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Website: ijcs.stmikindonesia.ac.id | E-mail: ijcs@stmikindonesia.ac.id

Factors Influencing Students' Continuance Intention in Learning through MOOCs: A Systematic Literature Review

Muh Syaiful Romadhon[1], Kasiyah Junus[2], Harry B. Santoso[3], Mubarik Ahmad[4], Endina Putri Purwandari[5]
muh.syaiful@ui.ac.id, kasiyah@cs.ui.ac.id, harrybs@cs.ui.ac.id, mubarik.ahmad91@ui.ac.id, endina.putri91@ui.ac.id
Faculty of Computer Science, Universitas Indonesia, Depok, Indonesia

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Abstract

Massive Open Online Courses or MOOCs advocate the "democratization of education", which makes education available for everyone anywhere and anytime. The number of students who registered for a MOOC demonstrates that their intention to use MOOCs is reasonably high, yet only 7-10% complete the course. This review conducts literature review on frameworks or theories, instruments, and major factors that influence the intention to persist in MOOCs. A total of 150 articles spanning the years 2018–2022 are initially reviewed guided by PRISMA framework, from which 20 are selected based on the selection criteria in this study. Self-developed model and TAM has become the most often used theory to determine a persons' continuance intention on MOOCs. The majority of studies utilized SEM and PLS-SEM as instruments to analyse the continuance intention data. Perceived usefulness is the most important and influential factor in MOOCs.

A. Introduction

E-learning platforms are the main tool for facilitating learning during the pandemic [1]. The digitization of education is becoming more ubiquitous and inclusive [2]. Online learning grew during the COVID-19 pandemic at all levels of education [3]. The potential for implementing e-learning during the COVID-19 pandemic especially in Indonesia is relatively high, with flexibility and independent learning [4]. One type of e-learning category is Massive Open Online Courses (MOOCs) [1]. The utilization of MOOCs has led to an enhancement in the efficiency of both teaching and learning [5]. Moreover, MOOCs allow students of different backgrounds, interests, nationalities, skills and others [6]. MOOCs have become a noteworthy focus in the field of education as an innovative approach [7]. MOOCs is different from online education systems or pre-existing online courses [8]. MOOC has such several unique features such as being open and massive, that it can be used by many people and offers many advantages [9].

MOOCs have the characteristics of "large scale, open, online" and attracts many learners to participate in learning [10]. Due to their online nature, MOOCs are readily available to students globally via the internet [7]. Additionally, MOOCs grant students access to education provided by prestigious institutions at no cost or a reduced cost, without the need to meet any eligibility criteria [11]. MOOCs give students access to a wide variety of resources [11]; MOOCs provide students with ample storage capacity for their materials [12], and also facilitate the sharing of learning resources with fellow participants[13]. MOOCs have become a new form of curriculum for online education and has also become a new form of education [14].

MOOCs promote the "democratization of education" which makes education accessible to everyone from anywhere and at any time [1]. Openness in education is "a term that builds bonds with critical pedagogy, a color with many shades, a notion with pluralistic and inclusive connotations, a stance that defends widening participation" [15]. The classification of MOOCs is typically based on both the course content and the intended audience. Presently, there are five primary configurations for MOOCs: xMOOC, connectivist MOOC, mixed MOOC, hybrid MOOC, and quasi-MOOC [13]. Everyone can register at a MOOC for free; however, certification in some courses may incur a fee.

MOOCs can be categorized into four types, namely cMOOC, xMOOC, hMOOC, and ahMOOC. By utilizing MOOCs, students are provided access to a diverse array of resources, and they are also afforded ample storage capacity for their materials [13]. Additionally, MOOCs enable students to share learning materials with other participants [13].

The MOOCs current opportunities are potential solution to improve digital capabilities in the face of digital transformation [16]. The intention to use MOOCs is relatively high, as evidenced by the many students who register [17]. Despite the large number of students who apply to MOOC, only about 7-10% finish the course [18][19]. MOOCs have a fairly high participant failure rate between 86%- 90% [2]. Information technology continuity theories concentrate on the determination made by individuals to either continue or discontinue using the technologies they have utilized and become familiar with, after the initial adoption stage [20][21]. Continuation intent is the intention to continually use or reuse a system [22]. The intention to continue the information system depends on user satisfaction, confirmation of user expectations and perceived utility [23]. The intention of continuity in an e-learning context has received increasing attention in recent years [12]. Computing enables a whole new environment and learning experience that goes far beyond the classrooms, programs and textual formats we are used to.[9]. Moreover, various theoretical frameworks have surfaced, which offer novel perspectives on the intention to continue using technology [20][21]. Of these frameworks, the most commonly employed models include the Technology Acceptance Model (TAM), the Unified Theory of Technology Acceptance and Use (UTAUT), and the Information System Success Model (ISS) [12].

For this reason, it is necessary to deepen and investigate the factors that influence the success and failure of MOOCs. This study aims to determine what factors influence the continuance intention of MOOCs. Therefore, the following research questions (RQs) guide this study:

1. What are the frameworks or theories used to measure continuance intention in MOOCs?
2. What are the instruments used to determine continuance intention in MOOCs?
3. What are the main factors that influence continuance intention in MOOCs?

This research is expected to help several stakeholders related to the implementation of MOOCs in finding factors for the successful completion of MOOCs. Furthermore, graduation in MOOC-based learning has increased and positively impacted technology-based education.

B. Research Method

This section will explain the method used in the research. Furthermore, it will explain the systematic literature review, the technique used as a reference, and the process of conducting a study. A systematic literature review is a method to find research articles in databases with specific topics. The results obtained are then used as material for discussion according to the predetermined objectives. Systematic literature reviews usually have more specific research questions with comprehensive and explicit sources in the search [24]. This method is used in several fields, such as [25], which examines content analysis of asynchronous discussion forum, and [26] in adaptive learning research. The method used in this study is following the image (Figure 1) PRISMA framework by the Ottawa Methods Center [26].

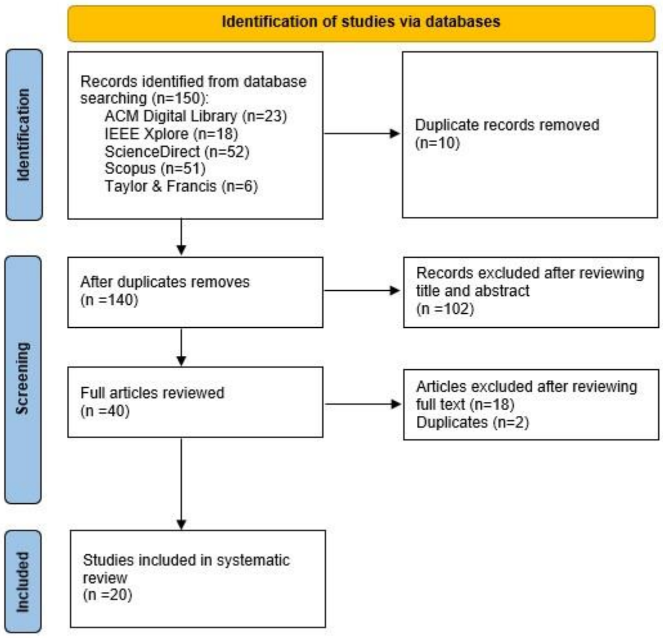

Figure1. PRISMA flow diagram (adopted from [26])

The researchers undertaking the present study performed a search for relevant papers in December of 2022, utilizing the set of compiled keywords. We used the keywords ((mooc OR moocs) AND (continue OR continued OR continuance OR continuous AND intention OR usage)) in registered databases. We searched potential articles from five databases: ACM Digital Library, IEEE Xplore, Science Direct, Scopus, and Taylor & Francis. The search found 150 related keywords, titles, and abstract. The search results that have been obtained will then be selected again.

Table 1. Article Sources

No	Sources	Total
1	ACM Digital Library	1
2	IEEE Xplore	0
3	ScienceDirect	12
4	Scopus	3
5	Taylor & Francis	4
Grand Total		20

We found 150 potential articles in initial phase. After abstract and title selection, 40 potential articles were selected to be included. In the full-text selection, we found 20 articles in total for the review after conducting quality assessment. The results based on the database source can be seen in Table 1. We extracted ata from 20 articles to be synthesized and answer the research questions based on the synthesize result.

C. Results and Discussion

Total of 20 papers are used in this research. The publication years varied from 2018-2022, with year 2018 and 2020 having the highest number of papers. Figure 2 depicts the distribution of publication years in detail.

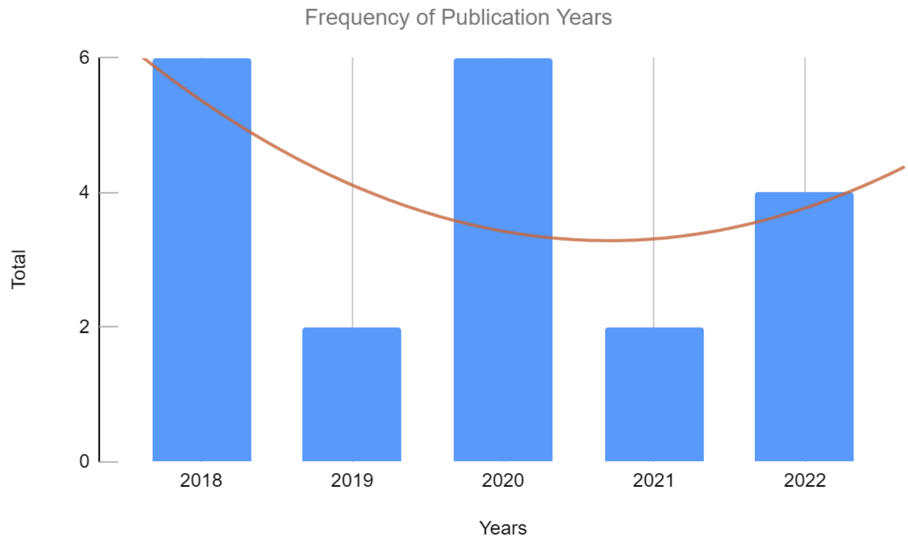

Figure 2. Frequency of Publication Years

Table 2 shows the types of articles and the places for their publication, most published in the journal Computers & Education.

Table 2. Articles by Publishers

No	Article Type	Published in	Number of Articles	Total
1	Journal Article	Computers & Education	5	19
		Interactive Learning Environments	3	
		Computers in Human Behavior	2	
		International Journal of Management Education	2	
		Telematics and Informatics	2	
		Behaviour & Information Technology	1	
		Education and Information Technologies	1	
		Education Sciences	1	
		Information and Management	1	
		Sustainability	1	
2	Conference Paper	Proceedings of the Seventh International Conference on Technological Ecosystems for Enhancing Multiculturality	1	1
Total				**20**

Figure 3 presents the geographic distribution of the participants in the previous studies. Six papers have yet to state the geographic distribution of the participants in their research. In previous studies, it came from China, with 40%. The MOE Minister of China stated that China's MOOCs originated in 2013 and have grown rapidly for seven years, resulting in over 32,000 online courses. Currently, China's MOOCs have the largest number of study programs and are the most widely used in the world [9].

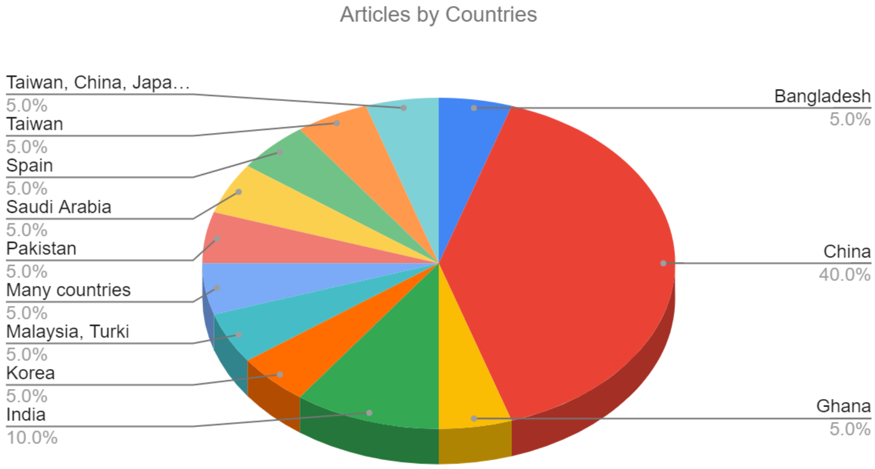

Figure 3. Articles by Countries

Figure 3 and 4 presents the study context and platform of MOOCs, respectively. Most research is aimed at universities, such as research conducted by [21] to find out the level of MOOC usage at universities in Ghana. Meanwhile, other research also shows the use of MOOC with gamification in universities [2], [9], [27]. Several studies have shown that using MOOCs requires metacognition [2], [28], [29] and self-efficacy [8], [9], [14], [21], [29], so that use for universities is considered appropriate because learning is self-based [9], [29]. The study results show that many platforms are not mentioned directly; this follows the context of use for universities that do not show the platform name in their use.

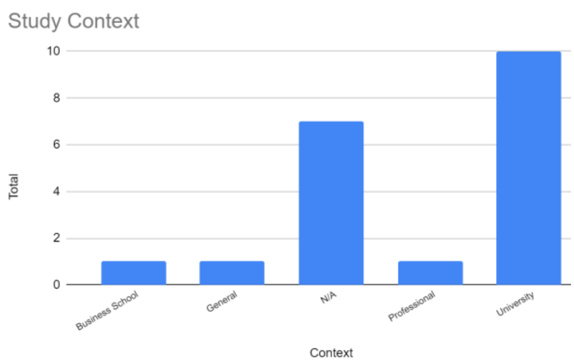

Figure 4. Articles by Study Context

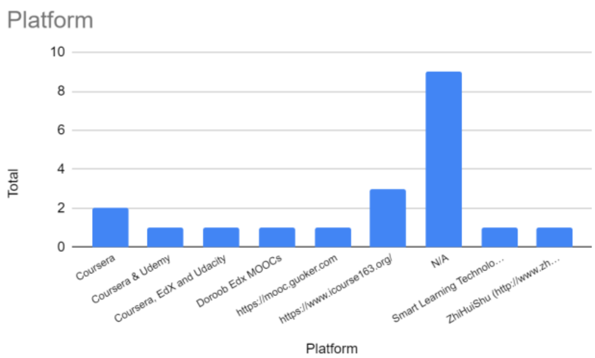

Figure 5. Articles by Platform

A. Addressing RQ1: The frameworks or theories used to measure continuance intention in MOOCs

The detail of the used theory is shown in Table 3. The self-developed model was found to be the most commonly employed theory, with the TAM framework ranking second with the second-highest number of reviewed papers. Extensive validation has demonstrated that the TAM is an effective means of explaining the adoption and uptake of technology [13][11].

Table 3. Used Theories

No	Used Theories	Research Purposes	Authors
1	Theory of Planned Behavior (TPB)	Analyze how personality traits contribute to explaining the discrepancies in the levels of intent to persist in using MOOCs	[2]
2	Expectation Confirmation Model (ECM)	Examination of students' determination to pursue their education through the MOOC platform during the COVID-19 pandemic	[23]
		Comprehending the psychological mechanisms that motivate learners to engage in MOOCs	[5]
		Investigate the determinants that influence the sustained motivation to learn in the context of MOOCs	[30]
3	IS Success Model	Understand the success factors when using MOOCs with gamification	[27]
4	Technology Acceptance Model (TAM)	Analyzing how knowledge management (KM) practices affect the adoption of MOOCs in a cross-cultural context	[13]
		Investigate the motivation of university students receiving credit to use K-MOOCs.	[31]
		Investigate the main features of user acceptance of interface design and emotional arousal of MOOCs	[32]
7	Self-developed Model	Identify factors creating resistance to the continued use of MOOCs	[33]
		investigate the associations between design elements of MOOCs, engagement of learners, self-directed learning, and intentions for future learning	[29]
		Examine how human factors mediate the impact of network externalities on users' persistence in MOOCs	[34]
		A proposed model aims to integrate metacognition and learning interest to understand persistent learning intention in the context MOOCs	[28]
		Understand how motivation and personality traits influence levels of intention to continue using MOOCs	[11]
		Understand how integrating resources impacts student perceptions of co-creation of value and how co-creation of value, in turn, affects users' intention to continue	[12]
9	Task-Technology Fit Model (TTF)	Explore the factors that influence the adoption of MOOCs among students in a developing country	[10]
10	S-O-R Framework	Examine the effects of the technological environment characteristics of MOOC systems using the Stimulus-Organism-Response (S-O-R) framework	[8]
11	UTAUT and IS Success Model	Identify factors influencing the adoption and use of MOOCs as an online educational technology to support student learning.	[21]
12	IS Success Model &	Explore the correlation between student learning outcomes and	[9]

No	Used Theories	Research Purposes	Authors
	Expectation Confirmation Model (ECM)	MOOCs	
13	Extended Technology-User-Environment (TUE)	Investigate the factors that influence the adoption, completion, and continuation of MOOCs using the Technology User Environment (TUE) framework, as well as the features and qualities of MOOCs.	[7]
14	Technology Acceptance Model (TAM) and Social Support Theory	A comparison of behavioral intention models among participants of traditional online learning platforms and MOOCs	[14]

Researchers develop self-developed models to discuss or solve specific problems [34]. The existence of a model developed by researchers can directly answer specific research questions according to the context [11] [28] . Researchers can also fully control all variables entered as needed. Integrating variables relevant to the theory used is an advantage of the self-developed model [11] [12].

While TAM is the theory most often used in research on technology acceptance[13], TAM has experienced developments since it was first developed in 1989 [21]. TAM theory has been well-tested for various contexts to prove technology acceptance research empirically [21][13]. In addition, this theory is also relatively easy to understand and apply in researchv[35].

Although TAM is frequently used in technology acceptance research, there have been some criticisms of the theory [14]. One of TAM's weaknesses is its focus on factors influencing technology acceptance at the individual level, while less attention is given to contextual and social factors [21]. Therefore, in several studies, other theories, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) [21] and the Technology-Organization-Environment (TOE) framework [7], [36], are used to overcome the limitations of TAM and consider other factors that influence technology acceptance.

B. Addressing RQ2: The instruments used to determine continuance intention in MOOCs

The quantitative method has emerged as the most frequently adopted method in the reviewed article. In addition, most of them use SEM and PLS-SEM methods to analyze data. The detail of the method and measurement is shown in Table 4. SEM allows researchers to easily analyze a complex model with multiple independent and dependent variables simultaneously [23]. PLS-SEM is primarily predictive and exploratory to maximize explained variance for dependent variables [34].

Table 4. Methods and Measurements

No	Methods	Data Collection	Data Analysis	Participants	Authors
1	Quantitative	Online Questionnaire	PLS	3000 participants who just finished the module in MOOCs within the last three months	[2]

No	Methods	Data Collection	Data Analysis	Participants	Authors
			PLS-SEM	285 participants from two universities	[23]
				215 participants	[27]
				414 participants	[10]
				346 participants from public university	[34]
				374 participants on the Chinese University MOOC platform	[8]
				270 questionnaires administered to students who had been assigned MOOCs	[21]
			SEM	540 participants	[13]
				192 participants from three different universities in China	[30]
				166 participants from university in Korea	[31]
				664 participants	[29]
				126 respondents	[28]
				212 participants from Saudi Arabia	[11]
				629 participants	[9]
				372 participants	[12]
			Stepwise Regression Analysis	97 participants from an Indian university	[7]
			Exploratory Factor Analysis (EFA)	357 participants	[14]
				668 participants	[32]
2	Mixed Method	Online Open-Ended Questionnaire and Empirical survey	Grounded Theory Approach and PLS-SEM	1. Empirical Survey: 233 participants Online Open-Ended 2. Questionnaire :112 participants	[33]
		Open online Textual Data, Focus Group Interviews and Questionnaire Surveys.	Exploratory Factor Analysis (EFA)	1. Focus Group Interviews: 13 participants from two universities in China 2. Questionnaire Survey :671 participants	[5]

SEM and PLS-SEM are multivariate data analysis techniques used to model the relationship between complex variables in a single model. These two techniques allow measuring latent variables (which cannot be observed directly) and testing complex hypotheses in one integrated model. The advantages of using SEM and PLS-SEM are being able to relate complex variables, analyze factors and paths, measure latent variables, and model data longitudinally. In MOOCs, SEM and PLS-SEM are used to model the relationship between complex variables, such as social interaction, learning experience, learning outcomes and motivation.

C. Addressing RQ3: The main factors that influence continuance intention in MOOCs

Various factors influence the willingness to continue MOOCs, which can be broadly divided into personal and contextual factors. Individual factors include personal characteristics and contextual factors relevant to MOOC design and quality. Complete factors influencing continuance intention in MOOCs can be seen in the Appendix A. Perceived usefulness is the main factor that most often appears from all the articles reviewed, details can be seen in Table 5.

Table 5. Factors Influencing Continuance Intention in MOOCs

No	The Factor	Total
1	Perceived Usefulness	6
2	Perceived Ease of Use	4
3	Satisfaction	4
4	Attitude	3
5	Confirmation	3

Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his/her job performance" [11]. Perceived ease of use is defined as "the degree to which a person believes that using a particular system would be free of physical and mental effort" [37]. In TAM, perceived ease of use influences perceived usefulness, and at the same time, these two variables influence acceptance intention [13][31]. Users' intent to continue using a particular service or system is primarily determined by their satisfaction with past experiences, with satisfaction mediating between initial adoption and continued use [31]. Intention to continue using MOOCs is defined by personal attitudes and perceptions that bias a cognitive state to accept the possibility of future use [11]. As previously stated [14] found that perceived gains and system experience influence behavioral attitudes via perceived usefulness and perceived ease of use, respectively. Affirmation has historically been defined as the extent to which a person's actual experience matches their initial expectations [23]. The Expectation Confirmation Model (ECM) suggests that technology users make cognitive comparisons when making decisions about continued use [30]. The results show that the main factor for the successful use of MOOCs is closely related to one's intention to join MOOCs. These factors are shown by the desired ease and increased ability when using MOOC. However, this must be in line with regular use, which external and internal factors can influence. A person's motivation in completing MOOCs is closely related to their goals. Routine use can be carried out if user satisfaction is obtained and MOOCs successfully provide knowledge and skills following user expectations.

D. Conclusion and Limitations

The successful completion of learning on MOOCs requires a well-planned strategy to be implemented. The main factor that is influential is perceived usefulness. Perceived usefulness is undoubtedly an essential factor in the successful completion of learning on MOOCs. When learners perceive that the course material is helpful to their personal or professional goals, they are more likely to engage with the material, invest time and effort into learning, and ultimately complete the course. Another factor is perceived ease of use, When learners perceive that the platform and interface of the MOOC are easy to use, they may be more likely to engage with the course material and complete the course. Understanding the factors that influence MOOC retention can help educational institutions and providers make more informed decisions about how to improve the effectiveness of their online learning platforms.

This study highlights that the theories commonly used to measure continuance intention in MOOCs are self-constructed and TAM. TAM is a widely-used theoretical framework for understanding users' acceptance and use of technology. It proposes that perceived usefulness and ease of use are the two primary factors that influence users' intention to use a technology, which in turn affects their actual use. Self-constructed theories, on the other hand, are developed by researchers based on their own observations and insights rather than based on an existing theoretical framework. Researchers may use self-constructed theories to develop new insights and understandings of the factors influencing learners' MOOC use. In the context of MOOCs, both self-constructed and TAM theories are commonly used to understand learners' continuance intention.

The results also show that most studies used quantitative methods, and that the best ways to analyze data are SEM and PLS-SEM. Rigorous statistical techniques such as SEM and PLS-SEM can assist researchers in obtaining reliable and valid results, which can be utilized to enhance online learning and inform future studies. The researchers should be used with qualitative methods such as interviews and surveys. Qualitative methods can provide a more in-depth understanding of learners' experiences and perspectives, which can be invaluable in improving the design and delivery of online courses.

This study provides insights for improving the completion rates of MOOCs. The main factors supporting the success found in this study need to be considered for implementation, Adopting such an approach, we can create online learning environments that are engaging, relevant, and effective and provide learners with the skills and knowledge they need to succeed in their personal and professional lives.

This study has some limitations, such as the range of languages and literature. Limited range of languages in the selection of literature because the literature used in this SLR is only in English. Another limitation is due to the database used. Further research can be increased, not only from a review of existing literature. Potential future research includes developing a model to increase empirically measurable continuance intention on MOOCs.

Appendix A

No	Factors	Authors
1	External motivation Internal motivation Agreeableness Extravert Conscientiousness	[2]
2	Task skill Task challenge Enjoyment Perceived usefulness Confirmation Satisfaction Psychological Safety Continuance intention	[23]
3	Information Quality System Quality Service Quality Use User Satisfaction Individual Impact Organizational Impact Gamification Enjoyment Challenge	[27]
4	Knowledge Access Knowledge Storage Knowledge Application Knowledge Sharing Perceived Usefulness Perceived Ease of Use Behavioural Intention Actual Behaviour	[13]
5	Knowledge transmission quality Confirmation Satisfaction Attitude Habit Continuance Intention Interaction quality	[5]
6	Confirmation Perceived Usefulness Attitude Satisfaction Curiosity Continuance Intention	[30]
7	Usage Barrier Value Barrier Traditional Barrier Image Barrier Resistance Towards MOOCs	[33]
8	Self-determination Perceived ease of use	[31]

No	Factors	Authors
	Perceived usefulness Satisfaction Continuance intention	
9	Task characteristics Technology characteristics Task-technology fit Social recognition Social influence Perceived Relatedness Perceived Autonomy Perceived Competence Behavioural Intention Perceived Reputation Usage Behaviour	[10]
10	Transactional distance Structure and organization Self-directed learning Commitment Future intention for future learning	[29]
11	Network Size Perceived Complementary Network Benefit User experience User preference Motivation to achieve Persistence in completing MOOCs	[34]
12	Metacognition Liking Enjoyment Engagement Continuance Intention to Use	[28]
13	Interactivity Media richness Sociability Telepresence Social presence Flow Continuance intention	[8]
14	Internal motivation External motivation Extraversion Agreeableness Conscientiousness Intention to continue using MOOCs	[11]
15	Performance Expectancy Social Influence Effort Expectancy Facilitating Condition Computer Self-efficacy System Quality Instructional Quality Intention to use Usage behaviour	[21]

No	**Factors**	**Authors**
16	MOOC Quality Information Quality System Quality Service Quality MOOC usefulness MOOC Satisfaction MOOC gamification perception Social interaction Entertainment Challenge MOOC continued usage Course performance	[9]
17	Direct benefits Indirect benefits Performance-to-cost value Self-efficacy Personal readiness Coercive pressures Normative pressures Mimetic pressures Openness Reputation Instructional quality Content quality Intention to adopt MOOCs Intention to complete MOOCs Intention to continue using MOOCs	[7]
18	Perceived Convenience Computer Self-efficacy Sense of Community Perceived gain Perceived ease of use Perceived usefulness Attitude Behaviour Intention	[14]
19	Platform interaction Course quality Passion Learner Acquired Knowledge Knowledge value Hedonic value Social Value Continuance intention	[12]
20	Usability Perceived Quality Perceived Enjoyment Perceived ease of use Perceived usefulness Behavioural intention Perceived effective use	[32]

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