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REGULAR ARTICLE

Examining the Influence of Teaching Presence and Task-Technology Fit on Continuance Intention to Use MOOCs

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Abstract This study aimed to examine the structural relationships among factors that affect learners' continuance intention to use Massive Open Online Courses (MOOCs). Drawing upon the Technology Acceptance Model (TAM), it posited teaching presence and task-technology fit as exogenous variables, examining how they affect continuance intention to use MOOCs, mediated by perceived usefulness and perceived ease of use. Based on survey data from 252 Korean MOOC learners, structural equation modeling was employed to assess the model. The results indicated that perceived usefulness affected continuance intention to use, while perceived ease of use did not; however, perceived ease of use did affect perceived usefulness. Further, teaching presence was not significantly related to continuance intention to use or perceived usefulness, but did affect perceived ease of use. However, task-technology fit affected perceived usefulness, perceived ease of use, and continuance intention to use. Finally, the mediating role of perceived usefulness and perceived ease of use on the relationships between teaching presence as well as task-technology fit and continuance intention were confirmed. Implications were suggested for designing courses in MOOCs to increase continuance intention to use.

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Introduction

There has been a shift in online higher education from a focus on small-scale for-credit courses to Massive Open Online Courses (MOOCs) that are freely available to anyone interested in lectures from renowned universities (de Freitas et al., 2015). Today, universities around the world are making their class offerings available through MOOCs on such online platforms as Coursera, edX, and Udacity. In this context, *platforms* refer to the online systems through which learners and instructors access course materials (Yang et al., 2017). Such platforms extend opportunities for higher education beyond traditional classrooms (Toven-Lindsey et al., 2015).

Although MOOCs platforms provide learners an affordable and convenient means to take courses, studies have questioned their efficacy (Breslow et al., 2013; Koutropoulos et al., 2012; Margaryan et al., 2015; Xing et al., 2016; Zhong et al., 2016). The overall average course completion rate for these courses is less than 10% (Hew & Cheung, 2014), with many students dropping out after only 1 or 2 weeks (de Freitas et al., 2015). Thus, additional research is needed on students' continuance intention to use MOOCs. *Continuance intention to use* refers to learners' willingness to continue participating in a course (Joo et al., 2018). If students have a strong continuance intention to use a given platform, they will be motivated to use it and will more likely persist in their learning.

Existing MOOCs studies on continuance intention to use are based on the Technology Acceptance Model (TAM), which explains why users accept or reject a new system and describes the mechanisms whereby users develop a continuance intention to use a specific technology or platform. According to this model, users' perceptions of technologies' usefulness and ease of use influence their behavioral intention to use technology (Davis et al., 1989). Since there is a limit to describing the mechanism by which continuous intention to use is formed by only employing the basic TAM, studies have, over time, added exogenous variables that affect the user's beliefs. For example, studies on MOOCs learning have examined variables, such as social motivation (Wu & Chen, 2017) and platform quality (Yang et al., 2017), to better understand continuance intention to use MOOCs. Despite these attempts to expand the scope of the TAM, such studies are limited because they do not include factors related to the characteristics of MOOCs. One important type of MOOC learning is the instructor-led massive course. The MOOC platform offers an affordable academic service for enrolling in courses with well-known instructors. MOOC instructors pave the path to obtaining course certificates by organizing a variety of activities, including lectures and assessments (Zhu et al., 2018; Zhu et al., 2018), and by enabling learners to experience their instruction on the platform (Bonk et al., 2015). Thus, determining the best means by which to deliver instruction with technological support is essential to encouraging continuing engagement in MOOC learning.

Given this instructional service is offered on the platform, an important exogenous variable to consider in promoting continuance intention to use MOOCs is *teaching presence*. Teaching presence refers to learners' feelings regarding course design, facilitation, and direct instruction (Garrison et al., 2001). In most MOOC courses, instructors lead the course and organize the schedule (Jung & Lee, 2018). Students' perception of teaching may relate to the facilitating conditions, often regarded as the perceived availability of environmental support, necessary information, or materials that affect attitudes toward technology use (Teo, 2010). Because instructional activities are present on the platform, teaching presence may facilitate learners' use of instructional services to locate the necessary information there. Previous qualitative studies reported that MOOC learners' perception of teaching presence facilitates learning (Cohen & Holstein, 2018; Watson et al., 2016). Teaching presence influences learning persistence in MOOCs (Jung & Lee, 2018). However, considering results that teaching presence only indirectly affects persistence mediated by satisfaction in traditional e-learning (Joo et al., 2011), the learners' internal beliefs can mediate the relationship in MOOCs. Thus, the mechanism between teaching presence and continuance to use is still required to be investigated.

Another exogenous variable that can be considered in relation to MOOCs is *task-technology fit*, which refers to users' subjective evaluation of whether a technology assists their individual tasks (Goodhue & Thompson, 1995). In MOOCs, learners enroll in the course according to individual motivations (Kizilcec & Schneider, 2015). Their motivations shape different learning pathway and individual tasks by choosing learning resources. To accomplish their individual tasks, learners first evaluate whether technology supports tasks they aim for, and their subjective evaluation on the technology assists their continuance intention to use (Wu & Chen, 2017). If MOOCs learners experience technological difficulties in accomplishing their tasks, their willingness to continue to use platform decreases (Peng & Xu, 2020). This underscores the importance of the perception that the MOOC platform offers adequate technological support to learn continuously.

This study, therefore, aims to understand the structural relationships between teaching presence, task-technology fit, and traditional TAM constructs to examine users' continuance intention to use MOOCs. By exploring the relationship between MOOC characteristics and continuance intention to use, this study will help develop instructional interventions that can be used to facilitate continuing engagement in MOOCs.

Theoretical Framework

Instructional Characteristics in xMOOCs

Early MOOCs emphasized collaborative knowledge construction, as demonstrated by one of the first public seminars titled "Connectivism and Connective Knowledge." As part of this course, students selected reading material based on their own interests and added them, along with other posts, to an interactive platform that served as a blog or discussion board. Each learner then further developed his or her own ideas based on the feedbacks received from other participants.

Over time, MOOCs have shifted away from this emphasis on collaborative knowledge construction and toward a focus on instructor-led teaching. A change occurred in 2012, when renowned universities, such as Harvard and Stanford offered open online lecture-based courses to large groups of learners using MOOC platforms (Toven-Lindsey et al., 2015) with the aim of making the learning experience at prestigious universities more widely available by allowing notable professors to teach learners on a larger scale. Such courses were later called xMOOCs (Ng & Widom, 2014), characterized by well-structured learning led by an instructor.

The instructional characteristics of xMOOCs are increasingly important. Instructors send out a weekly email to guide learning (Adams et al., 2014), offer feedback on assignments (Tseng et al., 2016), facilitate the peer-review process (Huisman et al., 2018), and provide constructive criticism to facilitate reflection (Salmon et al., 2017). Combined with the instructional efforts of instructors, platform learning experiences are designed to be similar to those of offline classrooms.

Using TAM to Analyze Continuance to Use MOOCs

Despite advances in platform capabilities, the problem of underutilized systems continues. Because the high drop-out rate remains a central concern, MOOC continuance research studies have been accumulated in favor of the TAM suggested by Davis (1989). TAM is a theoretical framework explaining the psychological mechanism by which system users accept or reject a particular system (Davis et al., 1989). "Acceptance" refers to users' predisposition toward using the system (Lee & Lehto, 2013; Swanson, 1988). The original TAM has been extended by combining exogenous variables. Sumak et al. (2011) conducted a meta-analysis on 42 studies related to e-learning technology acceptance, reporting that TAM was the most widely used acceptance theory in e-learning acceptance studies. Studies on MOOC acceptance also mostly confirm the mechanism using the TAM (e.g., Joo et al., 2018; Wu & Chen, 2017; Yang et al., 2017).

TAM theorizes that an individual's behavioral intention to use a system is influenced by two elements: perceived usefulness and perceived ease of use. *Perceived usefulness* is the subjective evaluation that a specific system will increase job performance, while *perceived ease of use* refers to the degree to which a user expects the use of a system to be effortless (Davis et al., 1989). In the context of MOOCs, perceived usefulness refers to the instrumental value of the MOOC platform, which may provide useful functions to enhance learning. If students believe that the MOOC platform enhances learning, they will be more likely to use the system. On the other hand, perceived ease of use is about expending minimal effort for learning the required functions of a user-friendly MOOC platform. In the TAM, the mediating variable *attitude* was included, although Davis et al. (1989) found that perceived usefulness and perceived ease of use rather than attitude have direct effects on continuance intention to use. Thus, studies have mainly focused on the relationship these two aspects and continuance intention to use (Lu et al., 2019; Yang et al., 2017).

Exogenous Variables: Teaching Presence and Task-Technology Fit

TAM is useful in tracing the impact of exogenous factors affecting internal beliefs and intention (Davis et al., 1989), allowing interventions that increase utilization and performance to be derived. Studies on MOOCs have investigated exogenous factors, especially focusing on learners' motivation (Wu & Chen, 2017; Zhu et al., 2018; Zhu et al., 2018). Recently, another research tried to focus on platform quality factors (Yang et al., 2017). Although these studies have extended the understanding of MOOC learners' acceptance mechanism, very few studies have explored factors that are related to the unique characteristics of MOOCs. Thus, how these characteristics of the platform affect learners' decision on continuance intention to use need to be explored.

One of the unique characteristics of MOOCs is that the instructor makes an effort to teach to ensure that learners obtain certificates (Bonk et al., 2015). In MOOCs, one of the factors influencing persistence is teaching presence (Jung & Lee, 2018). *Teaching presence* is learners' feelings regarding course design, facilitation, and direct instruction (Garrison et al., 2001). It includes three dimensions: *course design and organization*, *facilitation of discourse*, and *direct instruction* (Garrison & Arbaugh, 2007). Course design and organization includes the planning and design of an online course's structure, process, interactions, and evaluation. It necessitates developing a curriculum, designing methods, establishing time parameters, and ensuring that the medium can be utilized effectively (Anderson et al., 2001). *Facilitating discourse* refers to supporting participant interactions in online learning and includes encouraging learners seeking to understand and assessing the efficacy of the process through presenting content/questions, summarizing discussions, and diagnosing misconceptions (Arbaugh & Hwang, 2006). Finally, *direct instruction* includes providing course content, asking questions, and correcting misconceptions (Anderson et al., 2001).

Another distinctive feature of MOOCs is that learners have autonomy to choose learning contents related to their individual goals and completion of the course is non-obligatory. MOOCs learners have various learning goals and find learning resources to achieve their goals (DoBoer et al., 2014). For instance, some learners who desire to get certificate tried to do "backjump" from assessment to a video repeatedly (Guo & Reinecke, 2014). Their tasks are finding the specific information required to get certificate. Meanwhile, other learners who aims at getting information spent most time watching videos and are less engaged in participating forum (Rizvi et al., 2020). In this case, their tasks are related to gathering information for the personal purpose (e.g., understanding basic concept or finding examples). Prior studies reported that technological support is important for MOOCs learners to achieve their goals. Technological support to meet individual tasks enhances the perception of technology and behavioral intention to use (Peng & Xu, 2020).

Considering individual tasks and the need of technological support, MOOCs learners' continuance intention to use might be affected by their *task-technology fit*, which refers to their subjective evaluation of whether a technology assists their individual tasks (Goodhue & Thompson, 1995). It is reported that task-technology fit of learners influences behavioral intentions and utilization of traditional online learning system (Isaac et al., 2019; Yu & Yu, 2010). Given the role of task-technology fit on self-regulated learning, the influence of task-technology fit on utilization should also be considered in MOOCs context.

Research Model and Hypotheses

This study develops a theoretical model to examine the effect of teaching presence and task-technology fit on the continuance intention to use MOOCs on the basis of TAM. The relationships between these constructs and corresponding hypotheses are described in the research model (Fig. 1).

Perceived Usefulness, Perceived Ease of Use, and Continuance Intention to Use

Perceived usefulness and perceived ease of use have positive impacts on the continuance intention toward use of MOOCs (Yang et al., 2017). In the Korean MOOC (K-MOOC) context, perceived ease of use for MOOC platform affected perceived usefulness (Joo et al., 2018). Therefore,

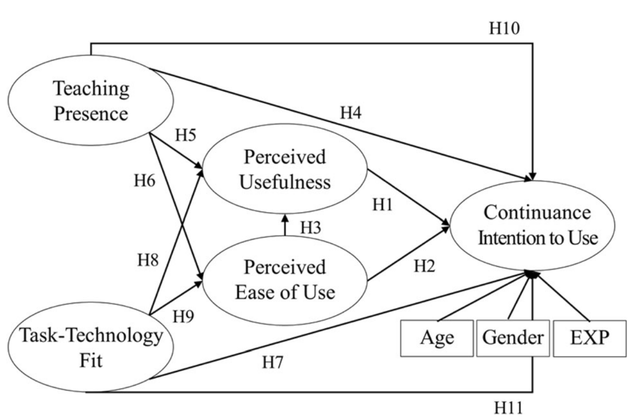

Fig. 1 Research model

this study proposes the following hypotheses regarding learners' acceptance of MOOCs:

H1: Perceived usefulness has a positive influence on continuance intention to use MOOCs.
H2: Perceived ease of use has a positive influence on continuance intention to use MOOCs.
H3: Perceived ease of use has a positive influence on perceived usefulness.

Teaching presence and TAM constructs

Teaching presence was found to have a significant influence on learning persistence in MOOCs and e-learning systems (Joo et al., 2011; Jung & Lee, 2018; Rodríguez-Ardura & Meseguer-Artola, 2016). Instructional activities can influence learning outcomes as one of main factors that affect teaching presence in MOOC courses. For instance, course instructor feedback and instructor facilitation were found to influence effectiveness, such as satisfaction (Eom et al., 2006), while positive sentiment toward and interaction with the MOOC instructor had a positive effect on and significantly predicted retention (Adamopoulos, 2013; Hone & Said, 2016). In addition, teaching presence facilitates for learners to use technology in the platform because all instructional activities are mediated by technology. That is, teaching presence can be a facilitating condition for the use of MOOC platform. Given that facilitating condition was revealed to affect perceived ease of use (Khlaisang, Teo, & Huang, 2019; Teo, 2010), the following hypotheses are suggested:

H4: Teaching presence has a positive influence on continuance intention to use.
H5: Teaching presence has a positive influence on perceived usefulness.
H6: Teaching presence has a positive influence on perceived ease of use.

Task-technology fit and TAM constructs

Learners' task-technology fit has been reported as a predictive variable affecting learning performance and continuance intention to use (Lin, 2012; McGill & Hobbs, 2008). A study on procedural learning through YouTube revealed that learners' task-technology fit affects perceived usefulness (Lee & Lehto, 2013). In MOOCs context, task-technology fit has a significant influence on perceived ease of use as well as perceived usefulness (Wu & Chen, 2017). As MOOCs allow free access to those who want to enroll, diverse learners acquire knowledge according to their individual interests. Learners perform individualized tasks shaped by their own personal interest. Prior to adopting the system technology, learners evaluate task-technology fit to achieve their own goals. Therefore, the following hypotheses are suggested:

H7: Task-technology fit has a positive influence on continuance intention to use.
H8: Task-technology fit has a positive influence on perceived usefulness.
H9: Task-technology fit has a positive influence on perceived ease of use.

Mediation Effect of Perceived Usefulness and Perceived Ease of Use

This study's model also includes serial mediating variables related to TAM that are expected to have mediating effects on the relationships among variables. The following hypotheses are suggested:

H10: Users' beliefs (i.e., perceived usefulness and perceived ease of use) mediate the relationship between teaching presence and continuance intention to use.
H11: Users' beliefs (i.e., perceived usefulness and perceived ease of use) mediate the relationship between task-technology fit and continuance intention to use.

Methods

Participants and Research Context

This study includes data from 252 out of a total of 924 participants of a K-MOOC course titled "Designing Future Education" offered in 2017 by one of the largest universities in Korea. After the completion of the course, researchers sent emails to the 924 total participants to solicit their responses to an online survey. Of the 293 questionnaires returned, 252 responses were used for the data analysis; the remaining were excluded due to missing data and outliers in the sample. This number of samples exceeds 232, the minimum number of samples recommended to detect the specified effect in consideration of number of observed variables, number of latent variables, effect size, and probability level (Soper, 2021; Westland, 2010). Of the 252 respondents, 114 (45.2%) were male and 138 (54.8%) were female. In terms of age, 39 (15.5%) were teenagers, 93 (36.9%) were in their 20 s, 42 (16.7%) were in their 30 s, 42 (16.7%) were in their 40 s, and 36 (14.3%) were over 50. Finally, 60 (23.8%) had completed MOOC courses before. Participants' motivation to take the classes were as follows: 114 (45.2%) participants were interested in the subject, 53 (21.0%) were curious about quality lectures at excellent universities, 29 (11.5%) were curious about MOOC, 22 (8.7%) found the course to be relevant to their current job, 19 (7.6%) took the course to complete certificate acquisition, and 15 (6.0%) took the course for other reasons.

The K-MOOC platform was designed by edX platform source. Courses were accessed through four main menus: *Lectures*, *Forum*, *Wiki*, and *Progress*. When students accessed the Lectures, they were able to see lists of weekly contents, which, when selected, presented them with more options, such as instructor-driven videos and quizzes. Students could use the Forum to introduce themselves to one another, to discuss particular topics, and to interact with instructors or tutors. For example, they could ask questions about the course content, deadlines, assignments, or technical issues. The Wiki was used for collaborating on assignments and the Progress menu was provided for self-monitoring grades and participation in course activities.

The "Designing Future Education" course spanned eight weeks, and its main goal was to understand the changes in the education paradigm triggered by technological and social changes. This course level was similar to general liberal arts and does not require any foundation or preparatory courses. Weekly lessons comprised watching video lectures, followed by quizzes, discussions, and Wiki participation. Three to four video lectures of about 15 min per week were provided, and it was recommended that learners finish watching video lectures about within an hour. All quizzes and debate participation scores were included in the final grade, and Wiki participation was optional. The final completion rate for this course was about 12%. Weekly learning contents and activities are detailed below.

In the first week, video lectures provided an overview of social changes and how they may affect education in the future. During the second week, an instructor analyzed Korea's educational problems and provided topics for discussion; students were required to post their opinions in the class Forum. In the third week, the instructor addressed global trends in K-12 education and gave the students a quiz. Students were also given the opportunity to participate in a collaborative activity that involved putting future educational trend keywords on the class Wiki; participation was optional and not considered for the final grade. In the fourth week, the instructor lectured students about likely future trends in higher education/lifelong learning and gave the students another quiz. The fifth week dealt with educational paradigm shifts due to the Fourth Industrial Revolution and yet another quiz was given to the students. During the sixth week, the instructors discussed future jobs and education, followed by a class discussion. The seventh week consisted of lectures on creativity education and a quiz. The final week covered future educational ecosystems, and students were provided with another quiz.

In this lecture, the instructor made the following teaching efforts so that learners could feel the teaching presence. First, instructor informed the students about weekly learning goals, the order of participation in learning activities in the platform, further reading materials, and the schedule for participation in weekly quizzes or discussion through weekly emails. By following this sequence, learners were able to achieve their weekly learning goals and ultimately succeed in completing the course. Second, the instructor checked each learner's progress along the pathway and promoted participation. When they successfully followed this pathway, the instructor sent individual complimentary emails. Meanwhile, the instructor sent emails to learners with low participation rates, encouraging them to take classes. In addition, the instructor notified the current status of participation in the collaborating projects in weekly mails, and encouraged more active participation from the entire class. Third, if the learner wrote his or her opinion on the given subject, the instructor provided feedback and additional questions that could deepen their understanding. In addition, the instructor recommended learning materials for further reading or video lectures based on the opinions expressed by the learners.

Instrument

The survey distributed to participants was designed to measure the TAM constructs (perceived usefulness, perceived ease of use, and continuous intention to use), teaching presence, and task-technology fit within the context of the K-MOOC system (see Appendix). Survey items were revised with minimal modifications to the original scale, considering the MOOCs' context. The questionnaire items corresponding to each construct were each rated on a five-point Likert scale.

To measure the three TAM constructs, the survey included nine items adapted from Venkatesh and Davis (2000), and Wu and Chen (2017). Each construct was measured using the following three items: "Using the MOOC improves my learning performance" (perceived usefulness), "It is easy to become proficient in using the MOOC platform" (perceived ease of use), and "I intend to continue using the MOOC in the future" (continuance intention to use). Cronbach's α values for perceived usefulness, perceived ease of use, and continuance intention to use were 0.802, 0.765, and 0.777, respectively.

Teaching presence was measured using 14 items adapted from Arbaugh and Hwang (2006) including "The instructor clearly communicated important course goals" (instructional design and organization), "The instructor helped keep students engaged and participating in productive dialogue" (facilitating discourse), and "The instructor presented content or questions that helped me to learn" (direct instruction). Cronbach's α for teaching presence was 0.881.

Finally, task-technology fit was assessed using seven items taken from Wu and Chen (2017) including "The MOOC fits my learning requirements" and "Using the MOOC fits with my educational practice." Cronbach's α for task-technology fit was 0.814.

Data Analysis

The data were analyzed using structural equation modeling to investigate the structural relationships among variables. Item parceling was used to cluster individual items for two exogenous variables. Item parceling is a measurement practice used to create an aggregate-level variable comprising the sum or average of the individual items in structural equation modeling (Little et al., 2002). This method reduces estimation errors by incorporating indicators measuring each latent variable and holding the multivariate normality assumption (Sass & Smith, 2006). Before parceling, the model was created using maximum likelihood estimation, and the model fit was evaluated using indices, such as Chi-square, Tucker Lewis Index (TLI), Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Residual (SRMR).

Results

Descriptive Statistics and Correlation

Table 1 presents the descriptive statistics for the observed variables and the correlations. The means for the variables varied from 3.770 to 4.370 and the standard deviations varied from 0.646 to 0.919. To assess normality, the data analysis included skewness and kurtosis. The absolute skewness value ranged from 0.251 to 1.150 and the absolute kurtosis value ranged from 0.096 to 1.759. The results met the assumption of multivariate normality, as the skewness was less than 3.0 and the kurtosis was less than 10 (Kline, 2010). Correlation coefficients of all items were between 0.069 and 0.681, which shows a mostly statistically significant positive correlation.

Item Parceling of Constructs

A model of teaching presence and task-technology fit was investigated to cluster items through a clustering method called item parceling. All of the individual items (see Appendix) measuring these two latent variable were formed into a parcel for each. For the each model, the results of the model fit are displayed in Table 2.

Table 1 Descriptive statistics and correlation

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Course design and organization	1													
2. Facilitating discourse	0.473**	1												
3. Direct instruction	0.513**	0.496**	1											
4. Task-technology fit	0.286**	0.069	0.162*	1										
5. Individual-technology fit	0.293**	0.156*	0.199**	0.678**	1									
6. Perceived usefulness 1	0.249**	0.133*	0.180**	0.279**	0.261**	1								
7. Perceived usefulness 2	0.214**	0.141*	0.108	0.393**	0.367**	0.681**	1							
8. Perceived usefulness 3	0.227**	0.180**	0.165**	0.346**	0.385**	0.472**	0.573**	1						
9. Perceived ease of use 1	0.397**	0.322**	0.402**	0.203**	0.226**	0.259**	0.309**	0.362**	1					
10. Perceived ease of use 2	0.480**	0.434**	0.442**	0.328**	0.318**	0.253**	0.311**	0.268**	0.480**	1				
11. Perceived ease of use 3	0.508**	0.408**	0.379**	0.299**	0.315**	0.293**	0.311**	0.228**	0.438**	0.666**	1			
12. Continuance intention to use 1	0.250**	0.212**	0.285**	0.331**	0.359**	0.410**	0.429**	0.389**	0.270**	0.274**	0.324**	1		
13. Continuance intention to use 2	0.239**	0.276**	0.165**	0.375**	0.407**	0.566**	0.521**	0.542**	0.292**	0.310**	0.341**	0.564**	1	
14. Continuance intention to use 3	0.242**	0.224**	0.204**	0.336**	0.315**	0.429**	0.426**	0.466**	0.201**	0.265**	0.313**	0.487**	0.601**	1
Mean	4.200	3.770	3.920	4.370	4.160	4.270	4.100	4.040	3.770	4.050	4.120	4.030	4.280	4.340
SD	0.646	0.919	0.696	o.777	0.711	0.768	0.841	0.820	0.820	0.789	0.701	0.897	0.739	0.687

*$p < 0.05$

**$p < 0.01$

For teaching presence, all indices (TLI = 0.939, CFI = 0.951, RMSEA = 0.061, and SRMR = 0.055) met the cutoff criteria [TLI (> 0.9), CFI (> 0.9), RMSEA (< 0.08), and SRMR (< 0.08)] (Brown & Cudeck, 1993; Hu & Bentler, 1999). In general, RMSEA and SRMR values less than 0.05 were found to indicate a good model fit and less than 0.08 an acceptable model fit (Brown & Cudeck, 1993; Hu & Bentler, 1999).

On the other hand, in the case of task-technology fit, most indices met the cutoff criteria (TLI = 0.906, CFI = 0.984, SRMR = 0.021), but the RMSEA index (0.145) showed somewhat inadequate results. A sample or a low degree of freedom may result in an inadequate RMSEA (Kenny et al., 2015). However, since all other model fit indicators showed excellent fit, it was eventually judged as an acceptable level for a model. In addition, with regard to the average of standardization factor loading of individual items used to measure each latent variable, teaching presence (0.702) and task-technology fit (0.816) showed a high explanatory amount. Thus, this study uses the parceling model of teaching presence and task-technology fit.

Measurement Model

As the measurement model's fit was appropriate, discriminant validity and convergent validity were examined (see Table 3). As the AVE values (0.622–0.794) were higher than the square value of the correlation between variables (0.102–0.640), discriminant validity was judged to be appropriate. The convergence validity of an item to the construct was examined by the statistical significance of the item's loading and magnitude. The standardized factor loading of all items was at least 0.6, and the mean magnitude of all standardized factor loadings was shown to be 0.749, which exceeds the convergent validity threshold of 0.5 (Hair et al., 2010). In addition, all standardized factor loadings were statistically significant. Hence, it was concluded that the convergent validity was appropriate.

To test the reliability of the latent variables, composite reliability (CR) analyses were conducted. The CR for all variables was higher than the acceptable value of 0.8 (Gefen, 2003).

Structural Model

The structural model verification focused on the evaluation of the path between the latent variables implemented through the measurement model. First, reviewing the fitness indices to evaluate the overall fitness of the structural model revealed that all indices exceeded the general fitness standard; thus, the study model was found to be suitable (χ^2 (47) = 177.709, TLI = 0.940, CFI = 0.953, RMSEA = 0.052, SRMR = 0.056). Figure 2 shows final structural model.

Next, the relationship between the latent variables was examined (see Table 4). The results show that H1,

Table 2 Overall fit of the confirmatory factor analysis model of parceling constructs

	Chi-square	*df*	TLI	CFI	RMSEA	SRMR
Teaching presence	141.283	73	0.939	0.951	0.061	0.055
Task-technology fit	6.280	1	0.906	0.984	0.145	0.021

Table 3 Result for assessing measurement model

Latent variable	Observed variable	Factor loading	AVE	CR
Teaching presence	Course design and organization	0.988 (0.740)	0.622	0.831
	Facilitating discourse	1.273 (0.670)		
	Direct instruction	1.000 (0.695)		
Task-technology fit	Task-technology fit	1.000 (0.833)	0.794	0.885
	Individual-technology fit	0.895 (0.814)		
Perceived usefulness	Improving learning performance	1.057 (0.775)	0.690	0.869
	Increasing productivity	1.253 (0.839)		
	Enhancing effectiveness	1.000 (0.687)		
Perceived ease of use	Ease of becoming proficient in using the MOOC platform	0.887 (0.599)	0.670	0.857
	Finding the MOOC platform easy to use	1.167 (0.819)		
	Interacting with the MOOC platform does not require much mental effort	1.000 (0.791)		
Continuance intention to use	Intend to continue to use MOOCs in the future	1.000 (0.679)	0.670	0.858
	Continuing using MOOCs increasingly	1.021 (0.842)		
	Possibility of using MOOCs	0.800 (0.709)		

Values in brackets indicate standardized factor loading

AVE average variance extracted, *CR* composite reliability

concerning the relationship between perceived usefulness and continuance intention to use, was supported. However, perceived ease of use had no significant impact on continuance intention to use, suggesting that H2 was not supported. Perceived ease of use did, however, affect perceived usefulness, supporting H3.

Next, this study examined the effect of teaching presence, an exogenous variable, on other variables. H4, which predicted that teaching presence affects continuance intention to use, was not supported. Likewise, teaching presence did not affect perceived usefulness, suggesting that H5 was also not supported. Teaching presence did, however, affect perceived ease of use, supporting H6. Another exogenous variable, task-technology fit, was shown to affect continuance intention to use, perceived usefulness, and perceived ease of use, thereby supporting H7, H8, and H9.

The study further analyzed the effects of control variables. Among participants' socio-demographic variables and prior experience, as shown in Fig. 2, only prior experience to complete MOOCs significantly affects the continuance intention to use (β = 0.186, $p < 0.001$).

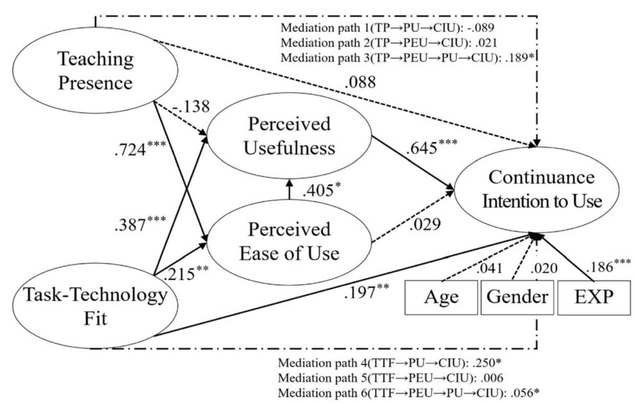

Fig. 2 Structural model with standardized estimates. *TP* teaching presence; *TTF* task-technology fit; *PU* perceived usefulness; *PEU* perceived ease of use; *CIU* continuance intention to use. Control variable: Age, Gender, and Prior experience to complete MOOCs**.** $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Mediating Variables

Given that this model comprised serial multiple mediators, a mediation significance test with phantom variables was performed (Chan, 2007). To assess the significance of

Table 4 Coefficients in the structural model

	Paths	Unstandardized	Standardized	*SE*	*t*-value
Teaching presence	Perceived usefulness	−0.162	−0.138	0.188	−0.864
	Perceived ease of use	0.829	0.724	0.107	7.772***
	Continuance intention to use	0.107	0.088	0.159	0.676
Task-technology fit	Perceived usefulness	0.341	0.387	0.079	4.348***
	Perceived ease of use	0.185	0.215	0.059	3.118**
	Continuance intention to use	0.180	0.197	0.070	2.581**
Perceived usefulness	Continuance intention to use	0.670	0.645	0.103	6.506***
Perceived ease of use	Perceived usefulness	0.416	0.405	0.175	2.373*
	Continuance intention to use	0.030	0.029	0.151	0.201

** $p < 0.01$

*** $p < 0.001$

Table 5 Bootstrap estimates of the mediating effects

Independent variable	Mediation path	Dependent variable	Indirect effect		Boot 95% CI[a]		Outcome
			Unstandardized	Standardized	Lower	Upper	
TP	PU	CIU	−0.109	−0.089	−0.567	0.191	n.s
TP	PEU	CIU	0.025	0.021	−0.448	0.315	n.s
TP	PEU → PU	CIU	0.231	0.189	0.007	0.716	Full mediation
TTF	PU	CIU	0.229	0.250	0.107	0.409	Partial mediation
TTF	PEU	CIU	0.006	0.006	0.076	0.075	n.s
TTF	PEU → PU	CIU	0.051	0.056	0.004	0.162	Partial mediation

TP teaching presence, *TTF* task-technology fit, *PU* perceived usefulness, *PEU* perceived ease of use, *CIU* continuance intention to use, *CI* Confidence Interval, *n.s* not significant

[a]Bootstrapping sample 5000 and bias-corrected 95% CI

indirect effects, the researchers used bootstrapping with a bias-corrected confidence estimate (see Table 5).

The results show that the indirect effect of teaching presence on continuance intention to use through perceived usefulness was not significant, but teaching presence had a significant indirect effect through the mediating variables of perceived ease of use and perceived usefulness. Since teaching presence had no significant direct effect on continuance intention to use, the serial mediating variables had a full mediation effect on the relationship between teaching presence and continuance intention to use (Fig. 3), thereby supporting H10.

On the other hand, the indirect effect of task-technology fit was significant. Perceived usefulness and perceived ease of use each partially mediated the relationship between task-technology fit and continuance intention to use, and the serial mediation of perceived usefulness and perceived ease of use was confirmed, thereby supporting H11 (Fig. 4).

Discussion

This study examined the factors affecting students' intention to continue using MOOCs, specifically within the context of the K-MOOC platform and its specific characteristics. In the hypothesized model, teaching presence and task-technology fit served as exogenous variables, perceived usefulness and perceived ease of use as mediating variables, and continuance intention to use as a dependent variable. The discussion of the key findings are as follows.

First, the results revealed that perceived usefulness affected continuance intention to use MOOCs. Perceived ease of use for MOOC platform did not affect continuance intention to use, but it did affect perceived usefulness. This is consistent with the existing research (Joo et al., 2018). In this study, the significant effect of perceived usefulness may be explained by the high ratio of adult learners who are motivated when they learn to fulfill their own goals (Huang, 2002). One of the most common motivators for participating in MOOCs were personal interest and

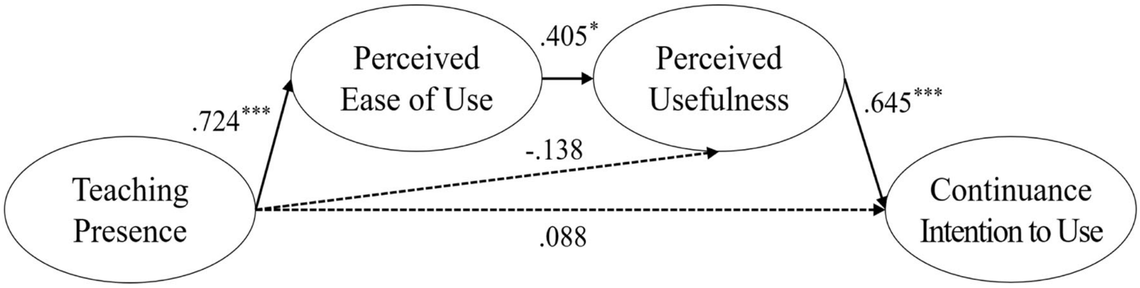

Fig. 3 Mediation structural model of teaching presence and continuance intention to use

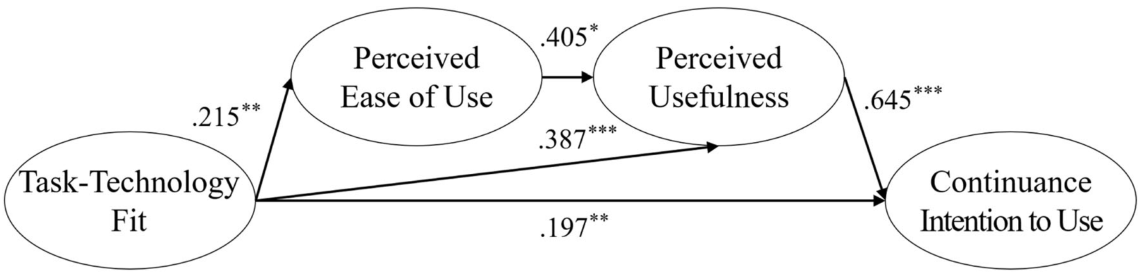

Fig. 4 Mediation structural model of task-technology fit and continuance intention to use

expertise development (Deng et al., 2019). Their individual learning goals may cause adult learners to rank the MOOC platform as more useful. However, while such learners may admire the affordability of the platform, they will not persevere in a course if they do not feel it is useful; therefore, perceived usefulness is the most significant factor for MOOC learners.

Second, this study also revealed that teaching presence, as an exogenous variable, was not significantly related to continuance intention to use or perceived usefulness. However, it did affect perceived ease of use. These findings were somewhat unexpected and inconsistent with those of previous studies, in which teaching presence was shown to directly affect learning persistence in university-level formal online classes (Joo et al., 2011). One reason may be that the characteristics of MOOCs learners differ from those of students in formal online education. Those who take a course in formal online education are more likely to perceive the influence of the instructors than are MOOCs learners, because the instructor's direction is essential for them to receive good grades. They are also expected to participate in all activities that an instructor suggests to complete the course. However, participants in this study did not receive credits and do not have to get a good grade. They may perceive an instructor as a guide to familiarize them with learning on the platform. Although teaching presence did not directly affect continuance intention to use, indirect effect, mediated by perceived ease of use and perceived usefulness, could have on continuance intention to use. This imply that learners will continue their learning if MOOCs instructors provide a teaching presence strategy that is easy and makes them feel that they can benefit from it. In fact, in this study, learners posted opinions on the Forum claiming that it was difficult to perform the instructor's activities due to the difficulty of using the platform. Thus, instructors should also consider providing guidance on the use of the platform to perform the task, when they send the weekly study guidance via email.

Third, task-technology fit as another exogenous variable affect perceived usefulness, perceived ease of use, and continuance intention to use. MOOC learners with diverse interests pursue a variety of individual tasks and require adequate technological support to complete them. Prior studies have underscored the need for appropriate technological support in MOOCs learning (Peng & Xu, 2020). The results of this study revealed that technological support to meet individual tasks enhances the perception of technology and behavioral intention to use. Prior studies on MOOCs focused on the motivational factors, such as self-determination (Joo et al., 2018; Zhou, 2016) and self-efficacy (Jung & Lee, 2018). If learning motivation is an internal factor of learners, and technical support can be viewed as an external environmental factor. The results of this study, which emphasize the importance of technical support for continuing learning, are significant in that they prove that not only the inner factors of the learner but also the external factors of the learning environment are important. MOOC instructors and instructional designers need to focus directly on providing the appropriate technology to enable learners to readily locate learning resources and perform self-directed learning; they must gather input regarding which features of the platform are hindering learning and provide guidance on where students can acquire technical help. In addition, MOOC instructor and tutors must improve learning support for the platform by evaluating usability from a learning perspective.

Lastly, this study confirmed the mediating roles of perceived usefulness and perceived ease of use, showing that each partially mediated the relationship between task-technology fit and continuance intention to use. The serial mediation of perceived ease of use and perceived usefulness was also confirmed. Meanwhile, only a serial mediation of perceived ease of use and perceived usefulness had an effect on the relationship between teaching presence and perceived usefulness. These results are inferred from the nature of the flexible learning environment of MOOCs in which learners can form their own paths by combining resources or constructing learning contents on their own, rather than strictly following the path suggested by the instructor (Crosslin, 2018; Rieber, 2017; Rizvi et al., 2020; Watson et al., 2018). Due to the learner agency allowed in an open learning environment, learners' perceived ease of use and usefulness of system are critical to enhance continuance intention to use.

Despite several implication in this study, this study is limited with data collection. First, the data were collected by means of a self-reported survey; future research should thus utilize more specific methods of observing MOOC teaching presence. Further, for a more rigid analysis, it is also necessary to differentiate between completers and non-completers.

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Appendix

Construct	Items
Individual-technology fit (ITF)	I can independently and consciously complete courses in MOOCs
	I actively participate in various types of discussions and evaluations in MOOCs
	I try to win awards for outstanding performance in MOOCs
Task-technology fit (TTF)	MOOCs are fit for my learning requirements
	Using MOOCs fits with my educational practice
	It is easy to understand which tool to use in MOOCs
	MOOCs are suitable for helping me complete online courses
Continuance intention to use	I intend to continue using MOOCs in the future
	I will continue using MOOCs increasingly in the future
	Given that I have access to MOOCs, I predict that I will use them
Perceived usefulness	Using MOOCs improves my learning performance
	Using MOOCs increases my productivity
	Using MOOCs enhances my effectiveness in my job
Perceived ease of use	It is easy to become proficient in using the MOOC platform
	I find the MOOC platform easy to use
	Interacting with the MOOC platform does not require much mental effort
Instructional design and organization	The instructor clearly communicated important course goals
	The instructor clearly communicated important course topics
	The instructor provided clear instructions on how to participate in course learning activities
	The instructor clearly communicated important due dates/time frames for learning activities
	The instructor helped me take advantage of the online environment to assist my learning
	The instructor helped students understand and practice the kinds of behaviors acceptable in online learning environments
Facilitating discourse	The instructor was helpful in guiding the class toward agreement/understanding about course topics that helped me learn
	The instructor acknowledged student participation in the course
	The instructor helped keep students engaged and participating in productive dialogue
	The quality of interactions with the MOOC instructor was high in this course

Direct instruction	The instructor presented content or questions that helped me learn
	The instructor helped focus discussions on relevant issues in a way that helped me learn
	The instructor provided explanatory feedback that helped me learn
	The instructor helped me revise my thinking

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