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Dongho Kim
Sungkyunkwan University

Eulho Jung
Boise State University

Meehyun Yoon
Ewha Womans University

Yunjeong Chang
University at Buffalo

Sanghoon Park
University of South Florida

See next page for additional authors

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Exploring the Structural Relationships Between Course Design Factors, Learner Commitment, Self-Directed Learning, and Intentions for Further Learning in a Self-Paced MOOC

Dongho Kim
Sungkyunkwan University

Eulho Jung*
Boise State University
eulhojung@boisestate.edu

Meehyun Yoon
Ewha Womans University

Yunjeong Chang
University at Buffalo

Sanghoon Park
University of South Florida

Dongsim Kim
Hanshin University

Fatih Demir
Northern Illinois University

The open and massive characteristics of Massive Open Online Course (MOOC) lead to a lack of instructor presence, which potentially hinders learners' commitment and learning processes. As a result, the effectiveness of MOOCs is contingent upon the extent to which learners direct their own learning. However, learners' self-directed learning and commitment are largely influenced by course design factors due to lack of direct learner-instructor interactions. In order to address the current gap in the literature with regard to how course design factors influence learning processes and outcomes, this study investigated the relationships between MOOC design factors, learner commitment, self-directed learning, and intentions for future learning, using survey responses collected from 664 learners who took a large-scale MOOC. We found that the transactional distance between learners and content was associated with students' self-directed learning. Course structure and organization predicted both students' self-directed learning and commitment to the MOOC. Importantly, self-directed learning mediated relationships between the course design factors and learners' intentions for further learning. Based on our findings, we provide design strategies for effective learner-content interaction in large-scale self-paced MOOCs.

Keywords: MOOC, instructional design, learner commitment, self-directed learning, continuance intention

Introduction

Over the past decade, Massive Open Online Courses (MOOCs) have paved the way for the decentralization of high-quality educational content (Blum-Smith, Yurkofsky, & Brennan, 2020) While the educational resources and content available on MOOCs were only accessible at a few prestigious academic institutions (Dillahunt, Wang, & Teasley, 2014), MOOCs have been attracting a large number of learners from all over the world, resulting in an increase in enrollments across the globe (Watson, Watson, Yu, Alamri, & Mueller, 2017). With the rapid growth of MOOCs, barriers to effective learning in MOOCs have also been identified, among which the lack of learner-instructor interaction has been recognized as one of the major concerns (Gutiérrez-Santiuste, Gámiz-Sánchez, & Gutiérrez-Pérez, 2015). As opposed to small-scale online courses, MOOCs are offered for an unlimited number of learners without time and space constraints, resulting in a high ratio of learners per instructor (Chiu & Hew, 2018). The unprecedented openness of MOOCs inevitably prohibits instructors from providing adequate personalized attention to individual learners (Johnston, 2015).

Although MOOCs have achieved scalability (de Freitas, Morgan, & Gibson, 2015), questions related to the quality of learning experiences remain unanswered. It is interesting that the open and massive characteristics of MOOCs lead to a lack of personalized feedback and instructor presence, which may hinder learners' commitment and learning processes (Mendoza, Jung, & Kobayashi, 2017). Given the minimal interaction between instructors and learners, learner achievement is largely dependent on learners' ability to direct their efforts toward accomplishing learning goals (Milligan, Littlejohn, & Margaryan, 2013). As not every learner possesses self-directed learning skills, instructional design factors play an important role in helping learners achieve the desired learning outcomes. Despite the importance of instructional design, only few studies have been conducted. For example, the current literature pertaining to the MOOC research emphasizes the quality of MOOC content, resulting in a lack of

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empirical evidence on instructional design (Authors, 2019). The significance of course design has been studied by a number of scholars, commonly arguing that the implementation of high-quality instructional design would allow students to experience a sense of control, successful learning progress, which in turn leads to successful learning experience and outcomes (Hsu & Shiue, 2005; Stansfield, McLellan, & Connolly, 2004). In the same sense, a recent systematic review conducted by Goopio and Cheung (2020) confirmed that a poor course design contributes to the high dropout rate in MOOCs. In other words, improving course design in a MOOC would prevent students from dropping.

In response to the lack of empirical evidence on instructional design in the context of MOOCs, some researchers have shed light on human factors, such as instructional strategies and peer interactions (Ouyang et al., 2020)). Researchers have started to recognize the need for a high level of learner-content interaction for optimal learning experiences in MOOCs and online learning environments (Deng, Benckendorff, & Gannaway, 2020; Miyazoe & Anderson, 2013). Recent research has produced evidence that completion is neither a goal of most MOOC participants nor an indicator of student learning experiences (Henderikx, Kreijns, & Kalz, 2017). MOOC learners come from diverse backgrounds and have different motivations for taking MOOC courses. Their completion or decision not to continue in a course cannot explain whether meaningful learning has occurred. Therefore, it is important to examine how MOOCs impact learners' attitudes towards course topics (Watson et al., 2016) — "beyond the artificial binary distinction between completers and non-completers" (Littlejohn, Hood, Milligan, & Mustain, 2016). Rather, intentions to continue the study of a course topic is viewed as an indicator of the prolonged impact of the MOOC (Rodríguez-Ardura & Meseguer-Artola, 2016). In order to address the current knowledge gaps in the literature on the role of instructional design in self-paced MOOCs, the present study investigated the relationships between instructional design factors, learner commitment, self-directed learning, and intentions for further learning.

Literature Review

Learner-Content Interaction and Transactional Distance in Online Learning Environments

Instructors in MOOCs spend a considerable amount of time preparing class materials, content, syllabi, and assignments in order to offset the lack of learner-instructor interaction (Author, 2018b). Therefore, the quality of learner-content interaction becomes critical to learners' successful learning experience (Zimmerman, 2012). For example, Kuo et al. (2013) discovered that, among the three types of online interactions—learner-content, learner-teacher, and learner-learner—student perceived learner-content interaction was the strongest predictor of satisfaction with the course (Moore, 1993). An important concept related to learner-content interaction is transactional distance, which is defined as barriers to students' engagement with course content (Zhang, 2003). Drawing upon Zhang's (2003) work, Paul, Swart, Zhang, and MacLeod (2015) proposed that transactional distance can be improved through the careful utilization of online course design components. The authors highlighted three design components as influencing learner-content transactional distance in online learning environments: (a) synthesis of organizing ideas or information, (b) emphasis on making one's judgment about the value of concepts, and (c) application of theories and concepts (Paul et al., 2015).

Since the concept of transactional distance was introduced by Moore (1993) and developed as a survey instrument by Zhang (2003), researchers have studied how design features (e.g., dialogue, learner autonomy) in online courses could decrease the transactional distance between learners and content (Östlund, 2008). For example, Martin, Kelly, and Terry (2018) proposed a framework for designing MOOCs that satisfy students' psychological needs that include autonomy, competence, and relatedness. They provided examples of MOOC features that focus on how students could be intrinsically motivated and engaged through appropriate support aligned with students' psychological needs. Based on Moore's (1993) framework, Gameel (2017) examined which MOOC feature was intended to support learner-content interaction and actually influenced the learners' satisfaction with the course. The results revealed that MOOC features that fostered critical thinking and resource use were positively associated with learner satisfaction. Shrader et al. (2016) also found that MOOC students that are highly active in working on content competition (i.e., lectures, quizzes, forums) demonstrated a strong level of engagement and learning success by earning a statement of completion. In addition, Pursel et al. (2016) found that MOOC students who intended to closely interact with course content (i.e. watching all the videos or earn a completion certificate) showed significantly higher likelihood of course completion by demonstrating a high level of self-directed learning.

Course structure also plays a pivotal role in student learning in MOOCs (Eom, Wen, & Ashill, 2006). With a very clear course structure, students and instructors can effectively interact with learners (Hung, Chou, Chen, & Own, 2010). Effective engagement in course content in turn leads to a strong sense of learner control (Anders, 2015). Considering that the vast majority of students enrolled in MOOCs are adults driven by personal interests in the topic, learner control is a critical component for successful learning in MOOCs (Terras & Ramsay, 2015). In other words, poor structure and organization in distance learning can contribute to poor learning outcomes (Chen & Wells, 1999). When a clear structure is lacking, a negative correlation with student learning exists between the levels of autonomy, diversity, and openness of a MOOC (Mackness, Mak, & Williams, 2010). In response to the needs of well-structured online courses, researchers have found that quality content of MOOCs, course navigation, and instructions on how to use the MOOC course were significant factors for student success (Kizilcec & Schneider, 2015). Although initial studies revealed some important findings, no study has investigated a structural relationship between course structure and learning experience in MOOCs.

While few empirical studies specifically investigate the relationship between online course structures and learner commitment, some have argued that online course structures are important for students staying in online courses. For instance, Frankola (2001) claimed that poorly designed online courses contribute to the high rate of student dropouts. A similar empirical study conducted by Moore et al. (2003) investigated factors influencing student retention in online courses. Using both archival and survey data, they performed an analysis of success rates to identify the primary factors of student retention in online learning environments. Their results showed that three structure-related factors were negatively correlated with the likelihood of taking another online course: (a) course was too unstructured (-.538), (b) didn't know where to get help (-.324), and (3) felt too alone or not part of the class (-.306). The results indicated that the course structure is important for students' willingness to take another online course.

Course structure is also important for promoting self-directed learning in an online learning environment. For example, Hammarlund, Nilsson, and Gummesson (2015) conducted a study to identify the factors that influence student learning processes and self-directed learning online. Their sample consisted of 34 students in a problem-centered, online, physiotherapy course. The authors analyzed the reflection data that the students wrote over the five weeks of the course. In the course of the qualitative analysis, the authors revealed that the students were able to utilize self-directed learning skills largely because of early access to the course for establishing study plans and because of a clear alignment between the course assignments and the examination task. Also, Maldonado-Mahauad et al. (2018) identified highly self-regulated learners followed the guided course sequence of the MOOC and earned greater depth of content comprehension

Learner Commitment and Self-Directed Learning Associated with Intentions for Further Learning

While researchers have purported that maintaining learner commitment during online learning process contributes to positive learning outcomes (e.g., Guo, Xiao, Van Toorn, Lai, & Seo, 2016), our literature review revealed that little empirical evidence has shown a direct connection between learner commitment and intention to enroll in future courses. Of the few, a study conducted by Wu and Chen (2017) revealed that behavioral attitude, which is largely about a learner's action, promotes continuance intention for further learning.

Rodríguez-Ardura and Meseguer-Artola (2016) one of the few studies to conduct an empirical analysis of users' experiences in online education and investigate what influenced learners' intentions to continue taking online courses in the future. They administered a survey to students who were registered in a purely online university in Europe. A total of 2,530 questionnaires were gathered. The results indicated that the online students with a higher level of engagement showed higher academic performance, and, in turn, higher performance positively affected student intentions to continue taking future online learning courses.

To measure learner commitment in online learning environments, learners' time commitment, learning trajectories and learning behaviors have been used in the previous studies. Kizilcec and Halawa (2015) reported that students with stronger time commitment to a MOOC course, prior knowledge of the course content, and an intent to finish the course achieved higher grades and showed higher levels of persistence. Similarly, Kizilcec, Pérez-Sanagustín, and Maldonado (2017) discovered that learners with higher levels of time commitment demonstrated higher levels of self-regulated learning strategies and desirable achievement in MOOCs.

Student engagement in assessments and exercises leads them to direct their effort, and in turn result in desirable learning outcomes (Charles, 2015; Tseng, 2018). For example, in Raimondi, Bennett, Guenther, Ksiazek-Mikenas, and Mineo (2020), first-year college students were asked to complete weekly tasks that required them to provide their hypothesis for given problems. The weekly assignment served as an assessment method aimed at making the students ready for the following course topic in a flipped classroom setting. The result showed that the students who engaged in the activity at least three times a week performed better than those who exhibited lower engagement. Ruipérez-Valiente, Muñoz-Merino, and Kloos (2015) reported that the average number of attempts adult learners made in assessment sessions in a MOOCsignificantly predicted their achievement. Similarly, by analyzing video-lecture watching patterns and quiz submission behaviors, Mukala, Buijs, and Leemans (2015)

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found learners who had more structured learning patterns and completed course recommended activities such as taking quizzes demonstrated better course grades than learners who studied in less structured ways. These findings reaffirm that learner commitment may be a more critical factor to achieve learning goals than learner competence, especially among adult learners.

In addition to commitment, possessing self-directed learning skills is critical for successful distance learning experiences (McLoughlin, & Lee, 2010), especially for MOOC success (Kop & Fournier, 2010). Self-directed learning is a process that involves the use of learning strategies for achieving a learning goal. The concept of self-directed learning emerged from adult education and thus holds the assumption that learners have control over goal setting and external learning environments (Saks & Leijen, 2014). According to Jossberger, Brand-Gruwel, Boshuizen, and Wiel (2010), self-directed learning is a broad macro-level construct that involves the use of self-regulated learning strategies such as planning, monitoring, evaluation of learning; strategies for self-regulated and self-directed learning are similar except that self-directed learning skills are situated to be at the macro level such as the planning of the learning trajectory whereas the self-regulated learning process concerns within-task execution (Saks & Leijen, 2014). While the concept of self-regulated learning gives an account for micro-level strategies learners may use in MOOCs, self-directed learning serves as a suitable framework for examining how MOOC learners manage external environments and direct their own learning as opposed to students in the traditional school environment (Rashid & Asghar, 2016).

For example, MOOC learners tend to study flexibly with their own learning goal and feel little pressure to complete the course focusing on their own learning needs (Loizzo, Ertmer, Watson, & Watson, 2017). Self-directed learning strategies such as self-monitoring and time and resource management are largely driven and managed by a learner's motivation, that "facilitate[s] and energize[s] meaningful and continuous learning." (Garrison, 1997, p.22). As a result of successful utilization of self-directed learning strategies, individuals can achieve positive psychological states such as confidence (Rager, 2003). For example, Gan, Humphreys, and Hamp-Lyons (2004) examined how the use of self-directed learning strategies affect foreign language learning. Their findings indicated that successful self-directed learners showed both self-efficacy in linguistic knowledge and a positive attitude towards self-development and growth as a person. The study's results are in line with Garrison's (1997) argument that adult learners' motivation helps learners maintain effort toward achieving desired learning goals and pursue long-term educational goals as a continuous learner. Consistent with these findings, Bonk et al. (2015) reported that self-directed adult learners tend to take MOOCs across the lifespan.

Relatively less research on self-directed learning in online or hybrid learning environments has been conducted. Of the few, Liaw (2008) reported that learner characteristics, including self-efficacy and self-directedness, positively influenced learner satisfaction, which determined behavioral intentions for future learning. Stephen, Rockinson-Szapkiw, and Dubay (2020) demonstrated that the levels of self-regulation and self-directedness of nontraditional online learners significantly predicted learners' persistence in a college. Similarly, Jansen, van Leeuwen, Janssen, Conijn, and Kester (2020) provided self-regulated learning instruction in three short videos in MOOCs and found its positive effect on learners' course completion. Within the context of learners' self-perceptions in learning, Jung and Lee (2018) found academic self-efficacy of learners significantly affected learning engagement in a MOOC, however, the study found no direct impacts on learning persistence in the MOOC. There is evidence that learning strategies and psychological factors related to self-directed learning are closely associated with learner perseverance and intentions to remain in a continuous program until learners reach their educational goals (Kember, 1989). Holder (2007), for example, examined the predictors of persistence in higher education online programs. Analyzing data from 259 distance learners, the study found students who were likely to persist in the course tended to report higher time and study management skills and self-efficacy levels. Yet, few studies have investigated the association between self-directed learning and learner intention for further learning in MOOC environments.

Research Model

This study explored the structural relationships between MOOC design factors, learner commitment, self-directed learning, and their intention for further learning (see Figure 1). Regarding the MOOC design factors, this study specifically focused on learner-content interactions rather than on other types of interactions—learner-instructor and learner-learner in consideration of the nature of general MOOC environments being self-paced and asynchronous (Bruff, Fisher, McEwen, & Smith, 2013). As such, we proposed a comprehensive MOOC learning model in order to examine how MOOC design factors influence learners' learning processes as well as whether the learning processes lead to the learners' intentions for further learning. Based on findings reported in prior studies, we attempted to test the following 10 hypotheses through examining our research model (see Table 1).

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Table 1

Research Hypotheses and Sources

Hypothesis	Source
Hypothesis 1: The low transactional distance between learners and MOOC content will have a positive effect on learners' commitments to the MOOC	Gameel (2017); Martin, Kelly, & Terry (2018); Shrader et al. (2016)
Hypothesis 2: The low transactional distance between learners and MOOC content will have a positive effect on learners' self-directed learning	Pursel et al. (2016)
Hypothesis 3: The structure and organization of the MOOC will have a positive effect on the learners' commitments to the MOOC	Frankola (2001); Kizilcec & Schneider (2015)
Hypothesis 4: The structure and organization of the MOOC will have a positive effect on the learners' self-directed learning	Hammarlund, Nilsson, & Gummesson (2015); Maldonado-Mahauad et al. (2018)
Hypothesis 5: The learners' commitments to the MOOC will have a positive effect on their intentions for further learning	Greene, Oswald, & Pomerantz (2015); Kizilcec & Halawa, (2015)
Hypothesis 6: The learners' self-directed learning will have a positive effect on their intentions for further learning	Bonk et al. (2015); Kop & Fournier (2010); Stephen et al. (2020)
Hypothesis 7: The learners' commitments will mediate the relationship between the structure and organization of the MOOC and their intentions for further learning	Suggested from Hypothesis 3 and 5
Hypothesis 8: The learners' commitments will mediate the relationship between the transactional distance between learners and the MOOC and their intentions for further learning	Suggested from Hypothesis 1 and 5
Hypothesis 9: The learners' self-directed learning will mediate the relationship between the structure and organization of the MOOC and their intentions for further learning	Suggested from Hypothesis 4 and 6
Hypothesis 10: The learners' self-directed learning will mediate the relationship between the transactional distance between the learners and the MOOC and their intentions for further learning	Suggested from Hypothesis 2 and 6

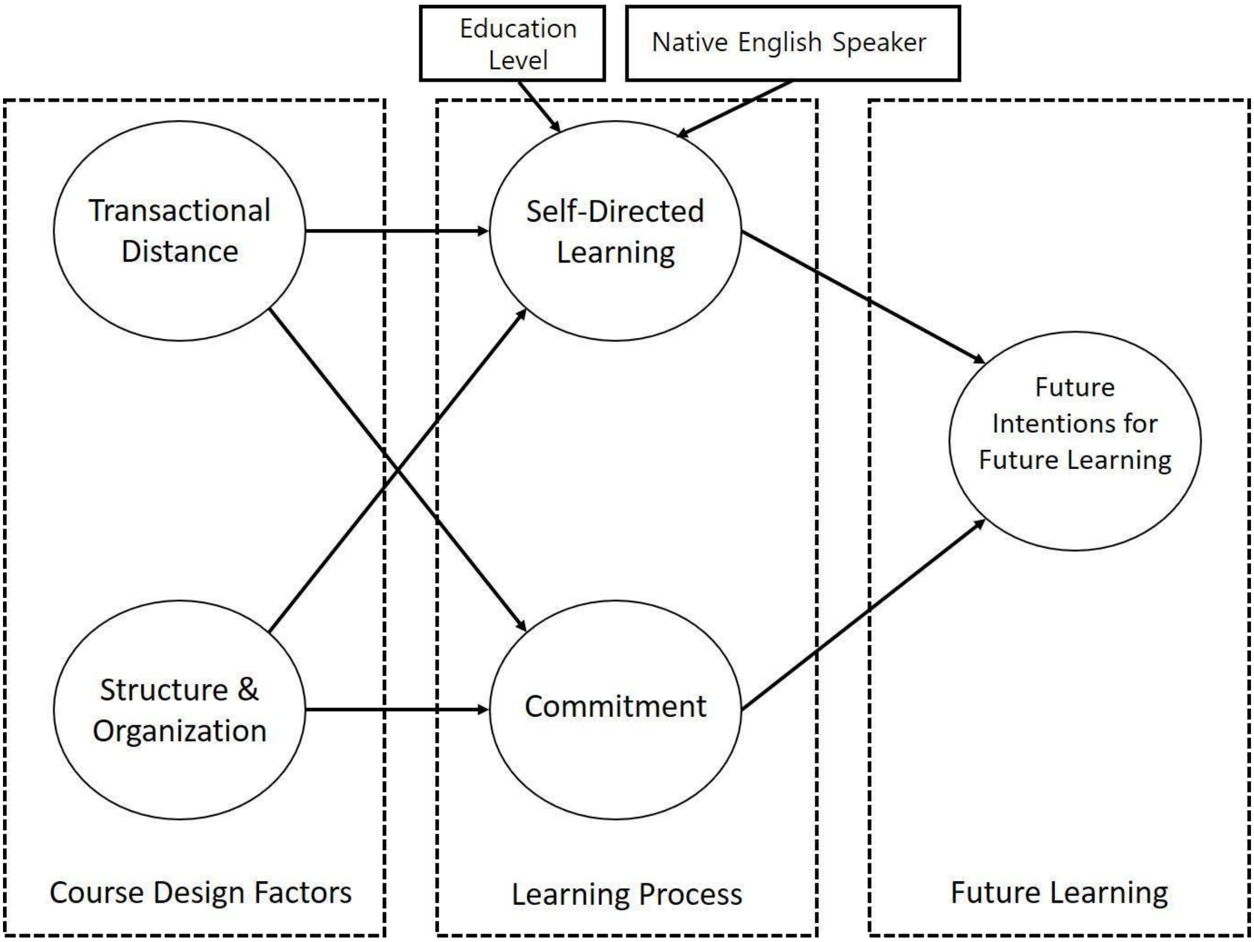

Figure 1. Research model.

Methods

Study Context

The context of this study was one of the self-paced large-scale MOOC courses, "*Learning How to Learn*," which has been offered through Coursera since August 2014. The course introduces a set of learning skills based on neuroscience and cognitive principles. The main topics of the course include chunking, metaphor, and pomodoro techniques for overcoming human memory limitations. The learners in the course have four weeks to complete the course's four modules. Each module consists of 10 required videos and two to four optional videos. Each video takes about 20 minutes to watch. The students are prompted to take a quiz at the end of each module as an assessment. Two instructors deliver the online course during which students can control their learning progress. New enrollment occurs every Monday, and new students register weekly. The course is free and the students have the option to purchase a Coursera certificate if they successfully complete the course. To help the students stay on track, the instructors send out reminders and announcements. The instructors also offer opportunities for the students to reflect on their learning through discussion boards. Even after the course is finished, the students can still access the course to review the materials.

Respondents

We sent a research invitation to learners who took *Learning How to Learn* between 2014 to 2017. We collected 1,364 survey responses, from which we excluded 753 incomplete responses and 24 survey results, as they skipped an excessive number of items. As a result, we analyzed 664 survey responses in total. The respondents' ages ranged from 16 to 85 with an average age of 45.48 (*SD*=15.322). As to gender, 283 (46.4%) of the respondents were male and 327 (53.6%) were female. In terms of language, 308 (50.5%) identified English as their first language, while 302 (49.5%) indicated another language as their first language. In regard to education level, seven respondents (1.1%) indicated that they did not have a high school-level degree, 28 respondents (4.6%) had a high school degree, 235 respondents (38.5%) had a college-level degree, 284 respondents (46.6%) had a master's degree, and 56 respondents (9.2%) had a doctoral degree.

Instruments

The anonymous online survey was administered using a survey tool called *Qualtrics*. The survey was composed of two major sections: (a) demographics and (b) questionnaire. The demographic section asked questions related to demographic information, while questionnaire section contained multiple questions related to the MOOC design factors, such as course structure, transactional distance between learners and content, learner commitment, self-directed learning, and intention for further learning. The survey used a five-point Likert scale ranging from 1 (i.e., *strongly agree*) to 5 (i.e., *strongly disagree*). Table 2 provides a summary of the instrument.

Table 2

Variables and Sample Items

Variable	Reference	N of items	Sample item	Reliability (Cronbach's α)
Organization & structure	Palmer and Holt (2009)	6	From the start, it was clear to me what I was supposed to learn in this unit.	.846
Transactional distance between student and content	Paul et al. (2015)	3	This course emphasized applying theories and concepts to practical problems or in new situations.	.678
Self-directed learning	Hung et al. (2010)	5	I set up my learning goals for this course.	.678
Commitment	—	2	How many exercises/assessments did you complete in this course?	
Intention for further learning	Wu and Chen (2017)	2	I plan to invest time to learn more about this topic.	.617

Next, we managed the missing values on the instrument variables following Little's Missing Completely at Random (MCAR) test. The results found the missing values at random. In order to fill the randomly missing values, we utilized the Expectation Maximization (EM) algorithms with statistical prediction. As the results of the multiple exploratory factor analysis indicated the unidimensionality of all constructs, we used parcels of individual items to ensure the stability of the data, as suggested by Matsunaga (2008).

Results

Descriptive Statistics and Measurement Model

Table 3 illustrates the correlations between latent constructs and the descriptive statistics of all of the constructs, including the means and standard deviations. According to our initial examination of the factor loading of each observed variable, two items from the self-directed learning variable had a factor loading of less than .5. Based on a suggestion made by Peterson (2000), we removed these two items prior to the parceling of the survey items. A subsequent confirmatory factor analysis revealed that all of the indicator factor loadings exceeded .5, which confirmed convergent validity (Fornell & Larcker, 1981). Discriminant validity was also confirmed as the square root of average variance extracted for each construct was higher than all of the correlations between the constructs (see Table 3).

As presented in Table 4, the chi-square was 53.623 ($p=.001 <.01$), which indicates a bad fit. However, Steiger (2007) asserted that relying only on chi-square statistics is impractical since structural equation models are restrictive. Therefore, we examined other indices for model-fit evaluation, including the root-mean-square error of approximation (RMSEA), incremental fit index (IFI), Tucker-Lewis index (TLI), and comparative fit index

(CFI). Browne and Cudeck (1993) suggested that RMSEA values under .05 indicate a good model fit. IFI, TLI, and CFI values higher than .9 indicate a good model fit (Kenny & McCoach, 2003). Taken as a whole, the measurements demonstrated a good model fit.

Table 3

Descriptive Statistics and Correlations Among Constructs

	1	2	3	4	5
Organization and structure	**.817**				
Transactional distance	.645	**.749**			
Self-directed learning	.636	.583	**.665**		
Commitment	.238	.104	.212	**.662**	
Intention for further learning	.473	.544	.540	.121	**.672**
Mean	4.166	4.234	4.245	4.421	4.094
SD	.822	.692	.682	.739	.702

**Note*. The diagonal values in bold represent the square root of the AVE. The non-diagonal values represent the correlations among the latent variables.

Table 4

Fit Statistics for the Measurement Model

	$\chi 2$	df	p	IFI	TLI	CFI	RMSEA
Measurement model	53.623	25	.001	.981	.965	.981	.043(.027-.059)

Structural Model

The proposed structural model demonstrated a good fit for the study data as presented in Table 5. We used the same indicators as used for the measurement model. The only difference was that we added two covariates—learners' education level and first language—which have been recognized as influencing students' self-directed learning (e.g., Derrick, Rovai, Ponton, Confessore, & Carr, 2007). For the education level variable, the learners chose the highest degree that they had completed out of the seven options, which ranged from "Less than High School" to "Doctorate." The RMSEA value was higher than .05 (.055); a value under .08 is considered acceptable, according to Browne and Cudeck (1993).

Table 5

Fit Statistics for the Structural Model

	$\chi 2$	df	p	IFI	TLI	CFI	RMSEA
Structural model	119.032	42	.000	.949	.919	.949	.055(.043-.067)

Each of the 10 hypotheses was tested by examining the significance of all of the proposed relationships among the variables. Table 6 presents the results of the hypotheses tests; five hypotheses were statistically supported.

Table 6

Hypotheses Tests Results

		Hypothesis	β	t	p	Support
Direct effect	1	Transactional distance → Commitment	-.046	-.748	.454	N
	2	Transactional distance → Self-directed learning	.308	4.568	.000	Y
	3	Structure and organization → Commitment	.262	2.776	.006	Y
	4	Structure and organization → Self-directed learning	.471	5.506	.000	Y
	5	Commitment → Intention for further learning	.013	.145	.885	N
	6	Self-directed learning → Intention for further learning	.782	7.753	.000	Y
	Covariate	English → Self-directed learning	.056	1.304	.192	N
		Degree level→ Self-directed learning	-.021	-1.297	.195	N
				Sobel value	p	
Indirect effect	7	Structure and organization → Commitment → Intention for further learning		.148	.883	N
	8	Transactional distance → Commitment → Intention for further learning		-.145	.884	N
	9	Structure and organization → Self-directed learning → Intention for further learning		4.471	.000	Y
	10	Transactional distance → Self-directed learning → Intention for further learning		3.953	.000	Y

Discussion

The Positive Effects of Low Transactional Distance Between Learners and Content as Well as Course Design on Self-Directed Learning

Both low transactional distance between learners and content as well as structure and organization were found to have positive effects on self-directed learning. That is to say, learners are likely to utilize self-directed learning strategies in the learning processes if they feel connected to or engaged with the content. This finding reaffirms prior studies that MOOC learners' self-directed learning is associated with their perceptions of the value they put on the courses (Fischer, 2014). Recognizing the importance of learner-content interactions in self-paced online courses, MOOC developers and designers should enable MOOC learners to intellectually engage with and realistically relate to the course content. Prior research revealed that learners in MOOCs are more intellectually motivated when engaged with learning activities related to personal interests and academic ability (Fischer, 2014). The findings from this study confirm that when the transactional distance between learners and content is low, the level of learner-content interaction is high. Yamagata-Lynch et al. (2015) recognized transactional distance as a barrier that potentially hinders learners' self-directedness in online learning environments. Since MOOC environments are less interactive by nature, engaging learners with intellectual learning activities or content is conducive to the pedagogical and psychological distance between the learners and the MOOCs (Hone & El Said, 2016).

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Furthermore, our findings related to the association between course structure and organization, and self-directed learning are consistent with previous research. Eom, Wen, and Ashill (2006) stated that course structure in self-paced learning environments is critical to student self-directed learning. Well-structured and organized course content helps learners keep on track, even with minimal guidance from the instructor or peers (Frank, 2012). Structural and organizational factors have been recognized as reducing the confusion that learners experience in online learning, largely caused by a lack of in-person instruction (Vrasidas & McIsaac, 1999).

Moreover, given that the vast majority of MOOC takers are adult learners, the clarity of the course would help them focus on utilizing their mental resources without unnecessary struggles (Author, 2019). Moore (1993) stated that the dialogue within and structure of distance learning help to reduce the transactional distance that learners feel. The present study provided empirical evidence of the association between course structure and organization, and learner self-directed learning, as conceptually suggested by Andres (2015), who claimed that course structure would have a greater influence on the self-directed learning in MOOCs of mature adult learners' than of younger learners. Given that the respondents' average age was over 40-years-old in this study, this finding indicates that course structure and organization in MOOCs contributed to the utilization of self-directed learning for the adult learners. The association between structure and organization, and learners' commitment can also be explained by a similar rationale—learners are likely to be engaged when they can control, manage, and direct their own learning without face-to-face contact (Palmer & Holt, 2009). In MOOCs, where instructor-student interactions happen less-than-optimally, the structure and organization of the course is critical.

Interestingly, we found that the transactional distance between learners and content did not predict their commitment, which is inconsistent with the finding that the structure and organization of a course leads to learner commitment. The insignificance of transactional distance can be attributed to the fact that learners perceived psychological distances from the content may not necessarily lead to their immediate commitment to the course. Course structure and organization are directly related to how course components are arranged as they help learners navigate and accomplish learning tasks; therefore, it might have influenced the degree to which the students completed their given tasks (i.e., commitment) more strongly than to the learners' perceived distance from the content. We suggest that future research should examine additional dimensions of commitment, such as emotional engagement with courses.

Positive Effects of Self-Directed Learning on Learner Commitment and Intention for Future Learning

Learners' self-directed learning was found positively associated with their intentions for further learning. This finding is consistent with previous research on Technology Acceptance Models (TAM) (e.g., Gou et al., 2016), which stated that users' continuance intentions to use technology are affected by their perceived usefulness and attitudes. In addition to course content and design, the effect of learners' self-directed learning on their intentions for further learning can also be explained by the nature of MOOC takers. As many MOOC takers are working professionals taking the course part-time, managing one's multiple duties, such as family, work, and personal matters, would require a strong time and resource management (Chang, Hung, & Lin, 2015). If MOOC takers fail to manage time and resources, taking a MOOC can be perceived as challenging and time-consuming and would less likely to consider taking another one in the future (Broadbent & Poon, 2015).

The current study confirmed the association between the learners' use of self-directed learning and their intentions for further learning; one interpretation that emerges here is that successful self-directed learning experiences allow learners to perceive MOOCs as manageable learning resources. The mediating effect of self-directed learning found in this study can be understood in the same way; design factors alone, such as transactional distance or course structure, may not lead to learners' future academic actions in MOOCs. We discovered that self-directed learning is an important process that motivates learners' intention to continue taking MOOCs.

Of the many ways of promoting learners' use of self-directed learning strategies, researchers such as Kizilcec, Pérez-Sanagustín, and Maldonadod (2017), employed technology by implementing a web-based note-taking tool to help MOOC learners self-monitor their learning progress. This tool was found to positively affect participants' metacognition and achievements. A growing number of researchers are paying attention to advanced, self-directed learning tools, such as a learning analytics dashboard that leverages various types of learning data. Log traces recorded in learning management systems are common sources for learning analytics dashboards (Authors, 2018a). We anticipate that MOOC platforms will greatly benefit from adopting self-directed learning tools involving multimodal learning data. In the absence of personal contact with peer learners and instructors, those tools can enhance learning experiences in MOOCs by managing course assignments, alerting missed assignments and/or monitoring time management.

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Aside from tools for supporting learners' self-directed learning, in-depth instructional activities that support learners' inquiries should also be considered. Unlike cMOOCs, which feature intensive peer activities, such as group discussions, xMOOCs, like the one in this study, are primarily composed of lectures delivered by a few experts for scalable audiences. Such courses allow minimal opportunities for peer interactions and inquiries and their instructor-led nature does not afford a great deal of autonomy for self-directed learning (Wang, Hall, & Wang, 2019). Given that MOOCs that can be designed beyond formal school curricula, innovative pedagogies should be implemented, allowing a higher level of self-directed learning and autonomy for quality, personalized learning experiences. For example, a combination of lecture-based and peer-led activities could be considered effective. MOOC instructors may facilitate peer evaluations or encourage local meetups (Bulger, Bright, & Cobo, 2015) for higher student-student interactions. Furthermore, providing a series of courses for advanced learners may be beneficial for those individuals wanting to explore the topics in depth.

It is important to note that learner commitment did not predict learner intention for further learning. This finding can be attributed to limitations in measuring commitment. The commitment variable in this study only measured the degree to which learners completed the learning tasks. As we discussed above, this measure is close to behavioral engagement. Student engagement is, however, a multifaceted concept that can be fully disclosed only when we include measuring learners' emotions and cognition. Therefore, future research should measure a full range of commitment. Another possible explanation is that some MOOC learners often choose to study only some of the course materials, but not complete all of the course activities. This tendency becomes more prominent in adult learning contexts where learners are not full-time students (Chamberlin & Parish, 2011). The selective use of course materials is common in MOOCs and, thus, the degree to which the learners completed the learning tasks may not have fully reflected the learner experience (Adamopoulous, 2013).

Finally, learners' commitments to MOOCs do not necessarily reflect a level of satisfaction, known to promote learners' intentions for further learning (Lee, 2010). According to the Technology Acceptance Models, primary factors related to satisfaction constitute user experiences, such as positive emotions, usability, and perceived effectiveness, which lead to continuance intentions to use technologies (Liu et al., 2010). Although evidence exists that frequent access to course pages or timely submissions are associated with positive learning outcomes (e.g., course completion/passing), they may not correlate with overall satisfaction (Rothman, Romeo, Brennan, & Mitchell, 2011). In sum, MOOCs should offer favorable learning experiences with user-centered designs beyond merely delivering the content.

Conclusion

While the nature of MOOCs emphasizes scalability, quality of interaction in a MOOC plays a pivotal role in MOOC learning experiences and outcomes. We studied the influence of those factors on learners' self-directed learning, commitments, and intentions for further learning with the goals of identifying ways of improving learner-content interaction. The implications of this study can be summarized as follows. First, this study investigated the structural relationships among multi-dimensional factors, course design, learning processes, and future behaviors, allowing us to propose comprehensive MOOC design strategies. Prior studies, including Author (2019), have explored the predictors of psychological outcomes in MOOC contexts and revealed limitations in terms of clarifying what learning processes play pivotal roles in bridging course design factors and learners' intentions for further learning. This study provides important evidence that self-directed learning facilitated by MOOC structure and organization and learners' perceived distance from the course content contribute to the learners' intentions for further learning the course topics. This finding is a valuable insight into what should be considered in MOOC design for both positive learning processes and outcomes.

Furthermore, this study considered perceived learning behaviors as meditating variables. Although learners' self-directed learning strategies and commitment were measured by self-report questionnaires, they revealed learning activities that need to be facilitated in MOOCs for continued learning. The inclusion of proxies for learning behaviors differentiates this study from prior studies of MOOCs that focused primarily on the relationship between psychological factors, such as satisfaction (Hone & El Said, 2016). In sum, this study provides empirical evidence that self-directed learning is conducive to meaningful learner-content interactions, which positively influences learners' pursuits of further learning.

Limitations

Two limitations of this study need to be addressed in future research. First, we relied on a self-reported survey to examine MOOC learners' self-directed learning and commitments. Although self-reported measures reveal respondents' perceptions about their learning, its reliability is largely contingent upon the respondents' subjective thinking. Future research should pursue a combination of behavioral data, such as log data, to accurately examine how learners actually interacted and engaged with the course materials. Furthermore, this study was conducted within a single MOOC, which limited the generalizability of the study. Findings from this study would inform the design of asynchronous lecture-based MOOCs (i.e., xMOOCs), but future studies should be conducted in different MOOC contexts to examine the roles of interaction in (i.e., cMOOCs).

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