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Role of course relevance and course content quality in MOOCs acceptance and use

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A R T I C L E I N F O

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A B S T R A C T

Despite several benefits attributed to the use of MOOCs for learning, acceptance levels remain low and studies investigating adoption and use of the technology are limited. This study draws from the literature on specific factors that influence online learning environments and extends the technology acceptance model (TAM) to understand if those factors can be used to explain and facilitate MOOCs acceptance and use behaviors among learners. The factors investigated include, course content quality, course relevance, course instructor quality, course design quality, learner-instructor interaction, and learner-interaction. There were 138 participants in the study. Partial Least Squares SEM (PLS-SEM) was used to analyze the relationships proposed for the study. The results suggest that the extended TAM offered a good explanation of MOOC acceptance and use, with course relevance and course content quality as external variables affecting MOOCs acceptance. Findings from this study provides practical implications for MOOCs implementation to increase acceptance and further lays a foundation for future research

Introduction

Massive Open Online Courses (MOOCs) are online courses that aim to make quality higher education more accessible to people across the world, regardless of their geographical location [16,45]. The term MOOC was first used to describe an online course taught by Professor George Siemens at the University of Manitoba in 2008 [16]. However, in 2012, a different form of MOOCs, sometimes referred to as xMOOCs was popularized by top MOOC providers such as Coursera and edX [16,21]. This new form is what we know and refer to as MOOCs today. MOOCs have become a major higher education advancement and continue to gain increasing popularity as they provide online learning opportunities on a large scale to people with no geographic limitations [15,37]. They are especially beneficial in providing quality higher education to those who have limited access, for instance, those in developing countries [21,22].

The benefits of MOOCs have since been enjoyed by both those in developing and developed countries, as anyone who needs to learn a new skill or improve on an existing skill with limited barriers to learning can turn to MOOCs for their educational needs. However, despite growing interest in MOOCs, there are limited studies investigating adoption behaviors of the learning technology [22] and how the perceptions people hold about the technology affect their intention to adopt or use them. This topic is especially important because, despite all the benefits associated with MOOCs, researchers have often pointed to the fact that MOOCs are not being utilized to their potential [7,14]. And this is potentially because users are not accepting and using them efficiently for their learning purposes [42]. Hence, it is important to continue to explore the subject of how to improve acceptance and use of MOOCs among learners if their potential is to be realized [37].

As a result, investigating ways to improve acceptance and use has become important for MOOC research and a few studies have examined this phenomenon using different theories such as Technology Acceptance Model (TAM) (e.g., [37,43,44]). However, a lot of previous studies examining acceptance and use of MOOCs have mostly focused on demographic, psychological and social factors [37]. With studies examining specific course-related factors that can aid in tangible improvements in MOOC quality and acceptance, still limited [43]. Although some of these course-related factors have been explored in the context of e-learning [1,31,43], the results of those studies may not directly translate to the MOOCs context. Hence, it is important to explore how those different factors affect acceptance and use of MOOCs. This is especially crucial because learning in MOOCs differ significantly from learning occurring in more traditional learning environments.

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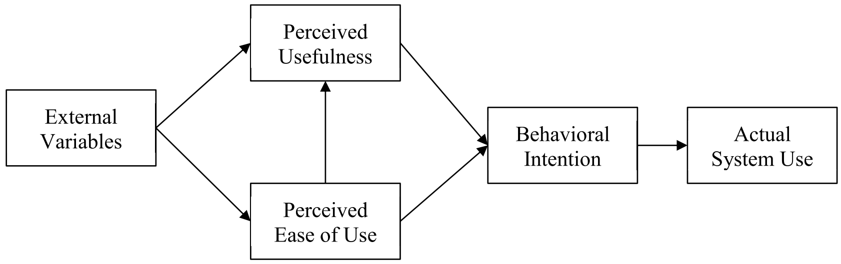

Fig. 1. Technology acceptance model [39].

Especially since MOOCs learning is primarily optional, informal, and self-regulated, requiring more self-motivation and persistence for success [43]. Understanding such specific factors that influence learners' intention to participate in MOOCs can enable and support MOOC developers and course designers to design content and strategies that will be valuable to students and increase their use of MOOCs [43].

This study therefore draws from the literature on specific factors that have been found to influence acceptance and use of traditional online learning environments to understand if they can be used to explain and facilitate MOOCs acceptance and use behaviors among learners. The phenomenon was explored using the TAM framework and the study proposes a MOOC acceptance framework that examines the roles of the identified factors, namely, course content quality, course instructor quality, course design quality, course relevance, learner-learner interaction and learner-instructor interaction in learner acceptance and use of MOOCs. The aim is to provide MOOC platforms and designers some guidance on course-specific factors to consider when developing MOOCs in order to increase learner acceptance and use. Hence, the main research question examined by the study was:

RQ. What specific factors associated with e-learning courses influence learners' acceptance and use of MOOCs?

To answer the research question, the study examined the well-explored TAM constructs (perceived usefulness and perceived ease of use) and less-explored course characteristics variables related to MOOCs use experience, namely, course instructor quality, course content quality, course design quality, course relevance, learner-instructor interaction, and learner-learner interaction. The TAM framework was considered appropriate because of its strong predictive power of an individual's intention to use a system [32,40]. Partial least squares structural equation modeling (PLS-SEM) was used to test the proposed relationships because of the exploratory nature of the study. Data for the study was collected using online surveys and a total of 138 people completed the survey.

Literature review and research model

Technology acceptance model

Technology Acceptance Model (TAM) is a technology adoption framework that proposes that peoples' behavioral intention to use a system is a strong predictor of actual usage behavior. It also stipulates that behavioral intention to use a system is a factor of an individuals' perceived usefulness and perceived ease of use of the system [6,40]. This theory further holds that perceived ease of use also influences perceived usefulness, as a system would be generally more useful if it is easy to use [41]. Perceived usefulness is defined as "the degree to which an individual believes that using a particular system will enhance his or her job performance" ([6], p.319; [40]). In other words, how useful they expect the system to be in their effort to achieve their goals. This construct deals more with the utilitarian value of a system, that is, how useful or advantageous users consider it to be in achieving their goals [6,40]. Perceived usefulness drives motivation in such a way that, the more useful a person considers a system, the more they are likely to intend to use it and vice versa [6]. Perceived ease of use on the other hand refers to the degree or extent to which "a person believes that using a particular system would be free of effort" [6,41]. In other words, how easy they believe it will be to use the system. This construct drives motivation in such a way that, the easier a system is to use, the more users are likely to accept and use it [6].

TAM remains the most widely utilized theory of acceptance and use, due to the superior predictive power of its constructs [6,40]. TAM was considered appropriate for this study because it is a framework that has been used by other researchers to examine acceptance and use of MOOCs [23,37] and other e-learning contexts [9,24]. For instance, Tao et al. [37] found that perceived usefulness and perceived ease of use significantly predicted intention to use MOOCs among college students. They also found that perceived ease of use was a strong predictor of perceived usefulness and that behavioral intention significantly predicted actual usage behavior of MOOCs among the students. Similarly, Ma and Lee [23], found perceived usefulness to be a strong predictor of behavioral intention to use MOOCs. Furthermore, while examining e-learning acceptance among university students, Mailizar et al. [24] found that perceived usefulness strongly predicted students' behavioral intention to use e-learning and that perceived ease of use was strongly associated with perceived usefulness of e-learning. Fearnley and Amora [9] also found that behavioral intention to adopt learning management systems (LMS) is influenced by perceived usefulness. Perceived usefulness on the other hand was influenced by perceived ease of use and behavioral intention significantly predicted actual usage of LMS among participants [9]. Based on evidence from previous studies on the use of TAM to predict acceptance and use of e-learning and MOOCs, the following hypotheses were proposed (Fig. 1):

H1. Perceived usefulness will positively influence behavioral intention to use MOOCs.
H2. Perceived ease of use will positively influence perceived usefulness of MOOCs.
H3. Perceived ease of use will positively influence behavioral intention to use MOOCs.
H4. Behavioral Intention to use MOOCs will positively influence actual usage of MOOCs.

Extending TAM: examining determinants of perceived usefulness and ease of use

The basic framework of TAM has been extended by several studies that examine external factors likely affecting the key constructs of perceived usefulness and perceived ease of use [1,31,32,40,41]. For instance, Venkatesh & Davis [40] suggested that factors such as result demonstrability, job relevance, output quality, and perceived ease of use all predicted perceived usefulness. And factors such as computer anxiety and playfulness predicted ease of use [41]. Similarly, Park et al. [32], found relevance and perceived ease of use to be significant predictors of perceived usefulness. These studies further emphasize the need to

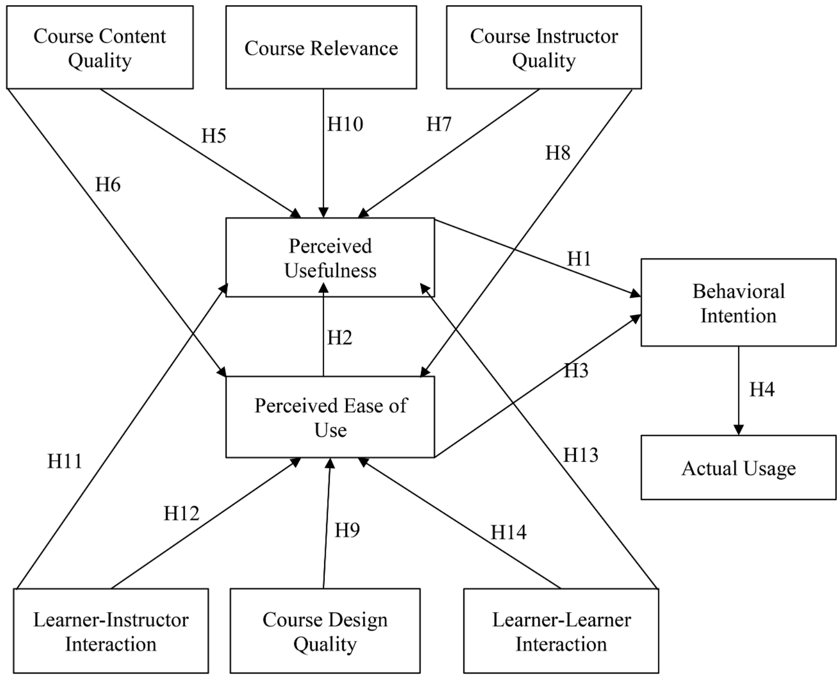

Fig. 2. Conceptual framework – Extended technology acceptance model.

consider the importance of external variables influencing TAM constructs in the design and implementation of effective information systems and to improve adoption of such systems [32]. Mathieson [26] further emphasizes the importance of such variables by suggesting that examining TAM without consideration for external factors that are likely influencing its main constructs will only provide a broad view of user opinions about the system with no specific information that can inform the design of a better or enhanced system. Hence, specifying external factors for TAM constructs not only predicts intention to use a system but further offers an explanation as to why a particular system is not being adopted, so that corrective measures can be implemented [6,40]. Discussed below are the external variables that were examined as potentially influencing the main TAM constructs in this study with regards to MOOC adoption and use:

Course content, instructor, and design quality

Providing quality instruction is important for any learning environment. This is even more so for online learning platforms (such as MOOCs) where the instructor is not always available to clarify any lack of understanding of the course content. As a result, course quality, instructor quality and overall quality of instruction are important factors that have been found to be affecting learner perceptions of usefulness and ease of use of online learning [1,31,43]. For instance, Abbas [1] found that students' perceptions of the quality of the instructor significantly predicted both perceived usefulness and perceived ease of use of the platform. Similarly, Lee, Yoon, and Lee [19] found instructor characteristics and quality of teaching materials to be positively related to perceptions of usefulness of e-learning, while finding content design to be positively associated with perceptions of ease of use. Furthermore, Ozkan and Koesler [31] found both instructor and content quality to be strong predictors of learners' perceived satisfaction with an e-learning system. Instructor quality was found to be significantly predicting perceived usefulness, while course design quality was significantly predicting perceived ease of use of e-learning [4]. Also, the content quality of an e-learning website was found to be positively associated with perceived usefulness and perceived ease of use [29]. And course content quality and course design quality were found to be predictors of perceived usefulness and perceived ease of use of mobile learning [2].

Although studies examining the relationship between these quality antecedents within the context of MOOCs are limited, a few studies have found a positive relationship between some of these factors and perceived usefulness and perceived ease of use of MOOCs. For instance, in their study examining the quality factors that influence students' continuous intention to participate in MOOCs, Yang et al. [43] found course quality to be positively associated with perceived usefulness of MOOCs. Also, Razami and Ibrahim [34] found a significant positive relationship between course quality and perceived usefulness while investigating factors influencing MOOCs acceptance in higher education. Furthermore, course interface design was found to be positively associated with perceived ease of use of MOOCs, while course quality was positively associated with perceived usefulness of MOOCs [37]. And Yang and Zhao [44] found that the information quality of MOOCs courses positively influenced their perceived usefulness.

In general, these studies show that instruction characteristics such as the quality of instructional materials, instructor feedback, teaching style, among others, positively affect students' perceptions of usefulness, ease of use of online learning, and overall perception of the course. Hence, within the context of TAM, this study proposes that (Fig. 2):

H5. Course content quality will positively influence perceived usefulness of MOOCs.
H6. Course content quality will positively influence perceived ease of use of MOOCs.
H7. Course instructor quality will positively influence perceived usefulness of MOOCs.
H8. Course instructor quality will positively influence perceived ease of use of MOOCs.
H9. Course design quality will positively influence perceived ease of use of MOOCs.

Course relevance

Relevance is a successful learning motivator, with different studies finding that materials that learners perceive to be relevant, either in their work or personal interests, successfully motivated them to learn [3,13]. Specific to MOOCs, Khalil and Ebner [18] found that when learners perceive that MOOCs hold relevance for them either in their professional or academic life, they are more motivated to learn using them. Furthermore, Keller [17] suggests that engaging strategies such as demonstrating the intrinsic value of the learning content to the students, explicitly suggesting how instruction can help students meet their future goals, and having learners relate instruction to their own goals, establishes relevance for the course content and can motivate students to learn.

The importance of relevance on perceived usefulness of a system was established in TAM2 by [40] where they identified job relevance as a determinant of perceived usefulness. They defined this construct as "an individual's perception regarding the degree to which the target system is applicable to his or her job"and found it to be significantly predicting perceived usefulness. In the context of e-learning, relevance has been found to be a strong predictor of perceived usefulness of e-learning systems [27,32]. It is evident from these studies that relevance is related to perceived usefulness in such a way that, the more relevance learners attribute to a MOOC, the more they are likely to consider it useful. However, there is a lack of recent studies examining online learning course relevance within the context of TAM. Although, some studies have examined the construct in understanding positive online learning perceptions and behavior in general. For instance, Cheng and Xie [5] found that students' perceived content relevance had an indirect effect on student procrastination in online learning, through task value. And course content relevance was also found to be a major factor influencing student satisfaction in online learning in higher education in Malaysia [38]. Hence, within the context of TAM, this study proposes that (Fig. 2):

H10. Course relevance will positively influence perceived usefulness of MOOCs.

Learner-Instructor and learner-learner interaction

The social information processing model of interpersonal interaction by Walther [47] assumes that participants in a computer-mediated communication (CMC) environment are essentially driven to develop social relationships. The model maintains that it is possible for players in CMC environments to attain and surpass the level of communication quality obtainable in face-to-face environments, especially given the unique affordances of CMC environments which make different kinds of communication possible. Following this, it can be argued that the absence of face-to-face interaction does not have to inhibit the level of communication that is required for online learning, however, the issue of lack of interpersonal interaction continues to be regarded as the biggest bottleneck for learning occurring in online spaces. For instance, Moore & Kearsley [28] argue that learners tend to feel isolated in online learning environments as they lack the level of rich interaction they experience in traditional environments. More recent studies have also referred to lack of sense of community and effective social interactions as major issues facing online learning, including MOOCs [14,15]. There is therefore a need for an enhanced level of interpersonal interaction to be designed into online learning environments for learners to be motivated more by such learning.

More (1989) defined two types of interaction related to interpersonal communication that he considers essential for online learning, namely learner-instructor interaction (i.e., interaction involving teacher and learners) and learner-learner interaction (i.e., interaction involving learners with each other). Consequently, many studies have since examined these types of interactions within online learning environments, to determine their effects on student learning. For instance, in their study involving 299 learners from an online MBA course, Peltier, Drago, and Schibrowsky [33] found student-student interaction and student-instructor interaction to be significant determinants of perceived effectiveness of the course by students. Similarly, Marks et al. [25] found that instructor-student interaction and student-student interaction had significant effects on learning effectiveness in online learning spaces, with instructor-student interaction having twice as much effect as student-student interaction. Furthermore, Hone and El Said [14] reported a lack of satisfaction with MOOCs among students who indicated feeling isolated as a result of a lack of interaction with another human in the course. Other studies have also linked these constructs to learning satisfaction [36], perceived effectiveness of online courses [33], increased motivation and retention in online learning [30] and MOOCs [10]. Hence, given that interpersonal interaction will likely affect perceptions about different aspects of the course as indicated by previous studies, this study proposes that interpersonal interaction perceptions will positively influence both TAM constructs (Fig. 2):

H11. Learner-instructor interaction will positively influence perceived usefulness of MOOCs.
H12. Learner-instructor interaction will positively influence perceived ease of use of MOOCs.
H13. Learner-learner interaction will positively influence perceived usefulness of MOOCs.
H14. Learner-learner interaction will positively influence perceived ease of ue of MOOCs.

Research methodology

Study design and measures

The study used a structured online questionnaire consisting of two parts for testing the theoretical model proposed. The first part of the survey was used to gather demographic information of the participants while the second part collected data on the main study constructs being measured. The construct items were measured using a 5-point multi-item Likert scale, where participants were asked to indicate to what extent they agree or disagree with a statement where (1) represents "strongly disagree" and (5) strongly agree.

All the construct items, except actual usage, were adopted from previously validated scales and were modified to fit the context of this study. The items for perceived usefulness and perceived ease of use were adapted from the original TAM model proposed by Davis [6], while items for behavioral intention were adapted from Venkatesh [41]. The item used to measure actual usage for this study was specifically measuring the level of MOOC enrollment among participants. This was considered appropriate as the study aimed to explore adoption of MOOCs by participants. The scales for course instructor quality and course content quality were adapted from Ozkan & Koseler [31] and Lee et al. [19], while that of MOOC design quality will be adapted from Lee et al. [19]. The items for course relevance were adapted from the scales of relevance established in Venkatesh and Davis [40] and Park et al. [32]. The items for learner-instructor and learner-learner interaction were adapted from the scales established in Peltier et al. [33] and Marks et al. [25]. Please find a full table indicating the items used for each scale in Appendix 1.

Participants and procedure

The study investigated perceptions of MOOCs learners to better understand how those influence their intention and actual use behavior of MOOCs. Participants for the study were recruited via Prolific (an online research data collection service). A purposeful sampling technique was used because the study aimed to include only those with some experience using MOOCs and participants who did not meet that criterion were filtered out using a screening questionnaire. Particularly, only those who indicated that they have enrolled in and completed at least one MOOC course in the past were selected for the study. Also, participant country was restricted to the US in the selection process to allow for a more focused sample, as the platform consists of people from different countries. The main survey was sent out on the 29th of July 2020 and was active for a total of 1 week. All respondents were required to be at least 18 years old to participate and were required to complete a consent form before proceeding. A total of 138 people completed the survey. Of the

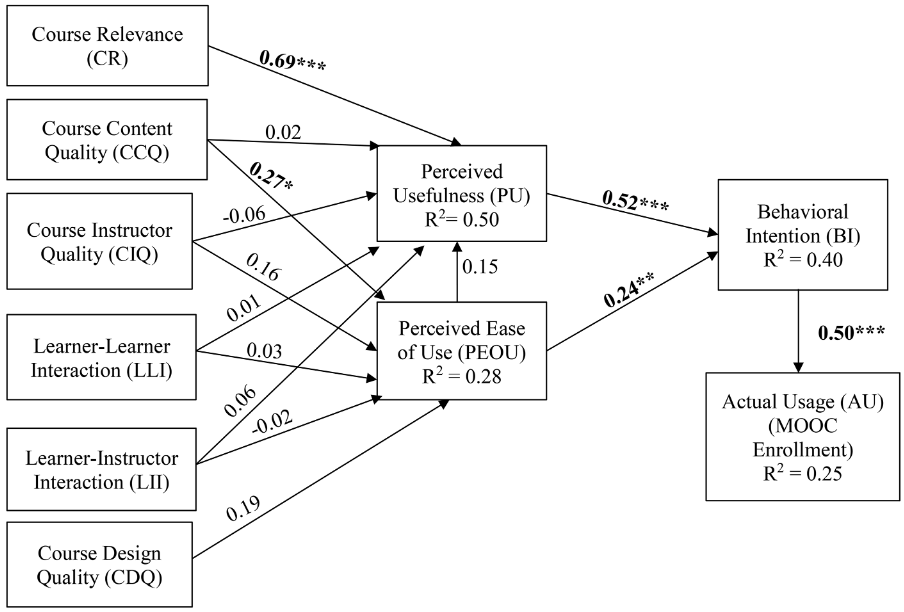

Fig. 3. Hypotheses testing results.

138 participants who completed the survey, 70 were male, 67 were female and 1 indicated as non-binary. The mean age of respondents was 28.41 ($SD = 8.991$), with about 60% of participants being 28 years or younger. Also, the participants were mostly educated, with about 57% of them having an undergraduate degree or above, and another 24% having some college or technical education.

Data analysis technique

Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for data analysis for the study. PLS-SEM was considered more appropriate than the traditional covariance-based SEM for this study because it is more suited for exploratory research and is more efficient for examining smaller sample sizes, as was the case in this study [11,12]. PLS-SEM was also considered desirable because it allows for the estimation of complex models without distributional assumptions [12]. SmartPLS3 software [35] was used to run the PLS-SEM technique for this study. As suggested by Hair et al. [12], a two-stage approach was used in the PLS-SEM data analysis process. First, the reliability and validity of the measurement (outer) model were assessed using the criteria proposed by Hair et al., [12]. Specifically, the outer weights, Cronbach alpha, composite reliability, and average variance explained of each construct were examined to ensure that they are within the recommended range [12]. Secondly, the structural (inner) model was assessed by examining the variance explained of the dependent variables, the predictive relevance of the constructs, and the level of significance of the proposed relationships [11,12].

Results

Assessing the measurement model

To assess the measurement model for reliability and validity, the factor loadings for the construct indicators were first examined. Almost all the reflective indicators had loadings that were higher than 0.50, indicating acceptable item reliability [46], except for CDQ5 (0.396) and LII3 (0.423). The two items were dropped from their respective constructs before the measurement model was assessed. Furthermore, the composite reliabilities and Cronbach alpha values of the constructs were all above the recommended value of 0.70, indicating good internal consistency and less than the recommended threshold of 0.95, indicating that items within the constructs are not redundant [8,11,12].

Convergent validity, which is the extent to which the variance observed in the individual indicators is explained by the construct they represent, was examined using average variance extracted (AVE). The AVE values were above the recommended value of 0.50 for all the constructs, indicating good convergent validity [12]. Finally, discriminant validity, which is the extent to which constructs are distinct from each other (i.e., the absence of multicollinearity across constructs), was assessed using heterotrait-monotrait (HTMT) ratio of the correlations as recommended by Hair et al. [12]. The HTMT values across the constructs were under the recommended limit of ≤ 0.90, indicating good discriminant validity [12], i.e., that the constructs measured are truly distinct as no multicollinearity was observed.

Overall, the measurement model showed satisfactory internal reliability, convergent validity, and discriminant validity, indicating adequate robustness for the structural model proposed for the study to be assessed. See detailed results of the measurement model in Appendix 1.

Assessing the structural model

Further, the structural model of MOOCs acceptance and use that was proposed for the study was assessed based on recommended criteria in Hair et al. [12]. First, it is recommended that before assessing the structural relationship in a model, it is important to examine the level of collinearity to ensure that the regression results obtained are not biased [12]. The variance inflation factor (VIF) values for all the predictors were between 1.000 to 1.985, which is well within the recommended limit of ≤ 5 [35], indicating that no collinearity issues were detected for the structural model in this study. Next, R-squared (R^2), predictive relevance, and significance of the path coefficients of the relationships specified in the study model need to be examined [12].

R^2 is the proportion of variance in the dependent variables explained by the independent variables in the study. The R^2 values of the endogenous (dependent) variables, namely, perceived usefulness, perceived ease of use, behavioral intention, and actual usage were 0.50, 0.28, 0.40 and 0.25, respectively. These values were all within the acceptable range of 0.10 and above for R^2 [12]. The results indicate that 50% of the variance in perceived usefulness is explained by its significant predictor, course relevance, and 28% of the variance in perceived ease of use is explained by its significant predictor, course content quality. The

Table 1
Factor loadings, Cronbach's alpha, composite reliability, and average variance extracted.

Construct	Indicators	Factor Loadings	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived Usefulness (PU)	PU1	0.84	0.88	0.92	0.68
	PU2	0.76			
	PU3	0.84			
	PU4	0.84			
	PU5	0.85			
Perceived Ease of Use (PEOU)	PEOU1	0.81	0.86	0.91	0.71
	PEOU2	0.85			
	PEOU3	0.85			
	PEOU4	0.86			
Course Content Quality (CCQ)	CCQ1	0.69	0.81	0.87	0.57
	CCQ2	0.71			
	CCQ3	0.83			
	CCQ4	0.73			
	CCQ5	0.79			
Course Instructor Quality (CIQ)	CIQ1	0.76	0.79	0.85	0.53
	CIQ2	0.75			
	CIQ3	0.77			
	CIQ4	0.52			
	CIQ5	0.80			
Course Design Quality (CDQ)	CDQ1	0.73	0.74	0.83	0.55
	CDQ2	0.78			
	CDQ3	0.67			
	CDQ4	0.79			
Course Relevance (CR)	CR1	0.85	0.88	0.91	0.67
	CR2	0.77			
	CR3	0.78			
	CR4	0.87			
	CR5	0.81			
Learner-Instructor Interaction (LII)	LII1	0.80	0.73	0.83	0.63
	LII2	0.89			
	LII4	0.67			
Learner-Learner Interaction (LLI)	LLI1	0.81	0.79	0.86	0.61
	LLI2	0.81			
	LLI3	0.76			
	LLI4	0.75			
Behavioral Intention (BI)	BI1	0.93	0.92	0.95	0.86
	BI2	0.95			
	BI3	0.91			
Actual Usage (AU)	AU1	1.00	1.00	1.00	1.00

Table 2
Discriminant validity (HTMT values).

	AU	BI	CCQ	CDQ	CIQ	CR	LLI	PU	PEOU	TLI
AU										
BI	**0.52**									
CCQ	0.22	**0.43**								
CDQ	0.19	0.39	**0.83**							
CIQ	0.13	0.20	0.65	**0.72**						
CR	0.38	0.48	0.69	0.68	**0.61**					
LLI	0.18	0.13	0.16	0.22	0.28	**0.21**				
PU	0.41	0.43	0.58	0.55	0.44	0.29	**0.12**			
PEOU	0.26	0.65	0.53	0.42	0.40	0.78	0.12	**0.34**		
LII	0.16	0.18	0.22	0.23	0.39	0.27	0.79	0.16	**0.11**	

combined effect of all the significant exogenous (independent) variables on behavioral intention to use MOOCs was 40%, meaning that, the total effect of the factors, perceived usefulness, perceived ease of use, course relevance, and course content quality explained 40% of the variance observed in behavioral intention to use MOOCs. Furthermore, about 25% of the variance in actual usage was explained by the combined effects of perceived usefulness, perceived ease of use, course relevance, course content quality, and behavioral intention.

The predictive relevance of the structural model was assessed using Q^2, a blindfolding technique that cross-validates a model for redundancy. The Q^2 values for the endogenous constructs were all greater than zero (BI=0.34, PU = 0.33 and PEOU = 0.18, AU=0.09), indicating acceptable predictive relevance of the proposed path model [12].

Finally, a bootstrapping technique using 1000 subsamples was used to test the study hypotheses for significance, as recommended by Hair et al. [12]. Only five (5) of the proposed hypotheses were supported. The results showed that perceived usefulness and perceived ease of use had significant positive impact on behavioral intention to use MOOCs ($b = 0.52$, $p<0.001$ and $b = 0.24$, $p<0.01$, respectively), supporting H1 and H3. Also, behavioral intention predicted actual usage behavior of MOOCs ($b = 0.50$, $p<0.001$), supporting H4. Furthermore, course content quality predicted perceived ease of use ($b = 0.27$, $p<0.05$), while course relevance predicted perceived usefulness ($b = 0.69$, $p<0.001$), supporting H6 and H10 respectively. All other hypotheses proposed for the study were not supported. Particularly, no relationships were found between course content quality and perceived usefulness, course design quality and perceived ease of use. And none was found between course instructor quality, learner-learner interaction, learner instructor

Table 3
Path coefficients.

Hypothesis	Path	*b*	*t*	95% *CI* [LL, UL]	Supported	f^2	VIF
H1	PU -> BI	0.52***	5.90	[0.33, 0.67]	**Yes**	0.40[b]	1.098
H2	PEOU -> PU	0.15	1.73	[−0.01, 0.33]	No	0.03	1.381
H3	PEOU -> BI	0.24**	3.15	[0.10, 0.39]	**Yes**	0.08[c]	1.098
H4	BI -> AU	0.50***	11.15	[0.38, 0.60]	**Yes**	0.33[b]	1.000
H5	CCQ -> PU	0.02	0.27	[−0.13, 0.21]	No	0.00	2.038
H6	CCQ -> PEOU	0.27*	2.29	[0.03, 0.49]	**Yes**	0.05[c]	1.898
H7	CIQ -> PU	−0.06	0.69	[−0.22, 0.10]	No	0.00	1.753
H8	CIQ -> PEOU	0.16	1.82	[−0.01, 0.34]	No	0.02	1.779
H9	CDQ -> PEOU	0.186	1.60	[−0.05, 0.40]	No	0.02	1.985
H10	CR -> PU	0.69***	8.05	[0.49, 0.82]	**Yes**	0.56[a]	1.697
H11	LII -> PU	0.06	0.99	[−0.08, 0.17]	No	0.01	1.554
H12	LII -> PEOU	−0.02	0.24	[−0.16, 0.15]	No	0.00	1.546
H13	LLI -> PU	0.01	0.14	[−0.14, 0.16]	No	0.00	1.478
H14	LLI -> PEOU	0.03	0.24	[−0.26, 0.30]	No	0.00	1.483

[a] Large effect size.
[b] Medium effect size.
[c] Small effect size.
***$p<0.001$, **$p<0.01$, *$p<0.05$.

interaction and perceived usefulness or ease of use. Fig. 3 below illustrates the results of the hypotheses testing is illustrated in Fig. 3 below and more detailed results of the test can be found in Appendix 2.

Discussion

Introduction

This study examined key course-specific factors that are likely contributing to people's intention to use MOOCs and their actual usage behavior, to better understand adoption behavior associated with the learning technology. This study specifically uses TAM as a theoretical framework to understand the acceptance and use of MOOCs. It extends TAM by investigating specific factors influencing people's perceived usefulness and perceived ease of use of MOOCs. The specific factors examined include, course instructor quality, course content quality, course design quality, course relevance, learner-instructor interaction, and learner-learner interaction. Learning in MOOCs is optional, informal, and self-regulated, hence, ensuring that a course possesses appealing characteristics is important to attract and keep learners. Therefore, investigating external factors like those proposed in this study can have important implications for instructors or MOOCs course providers that want to create courses that are appealing, and that people want to enroll and learn from.

Perceived usefulness mediates the relationship between course relevance and behavioral intention to use MOOCs

The results showed that MOOC learners in this study consider tangible value (e.g., educational, and job-related benefits) associated with MOOCs to be an important determinant of the decision to use them. Specifically, the more useful they considered a MOOC to be, the more likely they are to consider using them for their needs. Additionally, course relevance was found to be affecting how useful learners in this study consider MOOCs to be such that more relevant learners consider the course content or materials covered in a MOOC to be for either their professional or personal purposes, the more they would consider that course to be, and they will in turn be more motivated to participate in that course. This is consistent with previous studies that found learners' perceived usefulness of a MOOCs course to be a reason why people want to participate in such a course [9,23]. It also supports previous findings that suggest that content that is relevant to participants' job needs is a major factor drawing students to participate in MOOCs [20]. In other online learning environments, it has also been found that course relevance is a strong predictor of perceived usefulness [27], motivation to learn [32] and student perceptions and behavior [5,38]. Hence from these findings, it can be argued that the MOOC learners are likely to consider how useful and relevant a course is to their needs as important factors when choosing to accept and use MOOCs. Therefore, it is important to develop strategies to demonstrate tangible value associated with the learning content to learners. For instance, explicitly providing details on how participating in the course can help students meet their future goals, whether it is academic or job-related. This can involve helping learners build their portfolio with projects and providing a more direct path from MOOC learning to real-life experience, whether it is through volunteer projects, internships, or job opportunities.

Perceived ease of use mediates the relationship between content quality and behavioral intention to use MOOCs

Additionally, the results also showed that, MOOC learners in this study consider the effort required to use MOOCs, a main factor influencing their decision to use them. Specifically, the less effort that is required to participate in MOOCs, the more likely learners were to consider using them. Furthermore, course content quality was found to be affecting how easy the learners find MOOCs to be such that, when the course content is of desirable quality, for instance, enjoyable, easy to follow, and have established guidelines, learners are more likely to consider the course easy to use. And as such, they would be more willing to participate in MOOCs. Although studies examining the relationship between content quality and perceived ease of use of MOOCs are limited, this finding supports a previous study that showed course content quality to be a significant predictor of perceived ease of use in online learning contexts [2,29]. Hence, the findings can be used to make the argument that, the effort required to use MOOCs and the quality of the content provided in MOOCs are important factors affecting people's willingness to accept and participate in them. Hence, it is essential that MOOC providers make the platforms and courses enjoyable and learner-friendly, to attract and keep learners. This may entail working with professional instructional designers to ensure that the content of the courses is clear and easy to follow, captures learners' attention (e.g., through use of real-world examples, multimedia, minimal text, and interactive components), and fits the objectives that the learner expects from any given course.

Behavioral intention to use MOOCs predicts actual usage of MOOCs

The results also showed that the actual usage behavior of the MOOC learners in this study reflected their intention to use MOOCs. Particularly, those who have a higher level of experience with MOOCs

Table 4
Constructs, measures, and sources.

Construct	Measures	Sources
Perceived usefulness (PU)	PU1: I find MOOCs useful in accomplishing my education or job-related goals PU2: Using MOOCs enables me to accomplish my education or job-related tasks more quickly PU3: Using MOOCs increases my learning or job productivity PU4: Using MOOCs is beneficial for me in preparing for further education or a new role PU5: Using MOOCs makes it easier for me to gain desirable skills I need for my studies or my job	[6,39,41]
Perceived ease of use (PEOU)	PEOU1: I find MOOCs easy to use PEOU2: Learning to use MOOCs is easy for me PEOU3: My interaction with MOOCs is clear and understandable PEOU4: It is easy for me to become skillful at using MOOCs	[6,39,41]
Behavioral Intention (BI)	BI1: I intend to use MOOCs in the future BI2: I will use MOOCs in the future BI3: I predict that I would use MOOCs in the future	[6,39,41]
Actual Usage (AU)	AU1: Approximately how many MOOCs classes have you enrolled in till date?	Created for this study
Course Instructor Quality (CIQ)	CIQ1: Instructors clearly provide students with relevant information in MOOCs CIQ2: Instructors promptly respond to student inquiries in MOOCs CIQ3: Instructors provide timely feedback to students in MOOCs CIQ4: Instructors encourage interaction among students in MOOCs CIQ5: Instructors deliver instructions clearly to students in MOOCs	[19,31]
Course Content Quality (CCQ)	CCQ1: MOOCs content and presentation attracts attention CCQ2: I find it easy to understand and follow the content of MOOCs CCQ3: MOOCs content is very enjoyable CCQ4: Learning objectives are clearly established in MOOCs CCQ5: MOOC course content fits with my learning objectives	[19,31]
Course Design Quality (CDQ)	CDQ1: The level of difficulty of MOOCs learning content is appropriate CDQ2: The content of MOOCs assignments is easy to understand CDQ3: The amount of learning content in MOOCs are appropriate CDQ4: The delivery schedule of MOOCs learning content is flexible CDQ5: MOOCs provide individualized learning management (**dropped**)	[19,31]
Course Relevance (CR)	CR1: MOOCs are relevant to my needs CR2: MOOCs are important for my needs CR3: MOOCs provide relevant information in my area(s) of interest CR4: Content provided in MOOCs relate well to my needs CR5: MOOCs have adequate resources for my needs	[32,40]
Learner-Instructor Interaction (LII)	LII1: Interacting with the instructor in MOOCs is more difficult than in other courses I have taken LII2: The interaction between students and instructors is inadequate in MOOCs LII3: The instructor seldom answers students' questions in MOOCs (**dropped**) LII4: Class discussions are more difficult to participate in MOOCs than in other courses I have taken	[25,33]
Learner-Learner Interaction (LLI)	LLI1: There is little interaction between students in MOOCs LLI2: Interacting with other students in MOOCs is more difficult than in other courses I have taken LLI3: Students seldom ask or answer each other's questions in MOOCs LLI4: There are inadequate opportunities to participate in class discussions in MOOCs	[25,33]

enrollment were more likely to be those that indicated intention to continue learning with MOOCs. Meaning that when people intend to use MOOCs, due to how useful and easy to use they consider them to be, the more they may be likely to have a high usage behavior. This is consistent with previous findings that have found behavioral intention to be a strong predictor of actual usage behavior in different technologies, including online learning [9,41].

Examined factors not influencing perceived usefulness and perceived ease of use of MOOCs

Furthermore, it was found that for participants in this study, having a high-quality instructor, course content, and course design may not be as important in influencing how useful and easy to use a learner will perceive a course to be. It was also found that interpersonal interaction may not be as important in MOOCs as it is in other more formal online learning platforms. These findings are contrary to those found for other more traditional e-learning platforms, where those factors were found to be important in predicting the perceived ease of use and perceived usefulness of the platforms (e.g., [4,10,14,30,37]). It is however important to note that the items for this study were adapted from studies examining traditional e-learning environments, so it is possible that the items are more suited to that specific learning environment. And the differences between the features of MOOCs and traditional e-learning environments can be a contributing factor to those differences observed in this study. For instance, as indicated earlier, MOOC learning is primarily optional, informal, and self-regulated and typically requires more self-motivation and persistence from learners for participation. Hence learners' assessment of these factors in MOOCs can differ significantly as it is generally easier for them to switch from one course to another, since the sense of commitment to a course is fundamentally different from that of traditional online learning courses. Also, interacting with the instructor and other students, which are major quality determinants in traditional learning environments, are not very integrated into the MOOC learning structure. So how those components will affect MOOCs acceptance and use will essentially be different for learners. In summary, the way that course content quality, instructor quality, course design quality and interaction components are measured may need to be redefined for MOOCs. This suggests a need for further studies to explore and develop these factors that are more specific to the unique context of MOOC learning environments for a better understanding on how they can influence MOOCs acceptance and use.

Theoretical implications

This study contributes to the literature in two important ways. First, it provides empirical evidence that the TAM framework is a viable framework in understanding the acceptance and use of novel technology such as MOOCs. Evidence from the study suggests that learners' perceived usefulness and perceived ease of use of MOOCs are important predictors of their behavioral intention to learn using them. However, contrary to previous studies, perceived ease of use did not predict perceived usefulness in this study, implying that making MOOCs easy to use may not be enough for learners to consider them useful. Future studies can explore the relationship between perceived usefulness and perceived ease of use, with regards to MOOCs to further support or contradict this assertion. Furthermore, this study created items for MOOC usage behavior and confirmed that people's intention to use a technology predicts their actual usage behavior, as suggested in TAM.

Secondly, the study also provides evidence of the importance of extending the TAM framework to include external determinants of the main constructs of perceived usefulness and perceived ease of use, to offer context-specific explanations for the acceptance of a particular technology. Specifically, it was found in this study that course relevance predicted perceived usefulness, and course content quality predicted perceived ease of use within the context of MOOCs. Hence, course relevance and course content quality are two factors that can be added to TAM to examine the acceptance and use of MOOCs as a learning technology.

Limitations and future research

This study is not without limitations, which creates opportunities for future research. First, participants for the study were recruited from a specialized research participation platform, Prolific, where only registered users on the platform and those who were active on the during the period of the study would have had a chance to participate. Hence, generalizing the results of this study to all MOOC learners should be done cautiously. Future research can recruit participants more randomly using varied means. Additionally, with regards to sampling, the participants in the study had varied level of MOOC experience, which may have influenced their responses. Although all participants were required to have enrolled in and completed at least one MOOC course in the past. Future research can modify the criteria for choosing participants to include those with similar level of experiences for a more unified outcome.

Furthermore, only specific course characteristics were explored in the study as determinants of the main TAM constructs. Future studies can explore other factors that may also be relevant within the MOOCs context. Furthermore, this study required learners to self-report their MOOC usage behavior, so there is a possibility that participants over-reported their usage, thereby introducing social desirability bias into the data. Future studies can determine usage behavior via other means, e.g., obtaining direct proof of completed courses and certificates. Finally, the survey items were close-ended and were therefore limited by the amount of information that can be obtained to explain a construct. Supplementing survey data with a qualitative component such as interviews would be beneficial for future studies to gather more in-depth perspectives about people's perceptions of the phenomenon being studied and get more insights on how to better design MOOCs to increase their acceptance by learners.

Conclusion

This study integrated specific course characteristics variables into the well-known TAM framework to enhance understanding of acceptance of MOOCs among learners. The findings show that perceived usefulness, perceived ease of use, course relevance and course content quality are all important factors affecting MOOCs acceptance. These results support previous findings that TAM constructs can be used in understanding acceptance of MOOCs and e-learning [9,23]. It also supports the argument that relevant external variables be added to TAM to better understand the technology being studied [26,41]. This study contributes to the literature by establishing the importance of less-explored variables, course relevance and course content quality in learners' acceptance and use of MOOCs. The results specifically confirm previous findings that perceived usefulness and perceived ease of use significantly influence behavioral intention to use MOOCs [23,37]. While two of the external variables explored, course relevance and course content quality, indirectly influenced behavioral intention through perceived usefulness and perceived ease of use respectively. These results are in support of those found in previous studies exploring other e-learning contexts [20,38].

The study concludes that, the relevance of a MOOC course to the needs of the learners and the quality of the content provided, are factors that need to be addressed to increase acceptance. These factors can be utilized by MOOC platforms and course designers when designing courses to appeal to learners. For instance, to create courses that are useful and relevant to the needs of learners, MOOC developers can ensure that the objectives of the course are clearly communicated early on during the course and that the content and activities provided to achieve those objectives are relevant to the topic being addressed. They can also ensure that adequate resources on the topic or subject are provided throughout the course. These will potentially enable the student to easily identify if the course or specific aspects of the course is relevant for their needs and that they have adequate resources to support their learning of the content. Also, MOOC platforms can ensure that there are strategies in place to demonstrate tangible value associated with the learning content to learners. For instance, creating a connection between the course and a tangible future goal for the learners, whether academic or job-related, through activities like, portfolio building, interview preparation, volunteer projects, internships or even job opportunities for best performers. Furthermore, to create courses that are easy to use, MOOC developers can ensure that the learning content is of good quality by establishing clear learning objectives and providing content that captures attention, is easy to understand and follow, and is enjoyable. They can do this by engaging the services of professional instructional designers. Overall, the study shows that the TAM framework, with course relevance and course content quality included as external variables, can be used to explain MOOC acceptance and use among learners.

This study therefore had the following major contributions:

The study investigates MOOCs acceptance and use, a topic that is still understudied regardless of the proliferation of the learning technology in question.

The study adds to the MOOCs acceptance literature by proposing a conceptual framework that investigates the roles of less-studied course-specific variables such as, course instructor quality, course content quality, course design quality, course relevance, learner-instructor interaction, and learner-instructor interaction.

This study explicitly identifies and adds to the literature, course relevance and course content quality, as specific course-related factors affecting MOOCs acceptance and use, providing more context to inform course design for better acceptance.

To the best of the researcher's knowledge, this is one of the first studies to investigate the course-specific variables outlined in this study within the context of MOOCs acceptance.

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Declaration of Competing Interest

None.

Appendix 1: Measurement model assessment

Tables 1 and 2.

Appendix 2: Structural model assessment

Table 3.

Appendix 3: Study measures

Table 4.

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