P ISSN 2301.9093 | E ISSN 2540.8259
JMDK
Jurnal Manajemen dan Kewirausahaan
https://jurnal.unmer.ac.id/index.php/jmdk/index
Vol. 11, No. 1, 2023: 57-65

Exploring Factors Influencing Technology Adoption among Generation Y: A Study of MOOC Users

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Abstract
The primary objective of this study is to investigate the factors affecting customers' intention and usage of MOOC (Massive Open Online Course) in generation Y based on the UTAUT 2 (Unified Theory of Acceptance and Use of Technology 2). The paper opted for a quantitative method involving 150 MOOC (Skill Academy and My Skill) users collected by spreading an online questionnaire through social media. The data analysis method used is PLS-SEM. The results show that performance expectations, effort expectations, social influence, facilitating conditions, price values, and habitss have a positive influence on behavioral intention. However, hedonic motivation does not appear to have a significant effect on behavioral intention. Then behavioral intention has a significantly positive influence on usage behavior.

Keywords: *Behavioral Intention, Gen Y, MOOC, Usage Behavior, UTAUT 2*

INTRODUCTION

Covid-19 pandemic has made e-learning modes even more popular as a consequence of advances in information technology (Raza et al., 2021) not only for students, but also for professionals (Altalhi, 2020; Anand Shankar Raja & Kallarakal, 2021). e-Learning can be indicated as technology-based learning which includes learning portals, mobile applications, video conference, free websites, online interfaces, to YouTube (Ahmed et al., 2021). Research by Máté et al. (2020) stated that the latest technology can affect productivity growth which that can be one of many reasons why e-learning market right now is one of the fastest growing markets in the technology industry (Davoli et al., 2010).

Among many e-learning forms, one form that is currently being extremely developed is MOOC (Massive Open Online Course), Anand Shankar Raja & Kallarakal (2021) considered MOOC as one of the most preferred e-learning methods. Anand Shankar Raja and Kallarakal (2021) argue that MOOCs have been an element of recent change in the education sector where the MOOCs themselves include web-based programs planned in such ways to make room for massive numbers of learners. Learning contained in the MOOC can be accessed online in recordings, courses, modules, and online exams which are also carried out online (Chaveesuk et al., 2022; Máté et al., 2020).

Although historically MOOC program has only been offered by formal educational institutions, now with the emergence of the Covid-19 pandemic, other various entities are also offering MOOC programs to enhance careers and support continuous learning (Máté et al., 2020). Along with the previous statement, MOOC by Edutech Start Ups start to grow and develop rapidly. Many platforms currently offer MOOC programs such as Coursera, Udemy, and edX to provide mass-scale courses and can be accessed from all over the world (Anand Shankar Raja & Kallarakal, 2021). MOOC can provide an opportunity for anyone to gain knowledge and develop skills. Based on the previous statement, it is estimated that MOOC will achieve significant profits in the future and that this market will continue to grow along with the growing popularity of broadband internet access and e-learning.

Global data analysis shows that MOOC business has a very large demand (Mozahem, 2021). Chaveesuk et al. (2022) consider that the increase in demand and users of MOOC is also seen as a consequence of many individuals who experienced jobs loss in the time of pandemic where they felt in need of skill upgrading to get a better job. The increase in MOOC users during the pandemic has been experienced by MOOC provider platforms such as Coursera and Udemy. This is shown by the skyrocketing number of MOOC applicants through the Coursera platform by 640% and on the Udemy platform by 400% in mid 2020 (Impey & Formanek, 2021). It is recorded that most of the individuals participating in the MOOC program are people of productive age (Chaveesuk et al., 2022).

Not only in the global level, the use and development of MOOC has also been familiar in Indonesia. Indonesia currently has various Edutech Start Ups that provide MOOC programs where most of the users are millennials who are motivated to improve their professional skills for career advancement (Nurhudatiana et al., 2019). Some examples of online course platforms that are most widely used in Indonesia in the professional skills category are MySkill.id, which has reached 700,000 users (EastVentures, 2022), and SkillAcademy by RuangGuru with more than 1 million users (SkillAcademy, 2022).

Chaveesuk et al. (2022) concluded that the users of MOOC have the goal of improving their skills which will then be followed by better job opportunities so that MOOC programs are considered as an alternative to certification of the courses they are interested in. In line with that statement, Anand Shankar Raja & Kallarakal (2021) revealed that corporate professionals are actively exploring MOOC for personal and career development, where this has brought transformation in the world of education.

Although MOOC is considered to be experiencing rapid development, a study conducted by J.P Morgan and Singapore Management University states that a big gap between the academic world and industry in Indonesia workforce quality still exists which has to be narrowed in order to develop a better quality (EastVenture, 2022). In order to narrow down the skill gap that still exists, it is important to examine the use of MOOC technology so that it can bring benefits to the users in the future (Haron et al., 2021) especially in Indonesia, where a lot of skill improvement is kindly needed and can be aided by increasing the use of MOOC.

There are several models that are used in most studies to examine the use of technology, including the TAM (Technology Acceptance Model) proposed by Davis et al. (1989), UTAUT advanced by Venkatesh et al. (2003), and UTAUT 2 which was extended by Venkatesh et al. (2012). Venkatesh et al. (2012) views UTAUT 2 has the highest predictive power compared to other models. UTAUT 2 is a developmental model of UTAUT (formerly TAM) by enhancing 3 constructs to UTAUT: hedonic motivation, habits, and price value. Venkatesh et al. (2012) stated that extension in UTAUT 2 upgraded a substantial escalate in the variance disclosed in behavioral intention (74%) and technology usage (52%). UTAUT 2 offers a framework outlining acceptance of information systems and technology that provides an extensive examination of acceptance and use of technology (Venkatesh et al., 2012).

UTAUT 2 has considered capable in identifying key additional constructs and relationships which make it adaptive in users' use (Venkatesh et al., 2012). Duarte & Pinho (2019) formulated several advantages possessed by UTAUT 2 compared to other frameworks: (1) UTAUT was developed taking into account developments in previous models (TRA, TAM, motivational models, TPB, innovation diffusion theory); (2) compared to other models, the UTAUT 2 model has advanced explanation abilities. In addition, UTAUT 2 has become highly efficacious to forecast technology adoption and use in various previous studies. Tarhini et al. (2017) conducted research using the UTAUT 2 model to predict e-learning, followed by research from Duarte & Pinho (2019) which also used the UTAUT 2 model to predict mobile-health use, as well as research results from Alalwan et al. (2018) using the same model to predict internet banking usage.

UTAUT 2 is able to explain behavioral intention (BI) in predicting usage behavior (UB) broadly by involving seven variables used, namely effort expectancy (EE), performance expectancy (PE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), habits (HB), and price value (PV) (Venkatesh et al., 2012). Venkatesh, et al. (2012) continued that ultimately, UTAUT 2 relies on intentionality as the main and basic theoretical mechanism that drives consumer behavior. Along with this statement, there are various literatures that establish an affirmative and significant correlation among behavioral intention and user behavior in technology using UTAUT 2 (Khechine et al., 2016; Raza et al., 2021).

UTAUT 2 is believed to be the right model to elaborate the use and acceptance of MOOC technology by consumers. However, in practice there are still few articles that study MOOC based on the UTAUT 2 model, especially in Indonesia. So in this context, this study aims to analyze MOOC acceptance based on UTAUT 2, which was previously stated by Venkatesh et al. (2012). This particular context will limit the subject to millennial generation in Indonesia who are currently 25-39 years old where according to Nurhudatiana et al. (2019), generation Y at that age has a strong motivation to use MOOC to obtain learning that will improve their careers. Together with analyzing the differential elements that affect the adoption of MOOC users, this research will later have important theoretical and practical implications for Edutech managers, web-developers, policy makers, and other stakeholders to improve quality MOOC technology because it has a high probability of success.

LITERATURE REVIEW

Relationship between Performance Expectancy and Behavioral Intention

Venkatesh et al. (2003) conceptualize performance expectancy (PE) as how individuals benefit from their performance through the technology use. Venkatesh et al. (2003) stated that PE is essential regressions in projecting behavioral intentions users to use technology-based educational platforms. The previous statement is reinforced by Chaveesuk et al. (2022) who said that performance expectancy which is under the UTAUT 2 theory involves how technology perceived by users can help them achieve increased performance in their activities.

PE is significantly consistent prognosticator of behavioral intention (BI) (Tarhini et al., 2017; Venkatesh et al., 2003). The results of other studies put forward by Alalwan et al. (2017) and Martins, et al. (2014) also conveyed that PE is a foremost influential BI driver in adoption as well as in user behavior in technology. Chaveesuk et al. (2022) say that PE could be applied in exploring MOOC adoption in developing countries because the growth of MOOC use is seen as a means of achieving interest in learning. Therefore, the researcher proposes hypothesis 1:

H_1: Performance expectancy has a positive effect on behavioral intention in using MOOC

Relationship between Effort Expectancy and Behavioral Intention

Effort expectancy (EE) is described by Venkatesh et al. (2003) as the level of easiness in using technology. Chaveesuk, et al. (2022) said that the EE construct under UTAUT 2 points to the user's confidence level that particular technology is easy to use. According to Alalwan et al. (2016), effort expectancy includes elements such perceived easiness in shaping customer intentions and perceptions the technology.

Alalwan et al. (2016) stated EE has considered contributing to behavioral intentions in the use of technology. Based on research conducted by Teo & Noyes (2014), the understanding of MOOC adoption by users must be based on the expected easiness to use the technology. EE of technology use in developing countries includes the communication technology existence, the complexity of technology use, and its application in system performance (Khalid & Kot, 2021). If there is a great level of easiness, then probability of behavioral intentions in MOOC use will increase (Chaveesuk et al., 2022). Therefore, the researcher proposes hypothesis 2 is:

H_2: Effort expectancy has a positive effect on behavioral intention in using MOOC.

Relationship between Social Influence and Behavioral Intention

Venkatesh, et al. (2003) defines social influence (SI) as how an individual feels that someone he considers important believes that the individual is expected to implement the related technology. SI is conceptually captured as subjective norms, images, and social factors (Venkatesh et al., 2003). Chaveesuk, et al. (2022) added that the concept is based on other people's views and suggestions for certain technologies so that they can influence individual intentions to use related technologies. Information from other individuals which includes family and friends plays principal role in MOOC adoption (Khalid et al., 2021).

Chaveesuk, et al. (2022) said that positive SI will play a positive role in influencing behavioral intentions in using technology. Adding to the previous statement, Chaveesuk, et al. (2022) convey that, users who believe their social cycle supports their use of MOOCs will have higher behavioral intentions for using the technology. Therefore, the researcher proposes hypothesis 3:

H_3: Social influence has a positive effect on behavioral intention in using MOOC

Relationship between Hedonic Motivation and Behavioral Intention

Hedonic motivation (HM) is described as pleasure or enjoyment that comes from technology use (Venkatesh et al., 2012). HM under UTAUT 2 explains the intrinsic motivation of users in adopting technology where the main influence of HM comes from novelty-seeking and innovation (Venkatesh et al., 2012). Huang, et al. (2013) said that HM is one of the main determinants for understanding the influence of BI. This is reinforced by the opinion expressed by Azrina, et al. (2015), where if individuals find the use of MOOC as fun, BI in using MOOC will increase. Based on the previous explanation, hypothesis 4 is:

H_4: Hedonic motivation has a positive effect on behavioral intention in using MOOC

Relationship between Price Value and Behavioral Intention

Venkatesh et al. (2012) defines price value (PV) as the exchange among perceived benefits and monetary costs from technology. Complementing the previous statement by Venkatesh et al. (2012) revealed if technology adoption achieves utility that is bigger than perceived financial expense, PV will positively influence customer's BI in technology use. Tvaronavičienė et al. (2022) in analyzing the adoption of the use of MOOC argues that BI will be influenced by users' perceptions of learning quality by comparing the costs of supporting facilities. This is necessary in educational decision making and learning intentions especially in young people (Tvaronavičienė et al., 2022). As an effort to validate this, the researcher proposes hypothesis 5 which is as follows:

H_5: Price value has a positive effect on behavioral intention in using MOOC

Relationship between Facilitating Conditions and Behavioral Intention

Venkatesh et al. (2003) define facilitating conditions (FC) as how individuals believe that the existing infrastructure is capable of supporting technology use. Chaveesuk et al. (2022) state, where FC hits high level, it will affect BI positively on the use of the MOOC program. Based on this, the following hypothesis 6 is proposed by the researcher:

H_6: Facilitating conditions have a positive effect on behavioral intention in using MOOC

Relationship between Habits and Behavioral Intention

Venkatesh, et al. (2012) define habits (HB) as a structure in which an individual performs an action continuously and is accompanied by regularity. Continuing the previous explanation, habits are related to automatic behavior that comes from the continuous aggregation of learning and competency (Venkatesh et al., 2012). Venkatesh & Zhang (2010) state, users who frequently use technology will have high potential in adopting new technologies. Research by Chaveesuk et al. (2022) concluded that increasing habits in technology usage can give positive impact on BI of MOOC's users. Based on the explanation, hypothesis 7 is said as:

H_7: Habits have a positive effect on behavioral intention in using MOOC

Relationship between Behavioral Intention and Usage Behavior

UTAUT 2 proposes that usage behavior (UB) is a frequency of using technology which is determined by behavior intention (BI) (Venkatesh et al., 2012). Venkatesh et al. (2012) revealed that behavioral intention can represent individual intentions in using technology. Alalwan et al. (2018) concluded that BI is determinant construct among main antecedents and customers' usage behavior (UB). Venkatesh, et al. (2003, 2012) also said that BI has continuously been validated as the strongest determinant of UB for technology acceptance. Based on this evidence, the researcher proposes hypothesis 8 namely:

H_8: behavioral intention has a positive effect on usage behavior in using MOOC

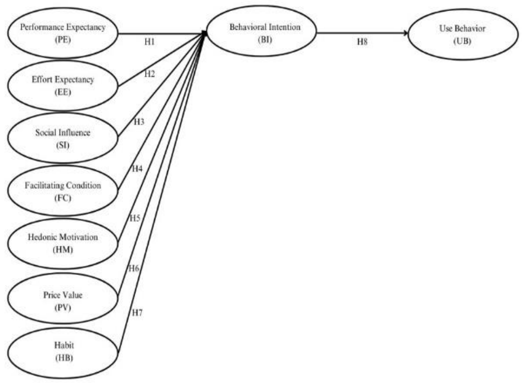

Figure 1. Research framework

METHODS

The subjects in this study are millennial generation (age 25-39) who are MOOC users (or have ever used MOOC). Sampling method using purposive sampling with criteria 1) MySkill.id and SkillAcademy users, 2) age range between 25-39 years, 3) minimum education among high school, undergraduate degree, and graduate degree, 4) already work as professional, employee, or entrepreneur. This study uses quantitative analysis, which is data processing using statistical methods presented in the form of numbers with a Structural Equation Model (SEM) approach using a software-based SmartPLS program.

In terms of measurement, UTAUT 2 is operationalized using the original work from Venkatesh, et al. (2012) that adapted to MOOC context, which is also used by Ahmed et al. (2021), Alalwan et al. (2018), Chakraborty et al. (2021).

Table 1. Respondent Demographic

	N	Percentage (%)
MOOC Platform		
MySkill	93	62
SkillAcademy	57	38
Gender		
Female	89	59,3
Male	61	40,7
Age		
25-27 years	84	56
28-30 years	31	20,7
31-33 years	16	10,7
34-36 years	11	7,3
37-39 years	8	5,3
Education degree		
D3	15	10
S1	94	62,7
S2	41	27,3
Occupation		
Private sector employee	79	52,7
Entrepreneur	27	18
Public sector employee	23	15,3
Freelance	12	8
Service-based (teacher, lecturer, psychologist, lawyer)	9	6

	N	Percentage (%)
Domicile (province)		
Jakarta	56	37,3
Central Java	39	26
DIY	26	17,3
West Java	15	10
Banten	9	6
East Java	4	2,7
South Sumatera	1	0,7

Total respondents were 150 MOOC users. The highest rate in age average of the respondents is 25-27 years (56%). Based on gender, there are 89 (59.3%) female respondents and the rest 61 (40.7%) are male. Meanwhile, the education degree was dominated by undergraduate graduates with 94 (62.7%) respondents (Table 1).

RESULTS AND DISCUSSION

Result

SEM-PLS used to analyze the data. The first step discussed the validity and reliability. Each construct indicator's factor loading value has met the fit criteria, and it will be significant if it is above 0.50 (Hair et al., 2019).

Table 2 shows factor loading and reliability indicators (Composite Reliability and Cronbach's alpha) that have values above 0.70 (Hair et al., 2019). The average variance extract (AVE) value that exceeds 0.50 (Hair et al., 2019) can be said to support convergent validity. Discriminant validity, which is shown in Table 3, was judged using Fornell-Larcker threshold of 0.85 (Hair et al., 2019). Diagonal square root of AVE is greater than of diagonal ones in the corresponding row, also column. Then, the second step is analyzing the structural relationship.

Table 2. Measurement Model

Construct	Factor Loadings
Behavioral Intention – CR = 0.920; CA = 0.870; AVE = 0,794	
BI1	0.889
BI2	0.885
BI3	0.889
Effort Expectancy – CR = 0.922; CA = 0.887; AVE = 0,746	
EE1	0.890
EE2	0.828
EE3	0.879
EE4	0.859
Facilitating Condition – CR = 0.93; CA = 0.901; AVE = 0,771	
FC1	0.879
FC2	0.869
FC3	0.876
FC4	0.887
Habits – CR = 0.927; CA = 0.882; AVE = 0,809	
HB1	0.924
HB2	0.870
HB3	0.903
Hedonic Motivation – CR = 0.928; CA = 0.884; AVE = 0,812	
HM1	0.912
HM2	0.868
HM3	0.923
Performance Expectancy – CR = 0.885; CA = 0.806; AVE = 0,719	
PE1	0.868
PE2	0.809
PE3	0.866
Price Value – CR = 0.931; CA = 0.889; AVE = 0,818	
PV1	0.899
PV2	0.889
PV3	0.925
Social Influence – CR = 0.931; CA = 0.889; AVE = 0,818	
SI1	0.904
SI2	0.896
SI3	0.913
Usage Behavior – CR = 0.927; CA = 0.895; AVE = 0,760	
UB1	0.892
UB2	0.866
UB3	0.880
UB4	0.850
CR = Composite Reliability; CA = Cronbach Alpha; AVE = Average Variance Extracted	

Table 3. Discriminant Validity Fornell-Larcker

	BI	EE	FC	HB	HM	PE	PV	SI	UB
BI	0.891								
EE	0.712	0.864							
FC	0.672	0.552	0.878						
HB	0.743	0.634	0.545	0.899					
HM	0.724	0.594	0.531	0.674	0.901				
PE	0.626	0.506	0.427	0.501	0.530	0.848			
PV	0.805	0.682	0.609	0.744	0.747	0.603	0.905		
SI	0.686	0.535	0.674	0.526	0.551	0.462	0.648	0.904	
UB	0.729	0.642	0.671	0.600	0.583	0.524	0.631	0.644	0.872

Path analysis will be examined in two steps (Figure 2 and Table 4). Step I investigates BI as dependent variable and PE, EE, SI, FC, HM, PV, and HB as independent variables. PV (OSE = 0.205, P = 0.017) was the most principal influence on BI. The other four were also significant: HB (OSE = 0.188, P = 0.011), EE (OSE = 0.156, 0.027), SI (OSE = 0.149, P = 0.018), PE (OSE = 0.138, P = 0.005), FC (OSE = 0.132, P = 0.027). However, HM (OSE = 0.126, P = 0.061) was considered insignificant in this study. H_1 shows that PE has a positive effect on BI in MOOC use and this hypothesis is supported significantly. Likewise, H_2 shows that EE has a significantly positive effect on BI in the use of MOOC. H_3 says that SI has positive effect on BI in the use of MOOC which is also supported significantly. Then H_4 shows that HM has a positive effect on BI in the use of MOOC and is supported. H_5 proposes that PV has positive effect on BI in MOOC use and is supported significantly. H_6 says that FC has a positive effect on BI in MOOC use which is supported significantly. The final hypothesis in this stage is H_7, namely HB has positive effect on BI in MOOC use and is significantly supported (Table 4).

Step II tested H_8 by namely to see the correlation among UB and BI. BI was found to be a predictor of UB (0.729) so that H_8 is supported significantly (Table 4). In summary, our empirical evidence supports the 8 hypotheses we proposed.

Table 4. Standardized Regression Weights

Hypotheses Relationship	Original Sample Estimate	P-value	Accepted/ Rejected
PE -> BI	0.138	0.005	Accepted
EE -> BI	0.156	0.027	Accepted
SI -> BI	0.149	0.018	Accepted
FC -> BI	0.132	0.027	Accepted
HM -> BI	0.126	0.061	Accepted
PV -> BI	0.205	0.017	Accepted
HB -> BI	0.188	0.011	Accepted
BI -> UB	0.729	0.000	Accepted

Discussion

Based on the results, performance expectancy has a positive effect on behavioral intention in using MOOC. PE involves how individuals think that the technology use will improve their performance (Chaveesuk et al., 2022). Users who have confidence that using MOOCs will improve their performance will enable them to adopt MOOCs with ease. In addition, these findings indicate that users are certain that MOOC use will help them more in their work (Haron et al., 2021). So it is believed that users who see the benefits of using MOOCs will be more willing to adopt and increase their use of MOOCs.

Users who find that MOOC can improve their performance will be more motivated to take part in various training and learning that comes from MOOC (Altalhi, 2021). Raza et al. (2021) also reveal that users will highly adopt the technology if it is useful. This is supported by International Labor Organization (2021) which states that changing learning styles to distance learning makes users see MOOC as capable of providing more benefits. In its learning, MOOC also provides instructors who come from various specialties and experts in their respective fields. This provides benefits for users who want to develop their skills for a better career.

Based on the results, effort expectancy has a positive effect on behavioral intention in using MOOC. These results are aligned with research from Chaveesuk et al. (2022) and Haron et al. (2021) which investigated the factors that influence MOOC user acceptance applying UTAUT 2. This finding suggested, individual expectations regarding the effort required to use MOOCs are an important factor in specifying intention in MOOC adoption. In this context there are several principal factors, such as easiness, understandable, and flexibility of interaction (Chaveesuk et al., 2022).

The results also indicate that users expect good convenience regarding the use of MOOCs. Users will highly adopt a technology if they find it easy (and useful) (Raza et al., 2021) and conversely, usage intentions will decrease and users will hesitate to use MOOCs if their use is deemed difficult or impractical by users. These are then the factors that must be taken into consideration for implementing MOOC technology. These results make us believe that users who see the convenience of using MOOCs will be more willing to adopt and increase their use of MOOCs.

The results indicate social influence has a positive effect on behavioral intention in using MOOC. The social influence of UTAU2 aims to link intention and others' perceptions about importance of technology (Chaveesuk et al., 2022). When users are certain that their social cycle justifying MOOC use, they will have high intentions in technology usage. And intention will be less influenced when users perceive that the use of MOOC is not supported by their social network. The role of social influence shows that the opinions of other people such as peers, colleagues, superiors will influence them to use MOOC ((Mulik et al., 2018). Tarhini, et al. (2017) states that in a similar context, people can be influenced by others' opinions and will engage in particular behaviors. Thus, these findings confirm that the behavioral intention of users towards the use of MOOC technology will be influenced by the beliefs of their superiors and/or colleagues about the technology.

The results indicate facilitating conditions have a positive effect on behavioral intention in using MOOC. In order to explore the aspects influencing the behavioral intention in MOOC use, facilitating conditions explains that existing infrastructure can influence MOOC use intention (Chaveesuk et al., 2022). MOOC is online platform which includes the internet where then facilitating conditions will directly influence technology usage behavior (Chaveesuk et al., 2022). The significant impact of facilitating conditions on behavioral intention means that respondents believe that they have the infrastructure supporting MOOC use (Mulik et al., 2018). Mulik et al., 2018) added, the existing resources such as compatible devices will be a determining factor in MOOC adoption.

Chaveesuk et al. (2022) also stated that aspects such as the availability of the internet and gadgets are important to specify MOOC adoption. Users perceive that the use of MOOCs that are compatible or in line with other technologies they use, will increase the adoption of MOOC usage. Therefore, MOOC service provider management can build a system where MOOC is easily accessible and supported by other technologies used by its users. Therefore, users who have the infrastructure, resources, and knowledge needed to use MOOC will be more inclined to adopt the technology.

The results indicate hedonic motivation has a positive effect on behavioral intention in using

MOOC in insignificant way. Hedonic motivation in the technological aspect includes fun, interest, and excitement (Chaveesuk et al., 2022). It is articulated that behavior intention in technology use will arise when users perceived the enjoyment from using the technology (Chaveesuk et al., 2022). It is believed that the pleasure that arises from using MOOCs didn't create essential impact on intentions because educational content is not related to entertainment.

Users who perceive that MOOCs are fun or interesting will have positive impact regarding their use. However, intention to use MOOCs tends to be minimal in individuals or users who find using online technologies that support MOOCs uninteresting and enjoyable. Learning activities are actually more attached to increasing cognitive activity and encouraging user independence (Kuimova et al., 2018). So that users who use or access MOOC technology do not aim to seek pleasure but to benefit from their learning process.

The results indicate price value has a positive effect on behavioral intention in using MOOC. PV involves quality and cost that will affect intention to use certain technologies (Chaveesuk et al., 2022). Thus, the intentions in MOOC use are affected by users' comparation of perceived learning quality and cost. This means that users find that their intention to use MOOC is influenced by the monetary costs they have to incur. Those aspects are principal in educational intention for young people (Chaveesuk et al., 2022). When users increasingly believe that the benefits or results obtained from using MOOC are greater than the costs incurred, users will be more inclined to adopt MOOC technology and behavioral intention or intention to use will increase.

The results indicate habits have a positive effect on behavioral intention in using MOOCs. Chaveesuk et al. (2022) stated that the increase of technology usage habits can affect users' intention in MOOC use. What's more, habit construction also involves users to show the behavior automatically. Meet et al. (2022) state, today's youth based on their innate familiarity with internet devices and technology will tend to have conditioned behavior in using technology which can then influence their intention to adopt MOOC. Ergo, it can be decided that the higher the level of doing something automatically, the subconscious behavior or action leads to an increase in opportunities to adopt and use MOOC technology.

The results indicate behavioral intention has a positive effect on usage behavior in using MOOC. Behavioral intention is theorized to positively affect UB. This relationship has been proven in research on various educational technologies (García Botero et al., 2018). Behavioral intention reflects users' intention, users' possibility to involve in certain behaviors, or users' commitment to engage in certain behaviors (Sitar-Taut & Mican, 2021). Usage behavior itself is the actual use of certain technologies where when an individual accepts a technology (behavioral intention) then he will use the technology (usage behavior) (Sitar-Taut & Mican, 2021). So, if the possibility to participate in certain behaviors provided by the MOOC is high, then the usage behavior will also be high (Sitar-Taut & Mican, 2021).

Conclusion

This study investigates and addresses eight hypotheses regarding the impact of performance expectancy, effort expectancy, social influence, hedonic motivation, price value, facilitating conditions, and habits on behavioral intention, as well as the influence of behavioral intention on usage behavior in the context of MOOC usage, employing the UTAUT 2 model. The respondents in this study belong to Generation Y, specifically individuals aged 25-39 years. The findings of this study demonstrate that price value is the primary factor influencing behavioral intention compared to the other six variables, followed by performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating conditions, and habits in sequential order. Additionally, the study confirms that behavioral intention significantly contributes to usage behavior. Among these results, hedonic motivation doesn't seem to have a significant effect on behavioral intention. As an effort to improve this aspect, company management can innovate by making learning through MOOC more fun (e.g., involving gamification). This aims to make users see the potential for fun that can arise and will ultimately affect the adoption and use of MOOC.

This research recommends that price value should be considered as significant factors that influence MOOC use. This implies that it is important to evaluate the benefits that users will derive from using MOOC must be higher than the monetary costs that they pay. From the theoretical implication, this study provides confirmation that UTAUT 2 is an appropriate theory for predicting behavioral intention and usage behavior. Therefore, future research should consider to adopt the UTAUT 2 model completely (or even with additional variables) and investigate the factors that influence MOOC use in different generation (e.g., generation Z).

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