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Analysis of Factors influencing the successful use of Massive Open Online Courses (MOOCs) to prepare Digital Talent

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Abstract. One type of e-learning category is Massive Open Online Courses (MOOCs). MOOCs or MOOC promote the "democratization of education" that allows education to be accessed by everyone from anywhere and anytime. The use of MOOCs gives students access to a wide variety of resources. MOOs enable students to have sufficient storage capacity to store their materials. MOOCs have the potential to improve digital capabilities in the face of digital transformation. The intention to use MOOC is relatively high, however, in terms of class completion rate and motivation to pass on MOOC is relatively low. These conditions need to be examined to increase the success rate of MOOCs usage. This research develops a model and identifies factors that influence the successful use of MOOCs to prepare digital talent. The approach is a mixed method that collects quantitative data using an online questionnaire and qualitative data via interviews. The researcher took data from 91 samples and eight informants for interviews. In the study results, 6 out of 12 hypotheses are accepted in this study. The factors that influence a person in completing MOOC either directly or indirectly include Performance expectancy, willingness to earn certificates, MOOC quality, and Intrinsic motivation. This research also produces recommendations that can be used as consideration for parties related to MOOC.

Keywords: Digital Talent; MOOCs; SEM-PLS; UTAUT

INTRODUCTION

The COVID-19 pandemic has forced most educational institutions worldwide to change their teaching and learning processes. They prepare online distance education to ensure uninterrupted education (Junus et al., 2021). E-learning is a method of learning and delivering material online, using information technology for learning, teaching, training, or acquiring knowledge at any time and in many different locations. E-learning is broader than online learning, which generally refers exclusively to web-based learning. E-learning includes m-learning (or mobile learning when the material is delivered wirelessly to a smartphone, tablet, or other mobile devices. E-learning is synonymous with computer-based instruction, training, online education, and other terms (Turban et al., 2018). According to Mastan (Mastan et al., 2022), there are several categories in the implementation of e-learning: Massive Open Online Courses (MOOC), Mobile Learning Systems, etc.

One type of e-learning category is Massive Open Online Courses (MOOCs); MOOCs or MOOC promote "education democratization," which allows education to be accessible to everyone from anywhere and anytime (Bozkurt, A., Jung et al., 2020). The use of MOOCs gives students access to a wide variety of resources; MOOCs allow students to have the sufficient storage capacity to store their materials. MOOCs also will enable students to share learning materials with other participants (Ibrahim Arpaci et al., 2020). MOOC or MOOCs promote the "democratization of education" that allows education to be accessible to everyone from anywhere and at any time (Bozkurt, A., Jung et al., 2020). MOOCs are usually classified according to the nature of the course content as well as the characteristics of the target population. Currently, MOOCs can be classified into one of five main configurations: xMOOC, connectives MOOC, mixed MOOC, hybrid MOOC, or quasi-MOOC (Ibrahim Arpaci et al., 2020). Everyone can register at MOOC for free; however, certification in some courses may incur a fee. MOOCs are classified into four types: cMOOC, xMOOC, hMOOC, and MOOC. The use of MOOC gives students access to a wide variety of resources; MOOC allows students to have the sufficient storage capacity to store their materials(Ibrahim Arpaci et al., 2020). MOOC also will enable students to share learning materials with other participants (Ibrahim Arpaci et al., 2020).

The COVID-19 pandemic has finally provided momentum for the growth of online learning in Indonesia at all levels of education. The potential for implementing e-learning during the COVID-19 pandemic in Indonesia is relatively high, with flexibility and independent learning, and increased participation (Hafidz, 2022). Students must study online-based learning with the implementation of technology during this pandemic. Nevertheless, there are several challenges, such as internet connection, expensive data packages, and the adoption process(Sufyan et al., 2020). The MOOCs adoption has not been accompanied by the readiness of students to take part in online learning (Martha et al., 2021).

In 2030 it is predicted that there will be an average digital talent shortage of 6-12 million people; for Indonesia alone, even the need for Indonesia, 12-18 million people (*Konferry*, n.d.). According to Sousa and Rocha (Khalid & Naumova, 2021)(Sousa & Rocha, 2019), the digital skills needed are Artificial Intelligence, nanotechnology, robotization, etc. In carrying out digital transformation, various roles and cross-functional teams are needed based on technical and interpersonal/business skills to be effective and fill gaps in IT competence (Abdulraheem Yamani & Elsigini, 2020)(Yamani, 2021). People are among the most critical and influential factors for any digital transformation. No technology can help if human problems are not solved. Success in digital transformation requires more than just looking back at technology; but requires a complete rethinking of organizational models, especially skills, incentives, structure, and performance management (Chandra Sharma, 2015). Education is one way to maintain information and disseminate it, as well as to create new information in the "information technology industry"(Mamlook et al., 2021)(Bensaid & Brahimi, 2021)(Cerezo-Narváez et al., 2021).

The current opportunities make MOOCs a solution to improve digital capabilities in the face of digital transformation (Yang et al., 2021). The intention to use MOOCs is relatively high, as evidenced by the many students who register (Littenberg-Tobias & Reich, 2020). It's just that in terms of class completion and motivation to pass is relatively low. MOOCs completion describes a situation when a learner fulfills all course requirements or obtains a certificate of course completion (Bozkurt, A., Jung et al., 2020). Despite the large number of students who apply to MOOCs, around 7-10% of them complete the course. This condition needs to be tested for the success rate to increase the use of MOOCs to increase the graduation rate and students' abilities (Tan, 2019)(Nada Ali Hakami, 2018). A few studies still discuss MOOCs graduation, even though it is very much needed. Currently, research in the field of MOOCs is more on intensity and use, while as the review described above, the pass rate is relatively low. In line with that, MOOCs are expected to support getting a job following the abilities that have been learned.

This research focuses on examining the adoption and use of the system for MOOCs. In increasing system usage, it is necessary to conduct technology adoption research, and it is also used to respond to changes that occur(Turban et al., 2018). Many theories are used in the service and acceptance of information technology, one of which is the Unified Theory of Acceptance and Use of Technology (UTAUT) model. UTAUT is a model developed by Venkatesh, Morris, Davis, and Davis in 2003 (Venkatesh et al., 2003) to overcome the limitations of the Technology Acceptance Model (TAM) and other popular models used in information systems adoption studies. Venkatesh (Venkatesh et al., 2003)(Fianu et al., 2018b) identified and studied eight predefined models, namely: (a) Theory of Reasoned Action (TRA) - Ajzen & Fishbein (1980); (b) Theory of Planned Behavior (TPB) - Ajzen (1985); (c) Technology Acceptance Model (TAM) - Davis (1989); (d) Model of Personal Computer Utilization (MPCU) - Thompson et al. (1991); (e) Motivational model (MM) - Davis et al. (1992); (f) Social Cognitive Theory (SCT) - Compeau & Higgins (1995); (g) C-TAM-TPB—a model combining TAM and the Theory of Planned Behavior (TPB) - Taylor and Todd (1995); (h) Innovation Diffusion Theory (IDT) - Rogers (1983 and 2003).

UTAUT was developed to become an integrated model based on the results of various models that have been developed previously (Venkatesh et al., 2003)(Fianu et al., 2018b). This UTAUT model is very appropriate for adopting technology use based on the individual's perspective (Ayuning Budi et al., 2021); in the context of this research are students from MOOCs. In contrast, the IS Success model is used to assess adoption that focuses on the organization with the context of the successful implementation of information systems that lead to technical matters (Ayuning Budi et al., 2021)(Burlea, 2009). UTAUT was chosen as the theoretical basis because UTAUT can use in various research contexts with high validity and stability (Venkatesh et al., 2003). It is proven that UTAUT has a 70% variance in behavioral intention, while other models such as TAM, TRA, and TPB are only around 40% (Nada Ali Hakami, 2018). The UTAUT model was found to perform better in terms of behavioral intention variance than any of the other eight models (Al-Qeisi et al., 2015)(Fianu et al., 2018b). In the context of e-learning, in this case, MOOC, UTAUT has also been used for previous research in related fields. The researchers also found that the moderating factor significantly increased the predictive power of the other eight models, except the motivational and social-cognitive models. UTAUT is one of the most potent and comprehensive theories to explain IT adoption, mainly due to the integration of as many as eight theories (Fianu et al., 2018a)(Y. S. Wang et al., 2009).

Previous research examined by Hakami (2018), the researcher should have explained holistically how the process from the beginning of students participating in the MOOC program was carried out on an ongoing basis until they were declared passed or finished. Research conducted by Fianu et al. (2018) also only shows the general use of MOOCs. While other studies only show further intention to participate in MOOCs (Hone & El Said, 2016) and interest in further course (Kim et al., 2021). This study aims to holistically discuss the factors supporting success from the participants' intention to participate in MOOC, using it regularly until graduation.

This research is expected to fill the gap in the existing literature by identifying the factors that influence the success of using MOOCs. This research is expected to provide recommendations to related parties in developing MOOCs to increase participants' motivation and graduation.

METHOD

The research design is used to plan research activities, be it data collection, calculation, or analysis (Arachchi et al., 2017). To answer the research questions posed, this study uses a mixed-method approach. According to (J. Creswell, 2014)(Tashakkori, A., & Teddlie, 2003), the mixed method allows research activities to use more than one method or the point of view of quantitative and qualitative methods. According to Johnson & Onwuegbuzie (Casasayas et al., 2021), mixing research methods can be done sequentially or simultaneously. Creswell & Plano Clark (Cheung et al., 2018) classifies mixed methods design into four main categories: triangulation, embedded, explanatory, and exploratory. This research is explanatory because it focuses on developing a model that tests several combined theories.

This study uses a Sequential Explanatory Mixed Methods approach (J. W. Creswell & Creswell, 2018), where the first phase uses quantitative-based research methods, then proceeds with qualitative methods. The purpose of using this method in research is to get views and relationships and a complete picture of the phenomenon (Venkatesh et al., 2013). There are three main advantages to using the mixed method (Venkatesh et al., 2013), especially in information systems. First, this research can examine phenomena to contribute to a theory. Second, providing solid conclusions and new views with the proper steps and stages of research. Third, the mixing method can provide opportunities to bring up many differences that complement each other. At the scene of forming the model, it refers to previous research analyzing secondary data. Meanwhile, quantitative-based analysis is carried out by testing the model made and validating the research hypothesis. Furthermore, qualitative-based research methods include interview sessions to capture arguments and strengthen the results of the previous stages.

Instrument Development

The research instrument is arranged based on the factors that have been obtained in the research model. The instrument's preparation is based on previous research by loading indicators in related research. Each indicator will be adapted to the research context, both in terms of language and sentence structure, so it is relevant to this research.

The readability test was conducted on five people to ascertain whether the questionnaire was unambiguous. The purpose of this stage is to ensure that the questionnaire can be appropriately read and completed by the respondent. The readability test was carried out to adopt the best practice made by Willis (Guntha et al., 2021) by adjusting the amount as necessary. This readability test includes a questionnaire and indicator test. This stage involves several prospective respondents who have been targeted according to the purpose of the research questionnaire. The result is that the instruments compiled are valid and can be distributed after revision.

Sample and Data Collection

Questionnaires are one way to complete quantitative-based research (Nada Ali Hakami, 2018). The research stage for model validation uses a quantitative basis to capture phenomena and test theories based on predetermined variables (Nada Ali Hakami, 2018). Data collection uses an online questionnaire with a predetermined sample or purposive sampling with coverage of MOOC users in Indonesia which is done to find a targeted selection (Littenberg-Tobias & Reich, 2020)(Fianu et al., 2018a).

The researchers made the sample of the questionnaire filler with criteria to determine the use and completion of MOOCs so that the expected results can provide recommendations for the benefit of MOOCs in the future. The target of filling out the questionnaire is users who have attended or registered for at least one course on the MOOC platform. This data collection method has been used several previously in proving the theories that have been built (Ibrahim Arpaci et al., 2020) to determine the relationship between culture and knowledge management in MOOCs. A study conducted by (Shen & Chen, 2021) used a similar data collection method to determine the intention to use MOOCs based on user habits that affect performance. Questionnaire questions consist of demographic questions and research model indicator questions. In collecting data, questionnaires were collected online to reach a broader range of respondents. In addition, the time used is also relatively more petite, so it is more efficient—to distribute questionnaires using social media such as WhatsApp, Telegram, and other supporting media.

Interviews were conducted to strengthen and confirm the results of quantitative data related to the proposed hypothesis (Littenberg-Tobias & Reich, 2020). Interviews were conducted on respondents who had filled out a questionnaire with indicators that they had completed at least one course using the semi-structured interview method. At this stage, it produces an output of qualitative data that can enrich the previous data from the questionnaire. The researcher will also analyze the results of the interviews following related research that has been done previously. In addition, at this stage, it produces outputs in the form of recommendations for developing MOOCs for associated parties, both the platform, teachers, and users of the MOOC itself.

The questionnaire survey was conducted from May 1, 2022, to May 20, 2022, through Google Forms. The results obtained as many as 130 responses with valid results of 91 responses.

Meanwhile, interviews were conducted with eight respondents who had filled out the survey. Resource persons are selected with different demographic ranges to increase the richness of the data obtained.

Conceptual Model and Hypothesis

Conceptual model development involves three activities, namely: (1) identification of factors and indicators, (2) conceptual model construction, and (3) hypothesis development. In this study, we will assess the use of the MOOC system for online-based learning methods from the user's perspective so that UTAUT is considered a suitable and appropriate method. The main reason that has been explained is that the user's intention to use the MOOC is relatively high, but only a few are successful or completed, so it needs to be assessed in terms of the level of use. UTAUT suggests that four constructs play an essential role in determining user acceptance and behavior: performance expectancy, self-efficacy, effort expectancy, social influence, and facilitating conditions, which form the basis for general IT adoption (Venkatesh et al., 2013). In this study, the UTAUT theory was further developed following the MOOC context by adding several factors obtained from previous research. The addition of these factors is adjusted to the MOOC context to answer existing problems, including MOOC quality (K. P. Gupta & Maurya, 2020; Hone & El Said, 2016), willingness to earn certificates (Nada Ali Hakami, 2018), and intrinsic motivation (Kim et al., 2021). The hypotheses are stated in the following sections:

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The hypotheses are stated in the following sections:

Performance expectancy

According to (Pynoo et al., 2011) that performance expectancy is a person's perception that using technology, will affect a person's performance. The Performance Expectancy factor in the UTAUT theory significantly influences a person's intention to use a technology (Venkatesh et al., 2003). This is in line with the research proposed by (Dečman, 2015) and (Y.-S. Wang et al., 2009). The following hypothesis is offered in the study presented by (Fianu et al., 2018b) on the application of the use of MOOC.

H1: Performance expectancy has a significant effect on students' intentions to use MOOCs.

Effort expectancy

Effort expectancy is a person's expectation that using technology will get convenient (Al-Shafi et al., 2009). In a study conducted by (Fianu et al., 2018b), effort expectancy included these factors as influential. In line with the theory and findings of the work (Dečman, 2015) and (Y.-S. Wang et al., 2009). These factors are sourced from the UTAUT theory (Venkatesh et al., 2003), that effort expectancy affects a person's intention to use certain technologies. This is the basis for developing the following hypothesis.

H2: Effort expectancy has a significant effect on students' intentions to use MOOCs.

Social influence

Social influence in the UTAUT theory developed by Venkatesh (Venkatesh et al., 2003), social influence is a factor that influences a person's use of technology. According to (Venkatesh et al., 2003), social influence is how much a person trusts others to intend to use technology (Hafidz, 2022). The effect was

developed by (Fianu et al., 2018b) on the use of MOOCs. This is the basis for developing the following hypothesis.
H3: Social influence has a significant effect on students' intentions to use MOOCs.

Self-efficacy

Self-efficacy means a person's level of understanding and skills to get results in the future (I Arpaci, 2017)(Fianu et al., 2018b). This theory initially refers to the TAM theory, which was later developed (Venkatesh et al., 2003). This is in line with research conducted by (Magsamen-Conrad et al., 2015) that Self-efficacy affects a person's intention to use technology. So, the following hypothesis is formulated.
H4: Self-Efficacy has a significant effect on students' intentions to use MOOCs.

Commitment

According to (Kizilcec & Halawa, 2015), that commitment affects the completion of MOOC, which requires high persistence. Similarly, (Kizilcec et al., 2017) found that MOOCs with higher levels of time commitment could achieve desired outcomes. Mukala, Buijs, and Leemans (Mukala et al., 2015) found students with more structured learning patterns will get better course scores. This finding reaffirms that student commitment may be an essential factor in using MOOC (Kim et al., 2021) so the following hypothesis is formulated.
H5: The learners' commitments to the MOOC will have a significant effect on their intentions for using MOOC.

Facilitating condition

Facilitating condition is a factor included in UTAUT theory (Venkatesh et al., 2003). This factor was also welcomed by (Fianu et al., 2018b), who focused on using MOOCs. Facilitating conditions are forms of support provided in terms of infrastructure and technical aspects in applying technology. This can affect the behavior of using technology, so the following hypothesis is formulated (Fianu et al., 2018b).
H6: Facilitating conditions have a significant effect on students' MOOC usage behavior.

MOOC usage intention and MOOC usage

A person's intention influences the behavior of using technology, following the UTAUT theory (Venkatesh et al., 2003). Other approaches also use the same factors, such as TAM, TPB, and UTAUT2 (Fianu et al., 2018b). Several studies have also confirmed the influence of behavioral intentions on usage behavior, such as (Dečman, 2015) and (Y.-S. Wang et al., 2009). In this case, the following hypothesis is formulated.
H7: Students' intention to use MOOCs has a significant effect on students' MOOC usage behavior.

The willingness to earn a certificate

According to (Bayeck, 2016; Littlejohn et al., 2016; Shrader et al., 2016), participants' intention to obtain a certificate is the reason for joining and staying in MOOC. A study conducted by (Liu et al., 2014) stated that getting a certificate was one of the reasons for joining MOOCs percentage of 18.75%. Research conducted by (Nada Ali Hakami, 2018) states that recognition is related to the behavior of MOOCs. So, on this basis, the following hypothesis is formulated.
H8: The willingness to earn a certificate will have a significant effect on students' MOOC usage behavior.

MOOC quality

MOOC quality consists of content and instruction quality (K. P. Gupta & Maurya, 2020)(Hone & El Said, 2016). Instructional quality represents a student's view of the instructor's effectiveness and the instructional methods used to deliver the course. Content quality refers to the overall quality of information and content provided in the study (Ozkan & Koseler, 2009). Previous research has shown that instructional quality is an essential predictor of a learning management system (K. P. Gupta & Maurya, 2020). Teaching materials are crucial determinants of student satisfaction that significantly affect the use of continuous online learning (Hone & El Said, 2016). Following the literature that has been described, the following hypothesis is formulated.
H9a: MOOC quality has a significant effect on students' MOOC usage behavior.

H9b: MOOC quality has a significant effect on the student completing MOOC.

Intrinsic motivation

Intrinsic motivation arises from oneself to increase curiosity and explore new things (Nada Ali Hakami, 2018). According to (de Barba et al., 2016; Magen-Nagar & Cohen, 2017) intrinsic motivation affects the use of

technology. In this regard, research (Nada Ali Hakami, 2018) shows the importance of intrinsic motivation for the service and completion of MOOCs. The following is a hypothesis that has been compiled.
H10a: Students' motivation has a significant effect on students' MOOC usage behavior.

H10b: Students' motivation has a significant effect on the student completing MOOC.

MOOCs Usage and Completing MOOC

Students' behavior in accepting MOOCs also goes through several stages, starting from the intention to use, becoming behavior, and then completing the course (K. P. Gupta & Maurya, 2020). The MOOC study (K. P. Gupta & Maurya, 2020) discusses the influence between adoption, settlement intention, and sustainable use. Therefore, the following hypothesis is formulated.
H11: Students' MOOCs usage behavior has a significant effect on the student completing MOOC.

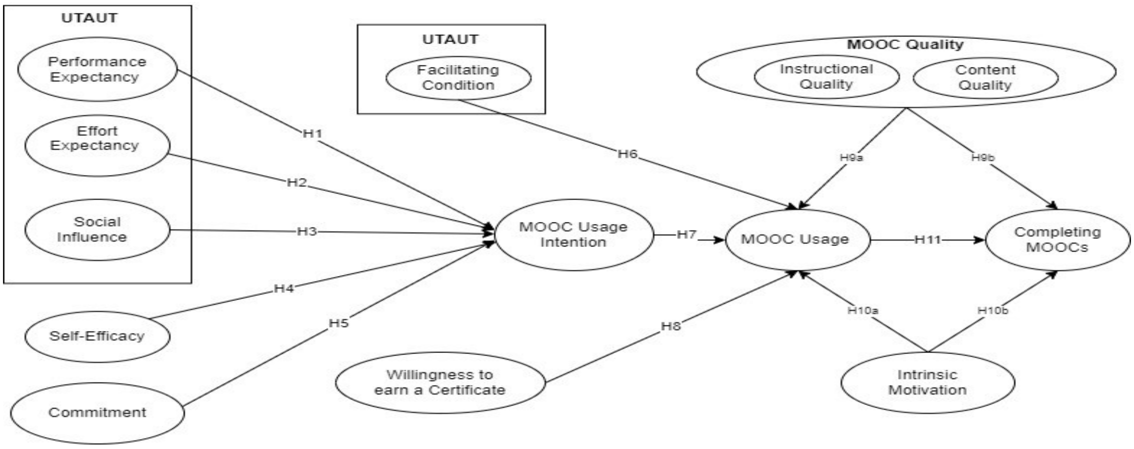

Figure 1. Conceptual Model

RESULTS AND DISCUSSION

Result

The purpose of the Results and Discussion is to state your findings and make a interpretations and/or opinions, explain the implications of your findings, and make suggestions for future research. Its main function is to answer the questions posed in the Introduction, explain how the results support the answers and, how the answers fit in with existing knowledge on the topic. The Discussion is considered the heart of the paper and usually requires several writing attempts.

The results of demographic data from the distribution of questionnaires collected using the Google form method can be seen in Table I. We can see that most of the questionnaires are male, and the average age is young with a profession as a student.

After getting the data from the survey, the first thing to do is to evaluate the measurement model for reliability and validity. After being declared valid, the results tested the structural path between the variables in the proposed model. The software used to try and analyze the data is Smart PLS 3. The measurement model is evaluated by testing the reliability, which consists of Cronbach alpha (CA) and composite reliability (CR). Then try the convergent and discriminant validity consisting of the Average Variance Extracted (AVE) and cross-loading values.

This test is carried out to test whether the indicators included are reliable. Cronbach alpha and composite reliability are used to measure this. The minimum value of Cronbach alpha and composite reliability of a factor is 0.7, but some say 0.6 (Nada Ali Hakami, 2018). The results obtained in Table 2 show that the facilitating condition does not meet, so it is removed from the indicator. Meanwhile, MOOC Usage is one of the essential factors, so it is maintained, if it follows the 0.6 standards, then it is still in the acceptable category. The Average Variance Extracted (AVE) value is used to measure convergent validity, while the minimum AVE value that needs to be met is 0.5. Convergent validity means that a set of indicators represents one latent variable that underlies the latent variable. Table 3 shows the valid and reliable results of the measurement model analysis.

Table 1. Demographic data

No	Type of Characteristic	Characteristic	Total	Percentage
1	Gender	Male	25	27%
		Female	66	73%
2	Age	<18 years old	60	66%
		18 - 24 years old	14	15%
		25 - 30 years old	7	8%
		31 - 35 years old	4	4%
		36 - 40 years old	3	3%
		41 - 45 years old	2	2%
		46 - 50 years old	1	1%
		>50 years old	0	0%
3	Profession	Employee (not teacher/lecturer)	24	26%
		Civil servant (not teacher/lecturer)	2	2%
		Private Teacher/lecturer	5	5%
		Civil servant Teacher/lecturer	2	2%
		Student	46	51%
		Entrepreneur	2	2%
		Other	10	11%
4	Educational background	Elementary school	0	0%
		Junior high school	0	0%
		Senior high school	37	41%
		Diploma	6	7%
		Bachelor's degree	44	48%
		Master's degree	4	4%
		Doctoral degree	0	0%
5	Frequency in one week	< 1 hour	6	7%
		1 - 4 hours	59	65%
		5 - 9 hours	12	13%
		10 - 14 hours	4	4%
		=> 15 hours	10	11%
6	Period of use	< 1 month	8	9%
		1 - 3 months	40	44%
		4 - 6 months	12	13%
		7 - 9 months	2	2%
		10 - 12 months	7	8%
		> 12 months	22	24%
7	Number of courses	1 - 3 courses	56	62%
		4 - 6 courses	19	21%
		7 - 9 courses	5	5%
		10 - 12 courses	1	1%
		> 12 courses	10	11%
8	Number of courses completed (without certificate)	0 course	19	21%
		1 - 3 courses	44	48%
		4 - 6 courses	15	16%
		7 - 9 courses	5	5%
		10 - 12 courses	2	2%
		> 12 courses	6	7%
9	Number of certificates	0 certificate	15	16%
		1 - 3 certificates	50	55%
		4 - 6 certificates	13	14%
		7 - 9 certificates	4	4%
		10 - 12 certificates	2	2%
		> 12 certificates	7	8%
10	IT field or not	Yes	80	88%
		No	11	12%

Table 2. Result of measurement model analysis

Latent constructs	CA	CR	(AVE)
CM	0.918	0.942	0.803
COM	0.883	0.904	0.517
EF	0.821	0.882	0.653
FC	0.614	0.773	0.462
IM	0.912	0.93	0.656
MQ	0.926	0.94	0.661
MU	0.656	0.792	0.492
MUI	0.927	0.949	0.822
PE	0.85	0.897	0.687
SE	0.765	0.844	0.581
SI	0.777	0.858	0.604
WEC	0.918	0.936	0.71

Table 3. Result of measurement model analysis (iteration 2)

Latent Construct	CA	CR	AVE
CM	0.918	0.942	0.803
COM	0.879	0.906	0.581
EF	0.821	0.882	0.653
IM	0.912	0.930	0.656
MQ	0.926	0.940	0.661
MU	0.626	0.801	0.574
MUI	0.927	0.949	0.822
PE	0.850	0.897	0.687
SE	0.765	0.844	0.581
SI	0.777	0.858	0.604
WEC	0.918	0.936	0.710

After testing the validity and reliability of the model, the research continued by testing the proposed hypothesis by bootstrapping using 5000 sub-samples using the Smart PLS application. Table 4 below is the result of hypothesis testing from this research. The factors that influence a person in completing MOOC either directly or indirectly include Performance expectancy, willingness to earn certificates, MOOC quality, and Intrinsic motivation.

Table 4. The result of hypothesis testing

Hypothesized Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values	Result
PE -> MUI	0.342	0.334	0.157	2.179	**0.032**	Accepted
EF -> MUI	0.176	0.179	0.178	0.990	**0.325**	Rejected
SI -> MUI	0.051	0.044	0.125	0.408	**0.684**	Rejected
SE -> MUI	-0.052	-0.066	0.153	0.338	**0.736**	Rejected
COM -> MUI	0.129	0.164	0.150	0.863	**0.390**	Rejected
MUI -> MU	-0.038	-0.034	0.093	0.405	**0.686**	Rejected
WEC -> MU	0.207	0.221	0.076	2.711	**0.008**	Accepted
MQ -> MU	0.325	0.326	0.135	2.417	**0.017**	Accepted
MQ -> CM	0.369	0.343	0.121	3.055	**0.003**	Accepted
IM -> MU	0.290	0.292	0.132	2.197	**0.030**	Accepted
IM -> CM	0.467	0.495	0.109	4.270	**0.000**	Accepted
MU -> CM	0.072	0.075	0.077	0.938	**0.351**	Rejected

Discussion

This section discusses the results of accepting or rejecting hypotheses based on the T-value test using a validated model and refers to the effects of exploratory interviews with interviewees that have been conducted to confirm the quantitative results obtained.

The hypothesis regarding the significance of performance expectancy and MOOC Usage Intention is accepted in line with research conducted by (Fianu et al., 2018b). Other studies that support this include (Dečman, 2015; Pynoo et al., 2011; Y.-S. Wang et al., 2009). This hypothesis indicates that student participation positively impacts their academic qualifications in line with the interviews conducted and that the initial intention to improve quality and add value to oneself is crucial. So, participating in learning at MOOC can improve student performance. The effort expectancy factor follows previous research (Fianu et al., 2018b). The study (Al-Shafi et al., 2009) also produced the same analysis. It is explained that students are not too focused on the use or efficiency of the technology used but on studying the existing material in contrast to other information systems in general, which are used to facilitate business or efficiency. This does not happen in online-based learning systems because technology does not necessarily reduce effort but only increases learning effectiveness (Fianu et al., 2018a).

According to (Fianu et al., 2018b), social influence is one of the factors that significantly affects the use of MOOC, which means it is not following the results of this study. Still, this study is in line with the results of Magsamen-Conrad (Magsamen-Conrad et al., 2015). Previous research has shown that individuals do not need encouragement from their environment to motivate them to follow MOOC. There are interviews that people around may affect the intention to participate in MOOC-based learning. It's just that it is self-motivation that can increase to follow this. In MOOCs that are not tied to certain people, such as rules from superiors and others, it is not so influential to follow them. The hypothesis related to the self-efficacy factor results in contrast to previous research (Fianu et al., 2018b); only the context is on confidence in using technology. Other studies, such as those conducted by (Artino, 2008; Chang & Tung, 2008), and (Alenezi et al., 2010), also showed different results. Previous research has shown that confidence in the ability to use technology impacts effectiveness in using MOOCs. The interview results show that the ability to use technology is not very influential, perhaps because most of the respondents are in the IT field. Meanwhile, in the non-IT sector, it shows the opposite.

MOOC usage intention has no significant effect on MOOC usage, which is contrary to the results of previous studies by (Fianu et al., 2018b) (M. H. Wang & Yang, 2016) and (Ain et al., 2016). Previous research has shown that a person's intentions influence subsequent use behavior. Insignificant hypothesis results can occur because the data used are from various platforms with different materials and completion times. The interview results show that a person's intention to register for MOOC is that the material offered is exciting and follows the needs, explained in detail. According to (Nada Ali Hakami, 2018) and (Mohapatra, 2019) certificates are essential in completing MOOCs. Previous studies have shown the same results as this study. A certificate of completion shows that a person has signed up for and completed the class they are taking, although it is sometimes paid. The interview results show that a certificate is essential in achieving the MOOC, especially if the certificate offered has legality and more value. Following what was conveyed by the informant, the student can use the certification provided to register for work, and internships, participate in competitions, get scholarships, and others.

In testing the hypothesis related to MOOCs quality, the results following research conducted by (G. Gupta & Bose, 2019), (Hone & El Said, 2016), and (Al-Fraihat et al., 2020). In a study conducted by (G. Gupta & Bose, 2019), MOOCs Quality consists of content quality and instruction quality. This is in line with research (Fianu et al., 2018b) which shows that instruction affects MOOCs' use, while research (Virani et al., 2020) describes the importance of content quality in MOOCs use. The interviews showed that interesting content and instructions would encourage students to access and use MOOCs consistently. Moreover, the content and pedagogy are complete and precise, along with the learning map. MOOCs quality also affects the completion of MOOCs, and the results are the following research (Hone & El Said, 2016) and (K. P. Gupta & Maurya, 2020). The quality of learning in MOOCs in the form of content and instructions given affects a person in completing the MOOCs. This follows the interview results that all informants agreed that the material and instructions were the main things someone saw in completing the MOOCs. If the material meets the needs and the way it is delivered is interactive, it will encourage someone to complete the MOOCs.

Tests related to the hypothesis between intrinsic motivation and MOOCs usage got significant results. This is following previous research conducted by (Nada Ali Hakami, 2018), (Technology, 2018), and (Al-Fraihat et al., 2020). Intrinsic motivation comes from oneself (Nada Ali Hakami, 2018); it is one indicator of the quality of students learning (Al-Fraihat et al., 2020). The interview results show that self-motivation is essential to using MOOCs consistently because learning is online, and students feel less attached, so they must grow motivation well. Intrinsic motivation also significantly affects the completion of MOOCs, according to previous research conducted by (Li et al., 2018) and (Technology, 2018). Self-motivation encourages a person to persist in participating in learning and completing MOOCs (Technology, 2018). The interview results also show that self-management starts from self-motivation to complete the courses that have been followed. External factors are not too influential if motivation from within oneself does not appear.

The results were insignificant in the hypothesis of MOOCs usage by completing MOOCs. These results are not in line with research (K. P. Gupta & Maurya, 2020) that a person's intention to conduct a MOOCs affects the use of MOOCs. This can happen because the respondents who are used for research follow the MOOCs with different platforms and materials. The various platforms show various features. Thus, the indicators in the use of MOOCs that affect success are also different. The interview results show that the material factor needed is the primary key in completing the MOOCs, besides setting a target or time limit. Paid content increases commitment when accompanied by a time limit but is inversely proportional to the intention to use MOOCs.

CONCLUSIONS AND SUGGESTIONS

In the study results, 6 out of 12 hypotheses are accepted in this study. The factors that influence a person in completing MOOCs either directly or indirectly include Performance expectancy, willingness to earn certificates, MOOCs quality, and Intrinsic motivation. The recommendations given in developing MOOCs in the future include (1) Building the quality of learning in MOOCs itself that focuses on user needs by creating exciting and interactive content, (2) Providing students with an understanding that MOOCs can improve self-quality, (3) Motivating to continue to participate by activating discussions, creating communities and so on, (4) paying attention to the legality of certificates that can be used to encourage student participation.

This research is inseparable from various limitations, so it is hoped that later it can be developed again in further study. First, the research was conducted using relatively little data with a total of 91 samples because it uses a purposive sample that is somewhat difficult to reach. The advice is to increase the number of samples used in the study to improve the data's accuracy. Next, it is necessary to spread the selection with a more diffuse range of differentiation and not be dominated by specific categories. Second, the research does not include geographical aspects, so it cannot be assessed from a technical and infrastructure perspective. Include geographical factors that may affect technical and infrastructure elements, especially in the territory of Indonesia. Third, interviews were conducted only with participants who successfully passed, not interviewing participants who did not pass or experts who could provide input. The next suggestion is to interview experts, developers, and policymakers to add data and provide new information. Fourth, several rejected hypotheses cannot be explained comprehensively, so they need to be further elaborated. Finally, the discussion of MOOCs in categories and characteristics with different indicators, for example, distinguishing between free and paid MOOCs. This study only examines the factors that support success; it is also necessary to study the obstacles and barriers to graduation in completing the MOOCs.

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