy is regarded as a key factor in influencing users' choice to adopt novel technology. To clarify, Im, Hong, and Kang (2011) and Jung and Lee (2020) reinforce the result that simplicity of use influences the adoption of new technologies. The former studies also showed the positive effect of effort expectation on adopting new technology (Venkatesh et al., 2003). Similarly, Al-Adwan's research (2020) found that perceived ease of use has a positive impact on users' behavioral intentions toward MOOCs, especially in non-compulsory courses. When technology is easy to use on a high level, there is a probability that more effort will be required to use MOOCs. Therefore, we also hypothesize:
H2. Effort expectancy impacts undergraduate students' behavioral intention to adopt MOOCs.

Another element that motivated students to enroll in MOOCs is shown to be social influence. It has a favorable impact on the usage of MOOCs because of how simple they are to use and the advantages they are supposed to provide. Users are more likely to have high intentions of using the technologies if they perceive that significant individuals in their social circles encourage their usage of MOOCs (Chaveesuk et al., 2022). In agreement with the finding, social influence was discovered to be a factor in the adoption of online teaching by school teachers (Tandon, 2020) as well as the acceptance of blended learning (Azizi et al., 2020), e-learning (Tarhini et al., 2017), the use of a learning management system (Ain et al., 2016; Widjaja et al., 2020), MOOC adoption (Tseng et al., 2019), and emerging information technology adoption, hence we also hypothesize:
H3. Social influence impacts undergraduate students' behavioral intention to adopt MOOCs.

Facilitating Conditions were commonly highlighted as an indicator of MOOC uptake. MOOCs were seen as beneficial for gaining free access to high-quality educational materials and providing a flexible online setting where learning may take place without regard to time or location. The utilization of transcripts from a multidisciplinary curriculum, linkages to resources of current events, and brief media files with explicit learning objectives all supported students' learning in the case of MOOCs (Rosell-Aguilar, 2013). In Nanayakkara's opinion (2007), teachers and technical support positively influence students' use of learning management systems. A similar finding is echoed by (Bakar et al., 2013) who postulated facilitating conditions have a beneficial impact on the acceptability level of e-learning. Taking cognizance of this, we also hypothesize:
H4. Facilitating conditions impact undergraduate students' behavioral intention to adopt MOOCs.

The behavioral intention to use online and internet-based technologies, such as learning management systems, mobile learning, e-learning, digital social media, mobile banking, etc., is preceded by hedonic motivation (Baptista & Oliveira, 2015; Moorthy et al., 2019; Raman & Don, 2013). In the same vein, prior research has identified hedonic motivation as a strong predictor of BI's adoption of technology (El-Masri & Tarhini, 2017; Moghavvemi et al., 2017). Digitalization and peer pressure from social media has inspired Gen Z to value experiences more than previous generations do and to lead lives that are accelerated, exciting, enjoyable, and full of experiences. Besides, Gen Z will lead the adoption of all new online consumer technologies because of

their intrinsic familiarity with electronic goods and services (Weinswig, 2016), thus it is hypothesized that:
H5. Hedonic motivation impacts undergraduate students' behavioral intention to adopt MOOCs.

According to the UTAUT2 hypothesis, a product's quality, cost, and price are likely to impact the behavioral intention of using MOOCs. As a result, in the analysis of the adoption of MOOC use, the user's intention to use would be influenced by their perception of the quality of learning attained through the programs in comparison to the cost of supporting facilities, such as the Internet, computers, and cost of the education programs. These elements have a significant role in determining one's educational goals and decision-making processes, particularly for young people given the significance of learning outcomes. Previous research on online learning has demonstrated a strong link between pricing value and behavioral intention (Raman & Don, 2013; Tseng et al., 2019). As a result, we hypothesize that:
H6. Price value impacts undergraduate students' behavioral intention to adopt MOOCs.

Alsharo et al., (2020) claim that obligatory online learning, as was the case, compels students to continually utilize technology, which leads to automated executions. Moreover, Limayem et al., (2007) proposed that thoroughness of usage, frequent repetition of the behavior in question, degree of pleasure with the activity's results, and reasonably stable circumstances result in automated actions. For example, when learning online, students frequently log onto their computers and learning management systems, checking for emails, new announcements, and reminders for impending assignments and activities. Also, students would routinely read assignment summaries, finish tests, research topics, download educational materials, participate in web conferences, solve problems, and interact (through email, chat, emoticons, posting and commenting to message boards or blog threads) (Limayem & Hirt, 2003; Polites, 2009; Vishwanath, 2015).
H7. Habit impacts undergraduate students' behavioral intention to adopt MOOCs.

According to Meet et al., (2022) that language competence did not affect the behavioral intentions of students participating in MOOCs while Aldahdouh & Osório, 2016; Anand Shankar Raja, and Kallarakal, 2020 postulated the relationship between language proficiency and behavioral intention was statistically significant. Connolly (2016) echoed similar findings, underlining the importance of language skills in MOOC participation and recommending that students only enroll in MOOCs offered in their language. As communication is crucial to learning in all contexts, including online and offline learning, Garcia Mendoza et al., (2017) emphasized the importance of examining the influence of language proficiency on MOOC uptake. Learners perform better in their mother tongue (UNESCO, 2016). Hence we also hypothesize that:
H8. Language competence impacts undergraduate students' behavioral intention to adopt MOOCs.

According to studies (Hoi & Mu, 2021; Al-Adwan et al., 2021a), teachers who play as significant social agents and nation-builders have a positive effect on student's mental health, behavior, and independent use of technology for learning. They also serve as an essential motivator for participants to sign up for MOOCs and foster a favorable attitude toward MOOC learning (Chang et al., 2015; Jung & Lee, 2020; Tseng et al., 2019). Likewise, teachers greatly influence students' offline and online learning activities (Garrison, 2000; Tseng et al.,

2019; Jung & Lee, 2020). Nonetheless, there is little correlation between instructors' impact and behavior intention (Al-Adwan et al., 2021a; Chang et al., 2015; Hoi & Mu, 2021). Therefore, it is hypothesized that:
H9. Teacher influence impacts undergraduate students' behavioral intention to adopt MOOCs.

Research model

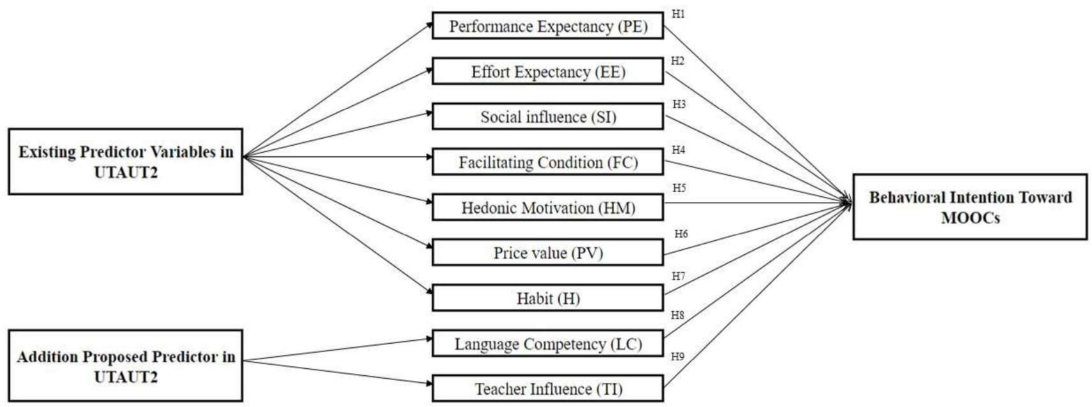

Figure 1. Research model showing the hypotheses relationships

Method

The quantitative research method is the more suitable one for this research as Creswell (2003) postulated that only an analytical view using data analysis that realizes the united strength of multiple variables can give a more definitive answer to the research problem. Additionally, purposeful sampling is commonly used to efficiently identify and select samples with valuable information, making use of the limited resources on the researcher's end. It is the process of using one's judgment to purposefully pick a specific demographic out of the population who's experienced a phenomenon of interest to participate in the research (Palinkas, L.A, 2015).

Participants

The present study consists of 322 students who are required to participate in at least one MOOC on the Coursera platform. They are chosen from all majors viz. English language, Business Administration, and Information Technology at the research site.

Research site

The university in the current research has implemented MOOCs on the Coursera platform since the summer of 2019. All students from all majors (Information Technology, Business Administration, Graphic Design, Linguistics, Multimedia Communication, and Hospitality Management) are required to take the courses in their curriculum. In each course on Coursera, students mandatorily spend 5 slots (7.5 hours) meeting with their offline mentor.

Research Instruments

The first research instrument in the study was the questionnaire designed to collect data from participants regarding their experiences with MOOCs. The survey was separated into main sections. The beginning of the survey is demographic information such as age, gender, year of study, major, and the number of courses they participated in. The second part of the survey is the constructs of the research model including the factors such as performance expectancy (4 items), effort expectancy (3 items), social influence (3 items), and facilitating conditions (4 items) were developed by Venkatesh (2003), and the UTAUT2 model adapted from Venkatesh (2012) consists of 4 items that measure the constructs of hedonic motivation (3 items), price value (3 items), habit (3 items), and behavioral intention (3 items) while language competency (5 items) and teacher influence (5 items) were adapted from Barak et al. (2016) and Sebastianelli et al. (2015). The questionnaire adopted a 5-point Likert scale where participants could rate their level of agreement or disagreement with the statements ranging from 1 "Strongly Disagree” to 5 "Strongly Agree”.

Data collection procedures

Piloting the questionnaire:

After receiving approval from the Ethics Committee of the English Language Department at the research site. The research team undertook the survey (both English and Vietnamese versions) sent to 40 participants who experienced at least one MOOC on Coursera to test the reliability of the questionnaire.

Table 1. The reliability of the questionnaire

Name of variables	No. Items	Alpha	No. Participant
Performance Expectancy (PE)	4	0.824	40
Effort Expectancy (EE)	3	0.643	
Social Influence (SI)	3	0.909	
Facilitating Condition (FC)	4	0.625	
Hedonic Motivation (HM)	3	0.926	
Price value (PV)	3	0.855	
Habit (H)	3	0.771	
Behavioral Intention (BI)	3	0.913	
Teacher Influence (TI)	5	0.828	
Language Competency (LC)	5	0.782	

We tested the reliability of the variables using the Cronbach Alpha scale on SPSS with the results obtained from 40 students who took the survey on Google Forms. The variables all reached above 0.6 over 0.9, showing that the reliability is acceptable (Cronbach, 1951).

Quantitative data collection:

To reach more participants, we emailed the teachers to ask for their permission to directly enter their classes to collect the data. Moreover, before participants answered the questionnaire, they had been asked to complete the consent form by scanning the QR code.
The data will be stored in personal researchers' laptops for 5 years. In case our laptop is broken, we still ensure your information, and data are stored and secured on google drive.

Results

Descriptive Characteristics of Participants

Out of a total of 322 participants, 32.3 % of them were male and the others were female. In terms of ages of participants, 44.1% of the participants were from 18 to 20 years old, 51.6% were from 20 to 22 years old and the other age groups accounted for 4.3%. Regarding the programs of the participants, students of Information Technology were 2.8%, students of Linguistics were 45.3%, and students of Business Administration were 51.9%. Next, while over half of the participants were second-year students (58.7 %), the remainder was made up of first-year students (4%), third-year students (8.7%), and final-year students (28,6%). Eventually, the number of courses the participants have taken varied. Specifically, 5.6% of the students took 1 course, 32.6% of the students took 2 courses, 14.6% of the students took courses, and 47.2 % of the students took more than 3 courses.

Table 2. Descriptions of participants in the study (N=322)

Demographic	Category	Number	Percentage
Gender	Male	104	32,3
	Female	218,0	67,7
Age	18 to 20	142	44,1
	20 to 22	166	51,6
	Other	14	4,3
Major	Business Administration	167	51,9
	Information Technology	9,0	2,8
	Linguistics	146	45,3
Year of study	First-year	13	4
	Second-year	189	58,7
	Third-year	28	8,7
	Final year	92,0	28,6
Number of courses	1 course	18,0	5,6

2 courses	105	32,6
3 courses	47	14,6
More than 3 courses	152,0	47,2

To test the correlation between behavioral intention (BI) and other variables of the extended UTAUT. We conducted the Pearson correlation table. In the results of Table 3, the sig test Pearson correlation among all variables is less than 0.05. Thus, the correlation between variables PE, EE, SI, FC, HM, PV, H, LC, TI, and BI was linear.

Table 3. The Pearson correlation coefficient between variables of the UTAUT2 model, LC, TI, and BI

		BI	PE	EE	SI	FC	HM	PV	H	LC	TI
BI	Pearson Correlation	1	.633**	.445**	.635**	.511**	.716**	.695**	.788**	.524**	.406**
	Sig. (2-tailed)		0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
PE	Pearson Correlation	.633**	1	.563**	.664**	.595**	.661**	.638**	.622**	.501**	.461**
	Sig. (2-tailed)	0,000		0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
EE	Pearson Correlation	.445**	.563**	1	.552**	.685**	.529**	.539**	.545**	.531**	.427**
	Sig. (2-tailed)	0,000	0,000		0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
SI	Pearson Correlation	.635**	.664**	.552**	1	.591**	.635**	.593**	.601**	.512**	.452**
	Sig. (2-tailed)	0,000	0,000	0,000		0,000	0,000	0,000	0,000	0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
FC	Pearson Correlation	.511**	.595**	.685**	.591**	1	.531**	.600**	.560**	.628**	.576**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000		0,000	0,000	0,000	0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
HM	Pearson Correlation	.716**	.661**	.529**	.635**	.531**	1	.631**	.715**	.415**	.385**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000		0,000	0,000	0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
PV	Pearson Correlation	.695**	.638**	.539**	.593**	.600**	.631**	1	.682**	.595**	.532**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000		0,000	0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
H	Pearson Correlation	.788**	.622**	.545**	.601**	.560**	.715**	.682**	1	.481**	.379**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000		0,000	0,000
	N	322	322	322	322	322	322	322	322	322	322
LC	Pearson Correlation	.524**	.501**	.531**	.512**	.628**	.415**	.595**	.481**	1	.696**
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000		0,000
	N	322	322	322	322	322	322	322	322	322	322
TI	Pearson Correlation	.406**	.461**	.427**	.452**	.576**	.385**	.532**	.379**	.696**	1
	Sig. (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	
	N	322	322	322	322	322	322	322	322	322	322

Table 4. Regression of Behavioral Intention.

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	0,005	0,186		0,028	0,978		
	Performance Expectancy	0,082	0,055	0,071	1,509	0,132	0,403	2,484
	Effort Expectancy	-0,195	0,057	-0,149	-3,414	0,001	0,463	2,158
	Social Influence	0,148	0,050	0,134	2,976	0,003	0,436	2,293
	Facilitating Condition	-0,058	0,068	-0,042	-0,859	0,391	0,374	2,675
	Hedonic Motivation	0,217	0,048	0,216	4,489	0,000	0,379	2,639
	Price value	0,189	0,052	0,175	3,639	0,000	0,382	2,619
	Habit	0,466	0,052	0,439	9,040	0,000	0,374	2,675
	Language Competency	0,208	0,062	0,157	3,335	0,001	0,397	2,519
	Teacher Influence	-0,072	0,061	-0,052	-1,188	0,236	0,465	2,150

a. Dependent Variable: Behavioral Intention

b. Independent Variables: PE; EE; SI; FC; HM; PV; H; LC; TI

c. Model Summary: R=.852a; R2=0,725; Adjusted R=0,718; Sig=0.000

The ANOVA table gives us the results of the F test to evaluate the hypothesis of the fit of the regression model. The sig value of the F test is 0.000 < 0.05, and using a linear regression model is appropriate and statistically significant.

The model summary showed that the behavior intention R Square index (0.725) is approaching 1, the more independent variables explain the dependent variable. Besides, adjusted R Square is equal to 0.718, showing that the independent variables (teacher influence, habit, effort expectancy, social influence, performance expectancy, language competency, price value, hedonic motivation, and facilitating condition) included in the regression analysis affect 71.8% of the variation of the dependent variable (behavior intention). According to Sarstedt et al., (2019), the Variance Inflation Factor (VIF) should be lower than 3 to avoid the degree of collinearity or even multi-collinearity among the independent variables. Therefore the regression of the model is accepted.

According to Table 4, the variables PE, FC, and TI did not affect the dependent variable BI (p>0.05) while the remaining variables viz. EE, SI, HM, PV, H, and LC affected BI (p<0.05). Specifically, habit is the most influential factor on behavioral intention (B=0.439), followed by hedonic motivation (B=0.216), price value (B=0.175), language competency (B=0.157), effort expectancy (B= 0.149), and social influence factors have the lowest influence on the behavioral intention of Vietnamese students using MOOCs (B=0.134).

Discussion

In the current study, we identified constructs affecting students' adoption of MOOCs through the quantitative approach. While all nine of the hypothesized variables had an influence on the behavioral intention variable. Through data analysis, only 6 variables had a significant influence consisting of habit (H), hedonic motivation (HM), price value (PV), language competency (LC), effort expectancy (EE), and social influence (SI) while the remaining factors containing performance expectancy (PE), facilitating condition (FC), and teacher influence (TI) were irrelevant.

To begin, H7 was accepted because the findings revealed that habit had the strongest effect on students' adoption of Coursera MOOCs. This finding agrees with previous conclusions by Limayem et al., (2007), and Alsharo et al., (2020). Furthermore, hedonic motivation also significantly influenced students' adoption of MOOCs. This result is consistent with previous studies that have demonstrated the importance of enjoying the learning process and finding pleasure in it as a motivator for using MOOC platforms (El-Masri & Tarhini, 2017; Moghavvemi et al., 2017). This led to the H5 being accepted from the research. Additionally, price value has a positive effect on BI, which has been supported. This finding is notable as it underscores the importance of considering students' perceptions of the monetary value they receive from MOOCs; this has proven the legitimacy of theories presented by previous research (Raman & Don, 2013; Tseng et al., 2019). Moreover, H8 was confirmed because the findings revealed that language competency was found to have a positive impact on students' behavioral intention to adopt MOOCs. This finding supports previous research that has highlighted the importance of language proficiency in MOOCs (Connolly, 2016, Garcia Mendoza et al., 2017, Anand Shankar Raja and Kallarakal, 2020) and opposes the previous study by Meet et al., (2022). This indicates that students at the sampled and studied university are not adept in communication skills as well as language competency, which causes them a feeling of discomfort with MOOC content delivery and its understanding. This is easily understood because English is neither the official language nor the second language in Viet Nam.

An emerging suggestion for stakeholders namely English lecturers and institutional managers at the studied location is that they should design effective English programs as well as encourage students' English learning to enhance their English language proficiency. H3 was also accepted as the findings also showed that social influence (SI) had positively influenced students' behavioral intention to adopt MOOCs. This is in agreement with the previous research by Singha Chaveesuk et al., 2022. Furthermore, H2 was accepted because the findings showed that effort expectancy significantly affects BI. This finding is similar to the previous conclusion by Azizi, 2020; Al-Adwan, 2020; Meet et al., 2022. However, in the current study, effort expectancy(EE) had negative values. Obviously, Coursera's platform doesn't require users much effort in enrollment, and the features of MOOCs have nothing special to stand out. Participants can use MOOCs easily and skillfully with just some mouse-clicking. Moreover, it can be inferred that MOOCs' design is not interesting enough to attract students' engagement. Besides, the course content is quite monotonous, just clips, quizzes, assignments, and capstones. Therefore, it is suggested that MOOC designers and providers need to consider adjusting and updating the " appearance" as well as the content of MOOCs to make them more compelling.

On the contrary, the results indicated that performance expectancy (PE), facilitating condition (FC), and teacher influence (TI) has a non-significant effect on behavioral intention (BI). Specifically, PE had no positive effect on BI. This finding is dissimilar to the previous studies conducted by Venkatesh et al., 2012; Kala & Chaubey, 2022; Mittal et al., 2021. This led to the rejection of H1 from research. This may be explained that the courses that students were forced to enroll in do not satisfy their needs, thus they do not find them useful. In other words, curriculum and plan developers at the research site should reconsider the MOOC courses they intend to implement. If possible, they can let their students choose the courses they like in the given list. Furthermore, our findings showed that facilitating conditions had not influenced BI, thus H4 was rejected, which contradicts the results from the previous research (Bakar et al., 2013; Kala et al., 2022). All of the students are Generation Z, hence it is easy for them to access and use technological gadgets as well as technology-related aspects. They could even resolve the problems by themselves. Maybe they only need support when violating plagiarism. Likewise, the findings showed that teacher influence (TI) did not impact the BI of students to adopt MOOCs, which opposes the previous studies in the same area (Hoi & Mu, 2021; Al-Adwan et al., 2021a). As a result, H9 was rejected. Students at the research site have the ability to deal with problems related to the course. For instance, if they do not grasp the content, they can watch the lecture videos again or read the tapescripts. More importantly, Coursera MOOCs have not truly attracted their involvement, hence the presence of offline mentors is not significant.

Conclusion

In conclusion, the findings of the current study revealed that habit, hedonic motivation, price value, language competency, and social influence had a positive impact on students' accessibility to MOOCs while effort expectancy negatively affected students' intention to use MOOCs. Specifically, the most influential variable on behavioral intention is habit, followed by hedonic motivation, price value, language competency, effort expectancy, and social influence. Conversely, the remaining variables viz. performance expectancy, facilitating conditions, and teacher influence did not affect the dependent variable-behavioral intention.

Recommendations

The completion of the research comes with important discoveries that should be addressed. We suggest researchers consider the following: the mixed research method should be considered when conducting any further research. Second, Diversification of demographic selection should be considered; specifically, because this research was conducted only at one high institution, further research should be carried out at other institutions where MOOCs are mandatory. Furthermore, the attention should be allocated to the K-12 demographic rather than Undergraduate students.

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