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The effects of learner factors on MOOC learning outcomes and their pathways

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ABSTRACT

Despite rapid growth in the popularity of massive open online courses (MOOCs), few studies have investigated learning outcomes among participating university learners. We first examined student growth in terms of knowledge, attitudes, skills, and aspirations (KASA). We then explored the relationships between learning outcomes and three learner factors: time management pattern, task persistence, and language match. A survey of 94 MOOC learners at five Japanese universities revealed growth in knowledge, attitudes, aspirations, and skills, in that order. Task persistence was most strongly associated with knowledge growth, with knowledge affecting aspirations indirectly via attitudes and skills. Learning frequency, time allocation, and participation in discussions had little impact on KASA growth. Compared with learners studying in a foreign language, those studying in their native language reported greater growth across all learning outcomes. We discuss theoretical and practical implications and offer recommendations for future research.

KEYWORDS

MOOC (massive open online course); KASA (knowledge; attitudes; skills; aspirations); learning outcomes; task persistence; time management

Introduction

Massive open online courses (MOOCs) have rapidly proliferated in higher education (Jung, 2016; Veletsianos & Shepherdson, 2016), which has inspired research on such varied areas as pedagogy, historical trends, learner experiences, technology (Liyanagunawardena, Adams, & Williams, 2013), and learning experiences (Veletsianos & Shepherdson, 2016). Bozkurt, Akgün-Özbek, and Zawacki-Richter (2017) conducted content analysis of 362 empirical MOOC studies published in refereed journals between 2008 and 2015 and discovered that the most intensively studied topics concerned theories and models (27%), learner characteristics (15.7%), and instructional design (11%). Yet, despite the interest in MOOCs, research has not addressed learning outcomes and associated factors.

Proponents of MOOCs hold that outcomes of MOOC learning include understanding new knowledge, staying apprised of the latest information, expanding skill sets, changing viewpoints or perspectives, improving various abilities, and increasing motivation for further learning or career development (Littlejohn, Hooda, Milligan, & Mustain, 2016;

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Watson, Kim, & Watson, 2016). However, most studies have focused on progression, retention and completion rates as success indicators of MOOC learning. Studies have criticized these measures as proxies that may not accurately reflect the unique outcomes of this new way of learning (Littlejohn et al., 2016), which suggests the need for more empirical research to reveal the true nature of MOOC learning.

Research suggests that learner factors may be one of the reasons for the variation in MOOC outcomes, as these factors may be particularly influential in MOOC learning. The most common form of MOOC is the 'extended MOOC' or xMOOC, which emphasizes collaborative knowledge building. xMOOCs are typically structured as weekly modules with specific learning tasks, such as short video lectures, quizzes, or self-assessment. Learners must complete these tasks in a certain sequence in order to master the course content. The features of MOOCs – their large-scale, casual enrolment, and minimal help from instructors – mean that learners must be self-motivated and self-regulated (García-Espinosa, Tenorio-Sepúlveda, & Ramírez-Montoya, 2015).

Skills in time management have been shown to be important in successful online learning (Cavanaugh, Hargis, & Mayberry, 2016; Littlejohn et al., 2016), particularly learner's allocation of time for learning. In one global survey (Beaudoin, Jung, Suzuki, Kurtz, & Grabowski, 2013), learners who established daily and weekly study schedules exhibited better performance. Moreover, how learners balance learning frequency and length of learning is critical for successful online learning. Liu and Cavanaugh (2011) observed relationships between learning frequency (how often learners access an online course), learning hours (how long they stay once accessing the course), and achievement in virtual learning, and found that more frequent access for shorter periods of time was effective in introductory courses, whereas less frequent access for longer periods of time led to higher achievement in advanced courses.

Learner persistence in pursuit of learning goals even when faced with challenges and time conflicts appears to be the biggest key to success in online learning. Persistent learners successfully complete an online course, whereas non-persistent learners drop out of the course. Persistence has not been operationalized beyond the concept of course completion. Such variables as time spent on tasks, number of items or tasks attempted or completed, and number of academic terms completed were examined in a meta-analysis by Multon, Brown, and Lent (1991) and have useful implications for MOOC learning. Although it stands to reason that time management and task persistence are critical in xMOOC learning, few investigations into these variables have been conducted in the MOOC learning context.

Language may also play an important role in MOOC learning outcomes, especially given that the majority of MOOCs are offered in English despite the enrollment of learners from around the world. It is not surprising that non-native English speakers who take courses in English are at a disadvantage (Barak, Watted, & Haick, 2016), although individuals sometimes take MOOCs in order to learn English (Mendoza, Jung, & Kobayashi, 2017). Communication is an important factor in all forms of learning, not only online learning; learners learn better and more readily achieve higher-order learning in their native language (UNESCO, 2008). Whether previous research into language as a factor in learning is applicable to MOOC learning remains unclear. Given the prevalence of non-native English MOOC learners, research examining MOOC learning in languages other than one's native tongue is needed.

To address the gaps discussed above, we set out to examine MOOC outcomes and to identify the effects of three key factors: time management pattern, task persistence, and language (Figure 1). To assess MOOC outcomes, we adopted Rockwell and Bennett (2004) knowledge, attitudes, skills, and aspirations (KASA) framework from their Targeting Outcomes of Programs model. Knowledge refers to awareness and understanding; attitudes are opinions, viewpoints, or perspectives; skills are verbal or physical abilities; and aspirations are desires, hopes, or ambitions. All of these elements may change or improve, directly or indirectly, as a result of learning. We posed the following research questions:

(1) What are the overall effects of MOOC learning in terms of KASA growth?
(2) What factors affect KASA growth?
    (a) How does time management (learning frequency, hours of learning, and time allocation for learning) by MOOC learners affect KASA growth?
    (b) How does task persistence (completion rate for specified learning tasks) by MOOC learners affect KASA growth?
    (c) How does language match between the MOOC and the learner (native or second language) affect KASA growth?

What interactions exist between MOOC learners' growth in KASA? How does growth in knowledge, attitudes, and skills affect aspirations?

Methods

Participants

The participants in this study were 94 learners from five Japanese universities. Participants were recruited via their instructors to voluntarily participate in a MOOC from a list of xMOOCs suggested by their instructors, each of which required four to eight weeks of study. The MOOCs selected by learners ranged across academic fields

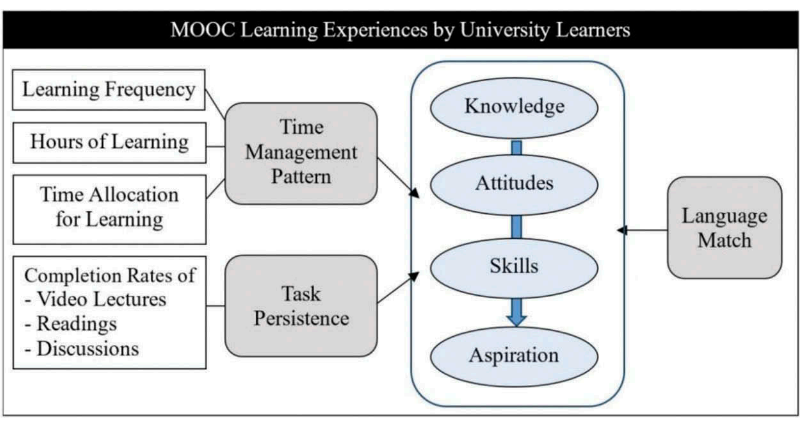

Figure 1. Conceptual framework of the study.

including the humanities, social sciences, natural sciences, art, and music. Sixty-seven percent (n = 63, 67%) of the participants were female. Twenty-seven percent (n = 26) were graduate students and 66.0% (n = 62) were undergraduates. The latter comprised 13.8% freshmen (n = 13), 34.0% sophomores (n = 32), 13.8% juniors (n = 13), and 4.3% seniors (n = 4). The native languages of the participants were English (39.4%, n = 37), Japanese (33.0%, n = 31), Korean (18.1%, n = 17), and Filipino (7.4%, n = 7). Fifty percent (n = 47) of the participants studied in a language other than their native tongue. More than half of the respondents had taken only one MOOC or had little experience with MOOCs (54.3%, n = 51), while 37.2% (n = 35) had enrolled in two to five MOOCs and 8.5% (n = 8) had taken more than six MOOCs prior to this study.

Data collection

Data were derived from an online survey between November 2016 and February 2017. After completing the MOOC, learners who agreed to participate in the study voluntarily answered (N = 94) questions regarding learning outcomes, time management pattern, task persistence, and impacts of language match. Pilot tests were conducted with 14 undergraduate and graduate students and two evaluation experts to detect unclear statements and items that might lead to biased responses. Upon modifications, the survey was posted on each university's course learning management system. The study was approved by the Research Ethics Committee of the first author's university (#2016–20).

Instrument

The survey asked participants to report on three topics: (1) prior MOOC experiences and time management pattern for the current MOOC, (2) completion of MOOC learning tasks, and (3) growth in KASA as a result of participation in the MOOC.

The first section included two questions about prior MOOC learning experiences ('Have you taken any Massive Open Online Courses MOOCs?', and 'How long did you take the MOOC?'), and three questions about their time management pattern ('In a week, how often did you access the MOOC?' 'In a week, how many hours did you spend on the MOOC?' and 'When (how regularly) did you usually study for the MOOC?').

The second section included questions concerning the completion of three types of MOOC learning tasks (video lectures, reading materials, and discussion forums), as well as a general question about task completion ('To what extent did you complete each component of the MOOC?'), with answers ranging from 1 (none) to 5 (all). The internal consistency of task completion was .730.

Finally, the third section assessed perceptions of MOOC learning outcomes by applying the KASA framework (Rockwell & Bennett, 2004). We used 19 items to measure learner perceptions about changes in KASA as a result of participation in the MOOC. Five items concerned knowledge growth due to MOOC learning (e.g. 'I gained new knowledge on the topic from studying the MOOC'; *Cronbach's* α = .829). Another five items concerned attitude changes toward the topic and MOOC learning in general (e.g. 'The MOOC changed my viewpoint on the topic'; *Cronbach's* α = .803). Four items concerned skill growth in the areas of problem-solving skills, self-learning skills, online learning skills, and collaboration skills (*Cronbach's* α = .689). Finally, five items addressed aspirations and intention to study more in the near future (e.g. 'I plan to study the topic of the MOOC further'; *Cronbach's α* = .835). The internal consistency of the 19 items was .903. The validity of the survey instrument was also assessed using structural equation modeling employing the partial least squares method (Table 3).

Data analysis

We used descriptive statistics and bivariate correlation analysis to examine the learners' perceived growth in KASA. Independent samples t-tests were then performed to compare the KASA of the language-match and -mismatch groups, and between those who participated in the MOOC within a designated time and those who participated in the MOOC irregularly. Multiple regression analyses were conducted to investigate the effects of time management (learning frequency and learning hours) and task completion on the development of KASA. The underlying assumptions of multi-collinearity, linearity, homoscedasticity, and independent residuals were assessed separately for multiple regressions of KASA as dependent variables. The Variance Inflation Factor and tolerance values of independent variables and the four dependent variables were all less than 10 and greater than 0.2, respectively, confirming that multi-collinearity was not a problem (Hair, Hult, Ringle, & Sarstedt, 2017). The scatterplots of the residuals against outcome predicted, histogram, and normal probability plot confirmed the assumptions of linearity and homoscedasticity. Dubin-Watson statistics verified the independence of the residuals.

In order to explore the complex relationships between latent variables using indicators, and their direct and indirect effects, we developed a research model hypothesizing that knowledge affects aspirations directly and indirectly via attitudes and skills. Structural equation modeling employing a partial least squares approach (PLS-SEM) was performed using SmartPLS2.0, which is considered an appropriate method for analyzing a complex model with small- to medium-size samples (Hair et al., 2017). When performing SEM, measurement validation was first conducted through confirmatory factor analysis, and construct validity and reliability were assessed. Then, structural relationships among KASA were validated by bootstrap analysis with 500 adjusted samples to approximate distribution.

Results

Overall effects of MOOC learning on KASA growth

As shown in Table 1, knowledge growth had the highest mean (M = 4.15) and skills growth had the smallest variance and the lowest mean (M = 3.65). The most growth was seen in knowledge, followed by attitudes, aspirations, and skills, in that order. Aspirations had the greatest variance, followed by attitudes, skills, and knowledge, in that order. The four variables were significantly and positively related to each other.

Factors affecting KASA growth

Time management pattern

We performed multiple regressions to calculate the predictive power of time management pattern (measured by learning frequency and learning hours) on KASA growth. Of the KASA

Table 1. Growth of knowledge, attitudes, skills, and aspirations by MOOC learners.

						Correlations			
	Min	Max	M		SD	1	2	3	4
1. Knowledge	2.80	5.00	4.15	(83.1%)	0.59	1			
2. Attitudes	1.80	5.00	3.84	(76.9%)	0.70	.51**	1		
3. Skills	2.00	5.00	3.65	(72.9%)	0.66	.50**	.54**	1	
4. Aspirations	1.20	5.00	3.65	(73.0%)	0.77	.73**	.84**	.80**	1

***p < .001, **p < .01, *p < .05

outcomes, only knowledge growth was related to time management. Learning hours were significant (β = .40, R^2 = 16.2%, *Adj.* R^2 = 15.3%) for predicting knowledge growth, but learning frequency was not. An independent-samples t-test revealed no significant difference in KASA growth between the designated-time and anytime groups, although the latter had higher KASA growth (knowledge: t (92) = −1.55, p > .05; attitudes: t (92) = −.77, p > .05; skills: t (92) = −1.35, p > .05; aspirations: t (92) = −1.29, p > .05).

Task persistence

We conducted multiple regression analysis to determine the predictive power of task persistence (on video lecture, reading materials, and forum participation) on KASA outcomes. A significant regression equation was found for knowledge growth (F (3, 90) = 13.36, p < .001, R^2 = .308). Completion of both the video lecture (β = .38, p < .01) and of reading materials (β = .24, p < .05) were significant predictors of knowledge growth. A significant regression equation was also found for aspiration growth (F (3, 90) = 7.34, p < .001, R^2 = .197). The completion of reading materials (β = .30, p < .05) was a significant predictor of growth in aspirations. We found no significant predictors or regression equations for growth in attitudes or skills.

Language match

When comparing the growth of KASA in language-match and mismatch groups, an independent-samples t-test detected significant differences in growth in knowledge, attitudes, and aspirations for the two groups (knowledge: t(92) = 3.45, p = .001; attitudes: t(92) = 2.86, p = .005; aspirations: t(92) = 2.87, p = .001). The difference in growth of skills between the two groups was not significant (t(92) = 1.86, p = .067) (Table 2). That is, learners who studied in their native language reported greater growth in knowledge, attitudes, and aspirations compared to those who studied in a second language. Language match did not influence growth in skills.

Relationships between knowledge, attitudes, skills, and aspirations

We applied PLS-SEM to assess the measurement model (Table 3) and the structural model (Table 4 and Figure 2). The measurement model was assessed in terms of internal consistency reliability, convergent validity, and discriminant validity. Reliability was assessed using composite reliability and Cronbach's alpha. All constructs had a Cronbach's alpha of greater than 0.7 and composite reliability between 0.6 and 0.9 (Hair et al., 2017). Per convergent validity, the outer loadings were all significant (p < .05) and exceeded the minimum threshold of 0.7 as suggested by Hair et al. (2017). The

Table 2. Differences in perceived KASA growth in language-match and mismatch groups.

	Language match (N = 47)	Language mismatch (N = 47)	*T*
Knowledge	4.35 (.57)	3.95 (.55)	3.45***
Attitudes	4.04 (.70)	3.65 (.64)	2.86**
Skills	3.77 (.73)	3.52 (.57)	1.86 (n.s.)
Aspirations	3.87 (.71)	3.43 (.77)	2.87**

****p* < .001, ***p* < .01, **p* < .05

Table 3. Measurement model assessment.

Construct	Composite reliability	Cronbach's alpha	AVE
Knowledge	.89	.84	.61
Attitudes	.86	.80	.55
Skills	.81	.70	.51
Aspirations	.88	.84	.60

Table 4. Structural model assessment.

Independent variables	Dependent variables	Standardized causal effects				f^2
		Direct	Indirect	Total	*T*-statistics	Effect size
Knowledge	Attitudes	.52		.52	5.12***	.37
	Skills	.56		.56	7.39***	.46
	Aspirations	.11	.37	.48	1.15 n.s.	.02
Attitudes	Aspirations	.36		.36	2.75**	.14
Skills	Aspirations	.34		.34	2.61**	.12

****p* < .001, ***p* < .01, **p* < .05

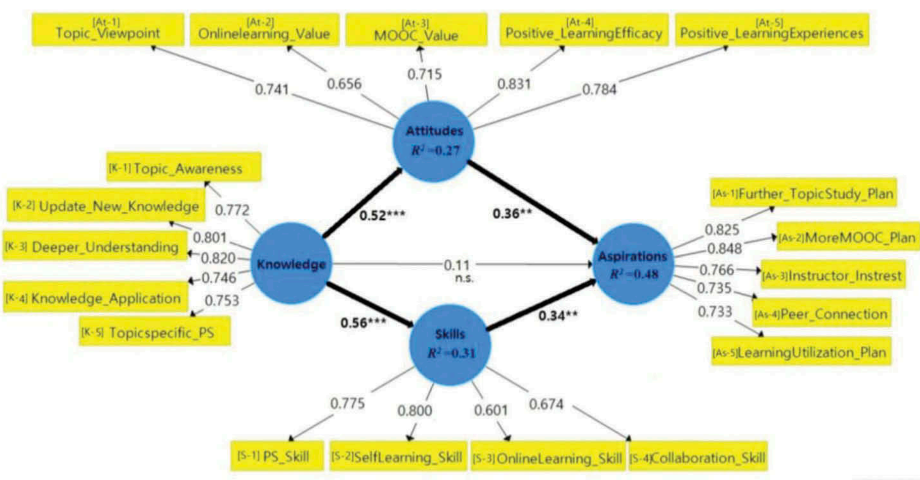

Figure 2. Partial least squares analysis results.

average variances extracted for the constructs were all greater than 0.5 as recommended. Discriminant validity was also indicated, with the all cross loadings less than the outer loadings and the square roots of the average variances extracted exceeding the corresponding construct inter-correlations (Chin, 1998). These results indicate that

Table 5. Explanatory power and predictive relevance of the structural model.

	R^2 = (Adj. R^2)	Q^2
Aspirations	.48 (.46)	.26
Attitudes	.27 (.26)	.14
Skills	.31 (.31)	.13

each item loaded most highly on its own construct as opposed to other constructs. Overall, all constructs demonstrated the required reliability and validity. The structural model was then assessed to examine path significance (Table 4 and Figure 2). The path coefficients were all significant except for the direct path from knowledge to aspirations, indicating that knowledge did not affect aspirations directly, but via attitudes and skills. Knowledge affected skills with β = .56 and attitudes with β = .52, skills affected aspirations with β = .34, and attitudes affected aspirations with β = .36. The f^2 effect size of each path showed that the paths from knowledge to skills and to attitudes had large effect sizes, the path from skills and attitudes to aspirations had a medium effect size, and the path from knowledge to aspirations had a small effect size (Hair et al., 2017). The model explains 48.0% of the variance in aspirations, which is indicative of strong explanatory power, and has acceptable predicative relevance with a Q^2 value exceeding zero (Hair et al., 2017). Table 5 presents the explanatory power with R^2 values and the predicative relevance with Q^2 values of the proposed model.

Discussion

Our primary aim in this study was to investigate the interrelationship between KASA and learner factors affecting KASA growth in MOOCs used in a university setting. We first examined the impact of participation in a MOOC on learners' growth in KASA, explored factors that affect learning outcomes, and identified interactions between learning outcomes. We found that MOOC participation affected learner perceptions of growth in knowledge most, followed by attitudes, aspirations, and skills, in that order. We also found that learners who devoted longer hours to learning reported greater knowledge growth than those who allotted less time to these tasks. Neither learning frequency nor designated time allocation seemed to influence perceived KASA growth, but task persistence/completion rates in learning tasks were related to growth in learner aspirations. Learners who learned in their native language reported more growth in knowledge, attitudes, and aspirations than their counterparts who studied in a second language. Finally, knowledge was found to affect aspirations indirectly via attitudes and skills.

Participants generally reported growth in all four KASA learning outcomes as a result of their MOOC experience. Growth in knowledge was particularly noticeable; most learners felt they had become more knowledgeable after four or more weeks of MOOC learning, had developed a deeper understanding of the topic, and could apply their knowledge to other problem-solving situations. Considering these findings, we posit that MOOC learning results in higher-order learning such as application and problem solving, provided that learners devote enough time to MOOC learning.

Participants reported significant changes in their attitudes, especially positive ways of thinking about the course topics and MOOC learning in general. This finding might be attributable to the novelty effect, due to the newness of the MOOC structure. Other factors, such as instructional design, social presence, and teaching presence may have also driven positive attitudes, as suggested by Watson et al. (2016).

As shown in Figure 2, knowledge did not directly increase aspirations, but did affect attitudes and skills, which, in turn, affected aspirations. The path of *knowledge – attitudes – aspirations* is consistent with the theory of planned behavior (TPB) (Ajzen & Fishbein, 1980). Aspiration in this study corresponds conceptually to the behavioral intention construct in TPB studies. While TPB does not include knowledge in its model, TPB researchers from various fields have shown interest in the effects of knowledge on behavioral intention and actual behavior, and a large number of TPB studies have supported the notion of the mediating effect of knowledge on attitudes, as well as attitudes on behavioral intention (Ajzen, Joyce, Sheikh, & Cote, 2011).

The path of *knowledge – skills – aspirations* may be relevant to self-efficacy research. The learners who participated in this study reported that they became more efficacious in self-directed learning, online learning, collaborative learning, and problem-solving as a result of their MOOC learning. Improvement in these skills is closely related to increased academic self-efficacy, that is, learners' beliefs about their capabilities to learn or perform tasks in particular contexts (Bandura & Locke, 2003). Such beliefs may play important roles in developing aspirations. Literature offers support for the relationship between academic self-efficacy and academic performance as well as academic motivation and aspirations (e.g. Richardson, Abraham, & Bond, 2012).

The *knowledge – attitudes – aspirations* and *knowledge – skills – aspirations* paths have practical implications for MOOC providers. To successfully prepare MOOC learners, teachers must carefully consider selecting and organizing course content and promote positive attitudes about MOOC learning. Instructional designs that will maximize learner competency in self-directed online learning also need to be developed. Even when a MOOC offers relevant and useful content, if it lacks motivational elements, the intended learning outcomes may not be realized (Margaryan, Bianco, & Littlejohn, 2015).

Among the three time management indicators, only learning hours were found to predict one of the KASA learning outcomes: knowledge. Learners who devoted long hours to their studies reported greater knowledge growth, although learning hours were not related to growth in attitudes, skills, or aspirations. This finding is inconsistent with those of other studies on online learning environments. Yang, Lin, She, and Hunang (2015) found that accessing courseware frequently and regularly, establishing regular schedules, and devoting the time and effort were key success factors in online learning. Similarly, a study found that focused study periods were more effective than longer study periods for successful online learning (Beaudoin et al., 2013). However, in this study, only one factor – learning hours – was found to be important for knowledge growth. The disparity may be accounted for by differences in motivation between the MOOC learners and typical online learners. In formal online learning contexts, learners take courses for credit, whereas the majority of MOOC learners take courses out of intellectual curiosity whenever and wherever it is convenient for them while multitasking (Jung, 2016), highlighting the need for research into the time management skills and learning patterns of today's MOOC learners in both traditional and non-traditional learning settings.

Task persistence was measured by the rate of completion of several tasks: watching videos, reading the texts, and participating in discussion forums. Of these, completion of reading assignments appeared to be the most important for learning outcomes, affecting growth in both knowledge and aspirations. We assume that only serious MOOC learners would complete assigned readings since reading is a more cognitively demanding task than watching video lectures. MOOC developers thus need to pay close attention to the relevance and levels of reading materials. Further research is needed into readings, vidlectures, discussion forums, and other assignments in MOOC learning.

Our findings revealed that learners who studied MOOCs in their native language reported greater growth in knowledge, attitudes, and aspirations (but not skills), compared with their counterparts. This is consistent with literature into the language effects on learning of young children (UNESCO, 2008). One possible explanation for the lack of difference in skill growth between the language match and mismatch groups is that skills developed in self-directed online learning contexts are supra-linguistic outcomes (Sasisekaran, 2014) and thus may not be affected by language. The finding that learning from a MOOC in a foreign language may act as a barrier for university students suggests that global MOOC providers need to consider offering their MOOCs in different languages so that the original promise of MOOCs – expanded educational opportunities for underserved populations – can be achieved.

This study was conducted in a specific context with a particular type of MOOC (xMOOCs) in Japanese universities, potentially limiting the generalizability of the results. Future research may be needed that will investigate a broader population of learners. The cross-sectional design of this study could also be limiting when considering the longitudinal aspects of MOOC learning, particularly as a tool for lifelong learning. Nevertheless, this study provides a starting point for further research into factors that may negatively or positively impact learning outcomes in MOOCs.

Conclusion

A large number of college students have enrolled in MOOCs for varying reasons. Because completion rates are typically low unless MOOC learning is a course requirement, research into factors that create better learning outcomes, as well as participant engagement, motivation, and behavioral patterns, is important. Better learning outcomes can be achieved by ensuring that MOOCs motivate and provide support for learners, maintain learners' attention to key points, help students develop skills in self-directed and collaborative learning, time management, and task persistence, and accommodate the needs of non-native English learners. It is our hope that this study will offer useful insights that may be applied to research in various MOOC-integrated higher education settings.

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