Hindawi
Human Behavior and Emerging Technologies
Volume 2022, Article ID 6444509, 12 pages
https://doi.org/10.1155/2022/6444509

Research Article

The Effects of Basic Psychological Needs, Task–Technology Fit, and Student Engagement on MOOC Learners' Continuance Intention to Use

Areum Shin and Hae-Deok Song

Department of Education, Chung-Ang University, Seoul, Republic of Korea

Correspondence should be addressed to Hae-Deok Song; hsong@cau.ac.kr

Received 28 December 2021; Accepted 1 August 2022; Published 22 September 2022

Academic Editor: Zheng Yan

Massive open online courses (MOOCs) continue to remain in the spotlight as a promising future education environment. However, more than 80% of learners stop learning before attending one-third of the course. Despite a continuous spread of MOOC and high dropout rate, little has examined the antecedent factors that influence student engagement in technology enhanced MOOC learning environment from the Job Demand-Resources (JD-R) model. The purpose of this study was to empirically identify the effects of individuals' basic psychological needs and the task–technology fit on MOOC learners' continuance intention to use, as well as the mediating effect of student engagement in MOOCs. Based on survey data from 201 Korean-MOOC learners, structural equation modeling was employed to assess the model. The findings are as follows: The basic psychological needs in MOOCs did not directly affect continuance intention to use, but did affect student engagement; the task–technology fit of MOOCs directly affected continuance intention to use and student engagement; and student engagement in MOOCs mediated between the basic psychological needs and task–technology fit, and continuance intention to use. It directly affected continuance intention to use. Implications were suggested for designing courses in MOOCs to increase student engagement for continuance intention to use.

1. Introduction

A massive open online course (MOOC) is open to anyone, anywhere, and anytime and is mostly provided for free; it is often taught by a professor from an eminent university, making it a prospective environment for education in the future [1]. Over 950 universities worldwide run more than 19,400 lectures with the cumulative number of learners reportedly crossing 220 million, as of 2021 [2]. Despite a continuous spread of MOOCs and high attendance rates, about 80% of learners drop out from most MOOC lectures after one or two videos or before reaching one-third of the course [3–5]. Although researchers perceive this learning pattern as a typical feature of MOOCs over time [6, 7], some argue that lecture completion rates are not a suitable measure for the success of MOOCs [8]. Given the large difference in the level of learners' behavioral and cognitive student engagement between those who discontinued learning at an early stage and those who finished the course [9, 10], one can conclude that success in MOOC learning depends on how consistent the learning has been [11].

Thus, recent research has examined the continuance intention to use of MOOC users. Continuance intention to use of users, with a consistent focus on learning and efforts to participate in the course or the will to do so to accomplish the learning objective, can be considered an indicator of the learners' motivational, emotional, cognitive, and behavioral elements [12, 13]. This thinking has led to research on the intention to continue using the MOOC environment. Prior studies regarding continuance intention to use considered various aspects, including learners' experience and motives [6], metacognition [14], and social media [15]. Most studies adopted the technology acceptance model to explore the purpose of using the technology [11, 16, 17]. According to the technology acceptance model, users' perceptions of technology usefulness and ease of use influenced their intention to use. However, these are limited that they do not consider in complexity according to individual characteristics in the process of the acceptance. Continuous learning in the MOOC environment can succeed only when their individual needs satisfy their learning requirements.

Individual attributes could include learners' background knowledge, readiness, self-regulation capacity [18–21], and motives and goals [9, 22]. One of the most vital factors of these individual attributes is the motivational aspect. In this context, the expected learning outcomes are high when learners' motives are sustained and strengthened throughout the process, from the beginning to the end of the lecture, to the subsequent learning transfer. In learning environments where individual variation, such as in age and working environments, is large and the learner has to study alone independently, the learner needs to be motivated to find interest and entertainment in learning itself. Intrinsic motivation arises when the individual's psychological need for growth and development is satisfied (Reeve, 2018; [23]). Much prior research has scrutinized the effect of basic psychological needs on continuance intention to use based on the task acceptance model. Most of the studies consider sustained exercise, such as in physical education [24, 25], while some examine continuous intention in the technological learning environment. Examples include studies on continuance intention to use in e-learning or the social media environment [26–29]. Relatively less research has been attempted to determine a direct causal relationship between basic psychological needs and continuance intention to use in technology-mediated environments.

Another variable that can be considered is the attributes of MOOC-learning technology applications and learners' learning requirements are in promoting continuance intention to use. The task–technology fit model is known for its usefulness in structurally revealing the relationship between the use of technology and the subsequent progress the user achieves [30]. The task–technology fit, the most critical variable in the task–technology fit model, represents the conformity between the given task and the technology. Prior research has found that the task–technology fit has a positive effect on continued MOOC use [11, 27, 31–33].

In the meantime, the effect on continuance intention to use in the MOOC environment could be influenced by whether the learner possesses psychological directivity. Among these psychological attributes, student engagement is a potentially important variable that merits consideration. Student engagement is defined as a state in which the learner conducts a proactive and consistent learning activity and is in deep concentration due to an intense degree of participation in that learning activity [34, 35].

Additionally, student engagement may have a positive influence on continuance intention to use. Prior research has reported that student engagement not only affects continuance intention to use but also mediates the relationship between other variables and learning outcomes [14, 36]. The perceived usefulness and realization of learners' expectations positively affect student engagement [36].

One of the theoretical models that explain engagement the Job Demand-Resources (JD-R) model [37]. Basically, it states that decreasing job demands and increasing job and personal resources increase engagement. Personal resources as one main job resources is defined as "positive self-evaluations that are linked to resilience and refer to individuals' sense of their ability to control and impact upon their environment successfully" ([38], p.236). Examples of personal resources are self-efficacy, optimism, and self-esteem. Studies report that the learners' basic psychological needs that underpin their intrinsic motives affect student engagement [39, 40]. Studies need to examine whether basic psychological needs act as a motivation process that lead engagement. In addition, according to the model, reducing demands such as work overload and conflict would affect engagement. The task–technology fit, which determines the learners' learning requirements and the suitability of the technology, may affect student engagement by decreasing work overload and conflict. Continuous learning in the MOOC environment can succeed only when learners feel that their learning requirements suit them or when their immersion in learning activities satisfies without a conflict. Hence, the task–technology fit can affect student engagement in environments where self-directed learning is required, such as MOOCs.

Therefore, this study sets the learners' basic psychological needs and the task–technology fit in the MOOC environment as independent variables, student engagement as the learning progress variable, and continuance intention to use as the dependent variable, to determine their structural relationship. Thus, it holds promise as an attempt to provide practical evidence to increase MOOC learners' continuance intention to use and to find ways to encourage student engagement.

2. Theoretical Framework

2.1. MOOCs and Continuance Intention to Use. MOOCs provide a significant level of scalability, time, and location flexibility [41]. MOOC has become popular among the developing as well as third-world countries, where it has increased opportunities for higher education [42]. However, despite the spread of MOOCs and the spotlight they attract in providing public access to higher education, there are strong voices of dissent that speak of the high early-stage drop-out rates, with more than 80% of the learners dropping out early in the course [19].

Multiple research studies have concluded, taking into account MOOC learners' learning pattern, that the success of MOOCs depend on learning consistency or continuance intention to use [11]. Continuance intention to use refers to consistent concentration in learning and committing to the learning program, or the will to do so. This can be an indicator of the learners' motivational, emotional, cognitive, and behavioral elements [12, 13]. Perceived values is important for adoption or continuance intention to use of a new technology [43]. Prior research about continuance intention to use in the MOOC environment identifies learning satisfaction [17], perceived benefit, and perceived convenience

[16], among others, as independent variables for consistent intention to use MOOCs.

Hsu et al. [16] reported, using the task–technology model, that perceived benefit and convenience had a significant effect on continuance intention to use and that MOOCs showed a higher degree of overall influential relationship with model fit than the conventional e-learning platform. Joo et al. [17] examined the effect of self-determination, perceived usefulness, and perceived ease of use on continuance intention to use, mediated through learning satisfaction. Results show that (1) the higher the learning satisfaction, the higher the continuance intention to use and (2) perceived usefulness and perceived ease of use had significant effects on continuance intention to use, mediated through learning satisfaction. Moreover, perceived ease of use positively affected perceived usefulness, and both perceived usefulness and ease of use had positive effects on learning satisfaction.

2.2. Continuance Intention to Use and Basic Psychological Needs. Prior research analyzed learners' motives because self-directed learning is emphasized in the MOOC environment, considering its e-learning features [6]. Methods to stimulate learning could include increasing extrinsic or intrinsic motivation. Extrinsic motivation occurs in circumstances where learning yield results or removes obstacles; in the latter case, the motive weakens when the obstacle has been resolved. Intrinsic motivation allows independence and high continuance in learning. It is the immanent desire for learning, or the pursuit of academic exploration that emerges from the psychological need for personal growth and development. Intrinsic motivation is expressed when psychological needs are satisfied (Reeve, 2018; [23]).

The basic psychological needs that provoke and encourage intrinsic motivation represent the requirements to perceive and meet the psychological needs based on motivational purposes. Its character is qualitatively different from that of physiological needs that derive from biological needs such as thirst or hunger ([44]; Reeve, 2018; [45]). For instance, a certain activity related to psychological needs causes personal interest, leading to pleasure when the psychological needs are satisfied. The energy from psychological needs can drive growth, given that it is proactive, voluntary, and thrives through interactions with the environment (Reeve, 2018). Basic psychological needs consist of three essential elements: autonomy, competence, and relationship. Autonomy in the educational context is also associated with the presence or absence of selection options and the number of selection options [46].

Khan et al. [27] structurally verified the relationships between autonomy, competence, relevance, and behavior intention in the MOOC environment while studying the direct causal relationship between basic psychological needs and continuance intention to use. According to the results, perceived relatedness and perceived competence affect learners' behavioral intention, the intention to consistently use MOOCs, which in turn positively affects the actual use of MOOCs. Roca and Gagné [28] report that three components of basis psychological needs influenced differently e-learning continuance intention through perceived usefulness, playfulness, and perceived ease. Results showed that perceived autonomy support and competence affected e-learning continuance intention to use that was mediated through usefulness, playfulness, and ease of use. In terms of relatedness, it had little effect on perceived usefulness; however, it did have an effect on e-learning continuance intention to use in mediating playfulness.

H1: The basic psychological needs will be positively related to continuance intention to use in MOOCs

2.3. MOOCs and the Task–Technology Fit. Technology is an important driving force behind individual behavior depending on the situation [47]. Considering the characteristics of the MOOC environment, the relationship between technology use and the subsequent progress of the user needs to be structurally examined; the task–technology fit is useful for this purpose. The task–technology fit, proposed by Goodhue and Thompson [30], is one of the variables of the task–technology fit model, which consists of task features, technology features, task–technology fit, utilization, and performance impacts. Goodhue and Thompson [30] suggested that task and technology fitness enhanced the use of informational technology and, as a result, improved personal progress. Task–technology fit shows whether the technology is fit for the requirements of a certain task the individual pursues. Task and technology fitness indicates that the technology helps the individual makes decisions and achieves their desired goal. According to Fuller and Dennis [48], the task is the action one must undertake to obtain a certain objective. The method to perform such a task is the technology [30]. Ouyang et al. [33] use classroom scenes as a metaphor; in the given learning process, the task is the completion of the course, and the technology necessary to complete the course is knowledge.

Task–technology fit is widely applied in areas such as information communication and management to assess the suitability of new technology and tasks. With its technology features, MOOCs allow research in the field of education in relation to task–technology, in terms of practical examinations [11, 27, 31, 33]. Prior research on the relationship between variables and task–technology fit is as follows. Jo [31] integrated the task–technology fit model and information system continuance model to study the influential relationship between MOOC's task–technology fit and continuance intention to use in adult learners. The results showed that the task–technology fit affected perceived ease of use and utilization while positively affecting continuance intention to use. Khan et al. [27] structurally verified the behavioral intention and actual use in the MOOC environment based on the technology acceptance model. According to the results, the task–technology fit affected behavioral intentions. Furthermore, it may have a positive effect on the actual utilization of MOOCs. Ouyang et al. [33] researched the structural relationship based on the expectation confirmation model and demonstrated that task–technology fit had a significant effect on continuance intention to use for MOOCs. Whereas the individual learning requirements and technology fitness positively affected the pursuit of MOOC learning, the effect of task–technology fit on learning satisfaction was insignificant in the MOOC environment. Wu and Chen [11] proposed an integrated continuance intention to use model in the MOOC environment by setting the two sub elements of task and technology fitness, individual technology suitability, and task–technology fit, as extraneous variables based on the task acceptance model. Results showed that task–technology fit affected perceived usefulness and perceived ease of use and that perceived usefulness had a significant effect on continuance intention to use.

H2: The task–technology fit will be positively related to continuance intention to use in MOOCs

2.4. Mediating Effect of Student Engagement. Student engagement implies that the learner devotes time and effort to actively concentrate and participate in the learning experience, to achieve the goals within the learning environment [49, 50]. The concept of student engagement was founded on the research conducted by Ralph Tyler, an education psychologist, about how much time students spend in learning and its effect. It began to be actively researched in the 1980s with the development of CSEQ by Robert Pace in 1979. In the 1980s, Alexander Astin defined student engagement as "the quality and amount of physical, psychological energy students invest in university experience." At the time, he used the term "student involvement," but later revealed that there was no difference between the two terms. In 1999, student engagement was mentioned in NSSE in relation to students' behavior in university education. Subsequently, Hu and Kuh [51] defined student engagement as "the quality of determination students show in educational purpose activities that directly affect the results or the learners desire."

Coates [52] saw student engagement as an umbrella concept that covers academic experience and experiences outside the learning environment. As such, early research regarding student engagement centered on behavioral dimensions, but gradually, a multidimensional structure, including behavioral, emotional, and cognitive flows, seemed more legitimate, leading to a broader explanation [50, 53]. Behavioral engagement refers to typical behavioral responses, such as following standard procedures—registration for learning activities or participation in various activities. Emotional engagement refers to the emotional state or reaction the learner feels in response to lessons or learning, such as interest or enjoyment. Cognitive engagement refers to the identified or perceived behavioral regulation strategy required to understand complex concepts or to perform a given learning task [53].

Prior research showed that student engagement had a mediating effect on the relationship between the antecedent variables and learning continuance intention to use [14, 36]. Jung and Lee [36] verified the mediating effect of student engagement in the relationship between the learner variable and learning continuance intention to use in the MOOC environment. They also proved the mediating effect of student engagement in the relationship between academic self-efficacy, teacher presence, perceived usefulness, and learning continuance intention to use. Further, Tsai et al. [14] revealed the mediating effect of student engagement in the relationship between metacognition and MOOC continuance intention to use.

The study potentially provides practical evidence required to increase MOOC continuance intention to use and suggests methods to encourage student engagement, by investigating the independent variables that affect the MOOC continuance intention to use and by verifying the mediating effect of student engagement. To that end, it sets following hypotheses:

H3: The basic psychological needs will be positively related to student engagement

H4: The task–technology fit will be positively related to student engagement

H5: Student engagement will be positively related to continuance intention to use in MOOCs

H6: Student engagement will mediate the relationship between basic psychological needs and continuance intention to use in MOOC

H7: Student engagement will mediate the relationship between task–technology fit and continuance intention to use in MOOC

The research model is shown in Figure 1.

3. Methods

3.1. Participants and Research Context. This study includes data from 201 participants in Korean MOOCs (K-MOOCs). The population of this research consists of students with participation experience in K-MOOCs. Subjects for the questionnaire survey were selected through convenience sampling, one of the nonprobability sampling methods. Specifically, they were attendees of one K-MOOC-installed lectures regarding education from universities in Seoul in 2019. The lecture, titled "The 4th Industrial Revolution and Human Resources Development," lasted from 27 May to 8 September 2019 and had 1010 attendees. Both lectures were first provided with weekly curriculums of 3–6 videos, approximately 10 minutes long. Learners were asked to watch the videos and then submit a quiz or discussion content. Subjects were informed about the aim of the research and were guaranteed anonymity and protection of personal information before proceeding with the questionnaires. Although this study specifically selected attendees of a particular online course, the samples are a convenient source of data for the researchers in this study. Thus, convenient sampling was used instead of purposive sampling that requires an expert judgement to select a representative sample. Of 230 questionnaires returned, 201 responses were used for the data analysis, while the remaining responses were excluded due to missing data and outliers in the sample. Of the 201 respondents, 120 (59.7%) were female, and 81 (40.3%) were male. In terms of final education, 87 (43.3%) were bachelor's degree holders, 63 (31.3%) were high school graduates or below, 35 (17.4%) were master's degree holders, 10 (5.0%) were PhDs, and 6 (3.0%) were associate degree holders, accounting for the lowest proportion. Of all participants, 169 (84.1%) had attended MOOC

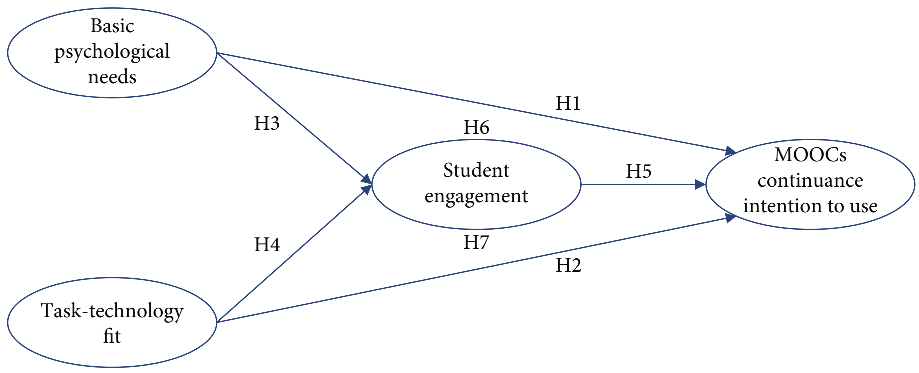

Figure 1: Task–technology fit to MOOC continuance intention to use l.

twice, and 148 (73.6%) still attended a MOOC, even at the end of the lectures. More than two-thirds of the MOOC attendees happened to partake in MOOC learning more than two times.

3.2. Instrument. This research used an apparatus with verified reliability for questionnaire composition to measure the basic psychological needs, task–technology fit, student engagement, and learning continuance intention to use and to examine the structural relationship between the variables.

To measure the basic psychological needs, the survey included 19 items from Deci and Ryan [54]. It included "I feel like I am free to decide for myself how to live my life"(autonomy), "People I know tell me I am good at what I do"(competence), and "I really like the people I interact with"(relatedness). Cronbach's *a* for the basic psychological needs was 0.89.

Task–technology fit was measured four items adapted from Wu and Chen [11] including "MOOCs are fit for the requirements of my learning." Cronbach's *a* for task–technology fit was 0.92.

Student engagement was assessed using 19 items adapted from Sun and Rueda (201) including "I follow the rules of the online class"(behavioral engagement), "I like taking the online class"(emotional engagement), and "I check my schoolwork for mistake"(cognitive engagement). Cronbach's *a* for student engagement was 0.91.

Finally, continuance to use was measured using three items adapted from Wu and Chen [11] including "I intended to continue using MOOCs in the future." Cronbach's α for continuance intention to use was 0.91.

3.3. Data Analysis. Structural equation modelling (SEM) was used to investigate the structural relationships among variables. For two variables, basic psychological needs and student engagement, the number of items was reduced through item parceling. Item parceling was used to reduce the item numbers and to simplify the model. It was appropriate for the following reasons. First, it prevents excess weighting on the measurement model. Second, the estimation of fewer model parameters results in a more optimal variable to sample size ratio and more stable parameter estimates, particularly with small samples [55, 56]. Item parceling reduces estimation errors by reducing the number of indicators for each latent variable so that the multivariate normality assumption can be met [57]. The precondition for this test is to prevent obscuring the factor structure of the data and biased estimates of other model parameters, with each item having reviewed unidimensionality [58]. The model was created through maximum likelihood estimation, and the model fit was evaluated with indices such as chi-square, the Tucker Lewis index (TLI), the comparative fit index (CFI), and root mean square error of approximation (RMSEA). Statistical analysis was conducted on 201 responses using SPSS 25.0 and Amos 25.0.

4. Results

Table 1 presents the descriptive statistics for the observed variables and correlations. The means for the variables varied from 3.64 to 5.97, and the SDs from 0.59 to 1.19. To assess normality, the data analysis included skewness and kurtosis. The absolute skewness value ranged from 0.05 to 0.74, and the absolute kurtosis value ranged from 0.13 to 0.99. Owing to the standard skewness being smaller than 3 and the kurtosis beings less than 10, the results met the assumption of multivariate normality [59]. Correlation coefficients of all items were between 0.15 and 0.88, which showed a mostly statistically significant positive correlation.

A confirmatory factor analysis (CFA) was conducted to examine the factor loading, reliability, and validity of the questionnaire items. The measurement model fit evaluation show that all factor loadings are statistically significant, with reasonable model fit ($\text{chi} - \text{square} = 112.636$; $p = 0.00$; $\text{TLI} = 0.96$; $\text{CFI} = 0.97$; $\text{SRMR} = 0.046$; and $\text{RMSEA} = 0.46$) (see Table 2).

As the measurement model's fit was appropriate, discriminant validity and convergent validity were examined (see Table 3). Since the AVE values (0.643–0.830) were higher than the square value of the correlation between variables (0.234–0.564), 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 0.624 to 0.930, which exceeds the convergent validity threshold of 0.5. Additionally, all standardized factor loadings were statistically significant. Hence, the convergent validity was considered appropriate. To test the

Table 1: Descriptive statistics and correlation.

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Basic psychological needs (1)	—												
2. Basic psychological needs (2)	0.40**	—											
3. Basic psychological needs (3)	0.50**	0.46**	—										
4. Task–technology fit (1)	0.15*	0.36**	0.23**	—									
5. Task–technology fit (2)	0.31**	0.38**	0.36**	0.70**	—								
6. Task–technology fit (3)	0.28**	0.31**	0.31**	0.72**	0.84**	—							
7. Task–technology fit (4)	0.23**	0.45**	0.27**	0.72**	0.74**	0.79**	—						
8. Student engagement (1)	0.27**	0.40**	0.33**	0.55**	0.52**	0.50**	0.52**	—					
9. Student engagement (2)	0.32**	0.47**	0.37**	0.61**	0.52**	0.51**	0.56**	0.55**	—				
10. Student engagement (3)	0.20**	0.44**	0.38**	0.48**	0.39**	0.39**	0.47**	0.46**	0.64**	—			
11. Continuance intention to use (1)	0.32**	0.37**	0.24**	0.67**	0.63**	0.64**	0.64**	0.50**	0.61**	0.47**	—		
12. Continuance intention to use (2)	0.28**	0.33**	0.27**	0.63**	0.57**	0.60**	0.59**	0.46**	0.63**	0.49**	0.86**	—	
13. Continuance intention to use (3)	0.29**	0.30**	0.32**	0.61**	0.57**	0.59**	0.56**	0.42**	0.60**	0.46**	0.80**	0.88**	—
Mean	3.80	3.96	4.10	5.51	5.74	5.89	5.76	3.72	3.80	3.64	5.97	5.90	5.89
SD	0.77	0.63	0.59	1.18	1.19	1.09	1.14	0.68	0.71	0.72	1.07	1.05	1.10
Skewness	−0.48	−0.11	−0.35	−0.23	−0.61	−0.56	−0.44	0.06	−0.14	−0.05	−0.74	−0.52	−0.54
Kurtosis	−0.13	−0.71	−0.55	−0.99	−0.65	−0.83	−0.86	−0.64	−0.43	−0.41	−0.35	−0.76	−0.88

Note. $^{*}p < 0.05$, $^{**}p < 0.01$.

Table 2: Measurement model.

	Chi-square	*Df*	TLI	CFI	RMSEA
Measurement model	112.636	56	0.96	0.97	.046
Level of acceptance			>0.90	>0.90	<0.05

Table 3: Result for assessing measurement model.

Variable		Factor loading	AVE	CR
Basic psychological needs	Autonomy	1.202 (0.624)	0.643	0.844
	Competence	1.202 (0.704)		
	Relatedness	1.000 (0.681)		
Task–technology fit	Task–technology fit (1)	1.026 (0.838)	0.710	0.907
	Task–technology fit (2)	1.085 (0.877)		
	Task–technology fit (3)	1.057 (0.934)		
	Task–technology fit (4)	1.000 (0.848)		
Student engagement	Behavioral engagement	0.885 (0.669)	0.724	0.886
	Emotional engagement	1.175 (0.856)		
	Cognitive engagement	1.000 (0.716)		
Continuance intention to use	Continuance intention to use (1)	0.968 (0.899)	0.830	0.936
	Continuance intention to use (2)	1.014 (0.960)		
	Continuance intention to use (3)	1.000 (0.906)		

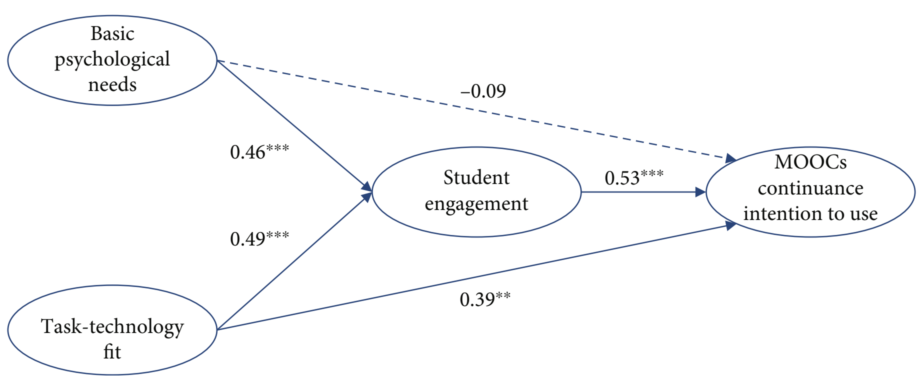

Figure 2: Path analysis. *Note.* $^{***}p < 0.001$.

Table 4: Structural model coefficients.

Relationships		Unstandardized	Standardized	*SE*	*p* value
Basic psychological needs	Student engagement	0.586	0.456	0.124	0.0001
	Continuance intention to use	− 0.232	− 0.094	0.250	0.353
Task–technology fit	Student engagement	0.264	0.492	0.045	0.0001
	Continuance intention to use	0.406	0.392	0.091	0.0001
Student engagement	Continuance intention to use	1.027	0.533	0.259	0.0001

Note. $^{***}p < 0.001$.

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 [60].

4.1. Structural Model. To confirm that the measurement model had good model fit, SEM with maximum likelihood estimation was used (see Table 3). The results demonstrate that all factor loadings were statistically significant, with reasonable model fit ($\text{chi}-\text{square} = 112.636$; $p = 0.00$; $\text{TLI} = 0.96$; $\text{CFI} = 0.97$; $\text{SRMR} = 0.046$; and $\text{RMSEA} = 0.07$). Figure 2 shows final structural model. Next, the relationship between the latent variables was examined (see Table 4). First, the basic psychological needs do not have a statistically significant effect on continuance intention to use. Second,

Table 5: Indirect effects of mediating variables.

Independent variable	Mediation path	Dependent variable	Indirect effect	Bootstrapping (95%) CI	
				Lower	Upper
Basic psychological needs	Student engagement	Continuance intention to use	0.24***	0.11	0.46
Task–technology fit	Student engagement	Continuance intention to use	0.26***	0.13	0.45

Notes. $^{***}p < 0.001$, perceived bootstrap sample size = 5000, and CI = confidence interval.

the basic psychological needs have an effect on student engagement, with the standardized coefficient being 0.456 ($p < 0.001$), which implies that the higher the learners' basic psychological needs, such as competence and relevance, the higher the student engagement. Third, task and technology fitness shows a positive effect on continuance intention to use, with the standardized coefficient being 0.392 ($p < 0.001$), which is significant. Fourth, task–technology fit has a statistically significant effect on student engagement, with the standardized coefficient being 0.492 ($p < 0.001$). This shows that the better the fit between learners' learning requirements and the K-MOOC technology, the higher the student engagement level. Lastly, student engagement has a positive effect on continuance intention to use, with the standardized coefficient being 0.533 at the $p < 0.001$ level. This implies that the greater the student engagement, the higher the continuance intention to use. In sum, hypotheses 1–5 explored the direct effect on the tested relationships. All hypotheses, except H1, were supported.

4.2. Mediating Variables. The model in this was expected to have serial multiple mediators; therefore, a mediation significance test with phantom variables was performed. To assess the significance of indirect effects, the researchers used bootstrapping with a bias-corrected confidence estimate (see Table 5).

The results show that basic psychological needs had a significant indirect effect on continuance intention to use through student engagement. Since basic psychological needs had no significant direct effect on continuance intention to use, the mediating variables fully mediated the relationship between basic psychological needs and continuance intention to use. Task–technology fit had both indirect and direct effect on continuance intention to use through student engagement. Student engagement partially mediated only the relationship between task–technology fit and continuance intention to use. H6 and H7 explored the indirect effect on the tested relationships, and H7 was supported.

5. Discussion

This study aimed to determine the structural relationship between learners' basic psychological needs, the task–technology fit, student engagement, and MOOC learners' continuance intention to use. It also intended to evaluate the mediating effects of student engagement in this relationship to explore the possibility of improving continuance intention to use and promoting student engagement.

First, the basic psychological needs of individuals in MOOC learning did not have a significant direct effect on the degree of continuance intention to use, while the indirect effects were significant. In other words, the basic psychological needs did not directly affect continuance intention to use, but had an indirect effect through student engagement. These results are somewhat different from assumption of the study that the basic psychological needs directly affect intrinsic motivation and intention to use. However, it is noticeable that prior studies mainly set continuance intention to use as a mediating variable of behavioral results for the dependent variable. For instance, Khan et al. [27] put behavioral intention as a moderating variable for usage of MOOC, the dependent variable. Unlike these studies, this study place continuance intention to use as the dependent variable and student engagement as an independent mediating variable. The cognitive-motivative-relational theory of Lazarus [61] explains that motivating factors cause changes in actual behavior through perceived appraisal. In such cases, the basic psychological needs work as emotional sources that affect directly student engagement. These are supported the finding that the basic psychological needs affect student engagement, which is consistent with prior results [10]. Findings from this study reveal that both basic psychological needs and student engagement are closely related in a motivation framework; thus, the basic psychological needs do not have a direct effect on continuance intention to use.

These findings suggest that to increase student engagement in MOOCs, teaching-learning intervention should satisfy their basic psychological needs in terms of the three factors of MOOC lectures: autonomy, competence, and relationships. To satisfy autonomy, learners should be able to select and plan their learning according to their own will. Likewise, to promote competence, relevant elements should be added to MOOC screen designs for learners to have successful experiences, including providing task feedback from the teachers. Another option could be to operate an online community to increase interaction with fellow learners to satisfy relevance. Using online community discussion sections to help students exchange understanding in the online education stage, students will experience deep learning through discussion instead of learning vague, fragmentary, and superficial knowledge [62]. Second, the task–technology fit, which indicates the compatibility between technology and individual learning requirements, had a direct impact on the degree of continuance intention to use. Prior studies have reported that the task–technology fit affects learning guidance in technology-based learning environments, because they considered continuance intention to use for various technology-based learning environments, such as e-learning, smart devices, and flipped learning. The results of this study are consistent with previous findings on continuance intention to use for technological environments [11, 33]. This study demonstrates that the task–technology fit variable proposed in prior research for the technology environment has the same effect in MOOCs, which is the latest form of technological environment in education. MOOC technology enables customized learning in open education, which is a major concept of learning agility that learners would require in the future; it provides the latest form of open education services utilizing public educational resources. In particular, the concept of personalized learning emphasizes the importance of target learning using technology, even as the learner is considered as a person. Thus, this study is significant in that it shows how the fitness of MOOC technology to individual learning requirements or tasks is important.

In addition, the study found that task–technology fit had a significant effect on behavioral, emotional, and cognitive commitments in learning. For example, if the task–technology fit is high, the student becomes more immersed in behavior, such as frequently accessing the MOOC classroom, and the emotional level of student engagement increases. As with the use of behavioral control strategies, cognitive commitment can also increase. In previous studies, the task–technology fit is examined mainly in terms of its perceived usefulness according to the technology acceptance model [36].

Third, the study confirmed that student engagement has a mediating effect, in that the basic psychological needs and task–technology fit affect continuous use intention. In various technology-based learning environments, student engagement has been reported to mediate the relationship between learner characteristics and learning outcomes [36, 63]. The results of this study imply that student engagement plays an important role as a mediating variable in the process of increasing continuous use even in the MOOC environment. It was found that basic psychological needs influenced continuous use intention through student engagement. In other words, in MOOC learning, the greater the basic psychological needs, the higher the learner's immersion level, and, therefore, the higher the willingness to continue learning. Lavigne et al. [64], Roca and Gagné [28], and Sørebø et al. [65] showed that basic psychological needs had an indirect effect, through the mediating variables, in the online environment. The finding is consistent with this study.

6. Conclusion

Recently, MOOCs have been extensively employed to help students involve in self-directed learning. Given the importance of supporting students active and sustainable participation in MOOC learning, the design of supporting students continuous learning should consider psychological conditions in relation to their motivation toward MOOC learning. Studies on continuance learning have mainly investigated factors that are related to users' usefulness in the process of technology acceptance. Very few studies have explored the mechanisms of the factors in terms of student engagement. The current study seeks to understand how crucial psychological constructs that are related to student engagement are function for MOOC continuous learning. Findings imply that instructors and course designers design the learning process to promote student engagement when designing MOOC learning, thereby reducing confusion for learners, encouraging participation in discussions, and presenting in-depth learning materials to increase learner participation. It was also found that the task–technology fit had an effect on learners' continuance intention to use through student engagement. In MOOC learning, the greater the skill suitability for the task, the higher the learner's immersion level. The better the task–technology fit of the learning environment, the higher the level of engagement, and the greater the continuance intention to use. The significance of the study is that student engagement appeared as a variable mediating continuance intention to use, confirming that student engagement medicate the relationship between task–technology fit and the learner's continuance intention to use.

Although this study showed the influence of basic psychological needs and task–technology fit through student engagement, further research need to be investigated how learners perceive each components of basic psychological needs, how they perceive task–technology fit according to different types of tasks, and how they perceive influence of antecedent variables on each dimension of student engagement. For instance, different basic psychological needs may have different impacts on different dimensions of student engagement. Future research model should shed light on the differential effects. Investigating structural relationships between subcomponents can provide a deeper understanding that can help designers determine specific strategies for specific MOOCs learning situations.

In this study, data were collected based on self-reported surveys after the end of learning. A problem with self-reported responses is that their objectivity is difficult to guarantee because they are based on learners' individual opinions. In addition, the survey was conducted privately, so the study failed to take into account when learners started studying and how long they intended to continue in the MOOC. Therefore, future research should consider not only quantitative but also qualitative methods such as case studies and Delphi surveys and log data analyses, such as text mining. Longitudinal studies with the same learners during the first to third, sixth to eighth, or fourteenth to sixteenth weeks of the lecture will reveal also how the level of participation and engagement of learners in MOOCs change over time. Future studies should therefore conduct in-depth research on learners continuing their learning in MOOCs, beyond merely understanding their continuance intention to use. Research methods, such as interviews, could allow a more practical analysis of the factors that lead to MOOC learners' continuance intention to use.

Data Availability

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflicts of Interest

The authors have no conflict of interest.

Acknowledgments

This work was supported by the Ministry of Education of the Republic of Korea and the National Research Foundation of Korea (NRF-2020S1A3A2A02091529).

References

[1] Q. Li and R. Baker, "The different relationships between engagement and outcomes across participant subgroups in massive open online courses," *Computers & Education*, vol. 127, pp. 41–65, 2018.

[2] D. Shah, *By the Numbers: MOOCS in 2021*, Class Central, 2021, Retrieved from https://www.class-central.com/report/mooc-stats-2021/.

[3] K. Jordan, "Massive open online course completion rates revisited: assessment, length and attrition," *The International Review of Research in Open and Distance Learning*, vol. 16, no. 3, pp. 341–358, 2015.

[4] R. F. Kizilcec, C. Piech, and E. Schneider, "Deconstructing disengagement: analyzing learner subpopulations in massive open online courses," in *Proceedings of the third international conference on learning analytics and knowledge*, pp. 170–179, Leuven, Belgium, 2013, April.

[5] G. Veletsianos, A. Collier, and E. Schneider, "Digging deeper into learners' experiences in MOOCs: participation in social networks outside of MOOCs, notetaking and contexts surrounding content consumption," *British Journal of Educational Technology*, vol. 46, no. 3, pp. 570–587, 2015.

[6] B. Li, X. Wang, and S. C. Tan, "What makes MOOC users persist in completing MOOCs? A perspective from network externalities and human factors," *Computers in Human Behavior*, vol. 85, pp. 385–395, 2018.

[7] H. Macleod, J. Haywood, A. Woodgate, and M. Alkhatnai, "Emerging patterns in MOOCs: learners, course designs and directions," *TechTrends*, vol. 59, no. 1, pp. 56–63, 2015.

[8] K. Jona and S. Naidu, "MOOCs: emerging research," *Distance Education*, vol. 35, no. 2, pp. 141–144, 2014.

[9] B. J. Evans, R. B. Baker, and T. S. Dee, "Persistence patterns in massive open online courses (MOOCs)," *The Journal of Higher Education*, vol. 87, no. 2, pp. 206–242, 2016.

[10] H. F. Hew, "Promoting engagement in online courses: what strategies can we learn from three highly rated MOOCS," *British Journal of Educational Technology*, vol. 47, no. 2, pp. 320–341, 2016.

[11] B. Wu and X. Chen, "Continuance intention to use MOOCs: integrating the technology acceptance model (TAM) and task-technology fit (TTF) model," *Computers in Human Behavior*, vol. 67, pp. 221–232, 2017.

[12] L. Corno, "Self-regulated learning: a volitional analysis," in *Self-regulated learning and academic achievement: theory, research and practice*, B. J. Zimmerman and D. H. Schunk, Eds., pp. 111–141, Springer-Verlag, New York, NY, USA, 1989.

[13] T. Müller, "Persistence of women in online degree-completion programs," *The International Review of Research in Open and Distributed Learning*, vol. 9, no. 2, 2008.

[14] Y. H. Tsai, C. H. Lin, J. C. Hong, and K. H. Tai, "The effects of metacognition on online learning interest and continuance to learn with MOOCs," *Computers & Education*, vol. 121, pp. 18–29, 2018.

[15] H. Bicen, "Determining the effect of using social media as a MOOC tool," *Procedia Computer Science*, vol. 120, pp. 172–176, 2017.

[16] J. Y. Hsu, C. C. Chen, and P. F. Ting, "Understanding MOOC continuance: an empirical examination of social support theory," *Interactive Learning Environments*, vol. 26, no. 8, pp. 1100–1118, 2018.

[17] Y. J. Joo, H. J. So, and N. H. Kim, "Examination of relationships among students' self-determination, technology acceptance, satisfaction, and continuance intention to use K-MOOCs," *Computers & Education*, vol. 122, pp. 260–272, 2018.

[18] J. D. Hansen and J. Reich, "Democratizing education? Examining access and usage patterns in massive open online courses," *Science*, vol. 350, no. 6265, pp. 1245–1248, 2015.

[19] R. F. Kizilcec and S. Halawa, "Attrition and achievement gaps in online learning," in *Proceedings of the Second (2015) ACM Conference on Learning@ Scale*, pp. 57–66, Vancouver, Canada, 2015, March.

[20] I. Nawrot and A. Doucet, "Building engagement for MOOC students: introducing support for time management on online learning platforms," in *Proceedings of the 23rd International Conference on world wide web*, pp. 1077–1082, Seoul, Korea, 2014, April.

[21] S. Zheng, M. B. Rosson, P. C. Shih, and J. M. Carroll, "Understanding student motivation, behaviors and perceptions in MOOCs," in *Proceedings of the 18th ACM conference on computer supported cooperative work & social computing*, pp. 1882–1895, Vancouver, Canada, 2015, February.

[22] P. G. Barba, G. E. Kennedy, and M. D. Ainley, "The role of students' motivation and participation in predicting performance in a MOOC," *Journal of Computer Assisted Learning*, vol. 32, no. 3, pp. 218–231, 2016.

[23] R. M. Ryan, "Psychological needs and the facilitation of integrative processes," *Journal of Personality*, vol. 63, no. 3, pp. 397–427, 1995.

[24] C. Fernández-Espínola, B. J. Almagro, J. A. Tamayo-Fajardo, and P. Sáenz-López, "Complementing the self-determination theory with the need for novelty: motivation and intention to be physically active in physical education students," *Frontiers in Psychology*, vol. 11, 2020.

[25] I. M. Taylor, N. Ntoumanis, M. Standage, and C. M. Spray, "Motivational predictors of physical education students' effort, exercise intentions, and leisure-time physical activity: a multilevel linear growth analysis," *Journal of Sport and Exercise Psychology*, vol. 32, no. 1, pp. 99–120, 2010.

[26] C. H. Ho, "Continuance intention to use of e-learning platform: toward an integrated model," *International Journal of Electronic Business Management*, vol. 8, no. 3, p. 206, 2010.

[27] I. U. Khan, Z. Hameed, Y. Yu, T. Islam, Z. Sheikh, and S. U. Khan, "Predicting the acceptance of MOOCs in a developing country: application of task-technology fit model, social motivation, and self-determination theory," *Telematics and Informatics*, vol. 35, no. 4, pp. 964–978, 2018.

[28] J. C. Roca and M. Gagné, “Understanding e-learning continuance intention in the workplace: a self-determination theory perspective,” *Computers in Human Behavior*, vol. 24, no. 4, pp. 1585–1604, 2008.

[29] Q. Zhao, C. D. Chen, H. W. Cheng, and J. L. Wang, “Determinants of live streamers’ continuance broadcasting intentions on Twitch: a self-determination theory perspective,” *Telematics and Informatics*, vol. 35, no. 2, pp. 406–420, 2018.

[30] D. Goodhue and R. Thompson, “Task-technology fit and individual performance,” *MIS Quarterly*, vol. 19, no. 2, pp. 213–236, 1995.

[31] D. H. Jo, “Exploring the determinants of MOOCs continuance intention to use,” *TIIS*, vol. 12, no. 8, pp. 3992–4005, 2018.

[32] R. Kim and H. D. Song, “Examining the influence of teaching presence and task-technology fit on continuance intention to use MOOCs,” *The Asia-Pacific Education Researcher*, vol. 31, pp. 395–408, 2022.

[33] Y. Ouyang, C. Tang, W. Rong, L. Zhang, C. Yin, and Z. Xiong, “Task-technology fit aware expectation-confirmation model towards understanding of MOOCs continued usage intention,” in *Proceedings of the 50th Hawaii International Conference on System Sciences*, pp. 174–183, HI, USA, 2017, January.

[34] J. P. Steele and C. J. Fullagar, “Facilitators and outcomes of student engagement in a college setting,” *The Journal of Psychology*, vol. 143, no. 1, pp. 5–27, 2009.

[35] W. B. Schaufeli and M. Salanova, “Efficacy or inefficacy, that’s the question: burnout and work engagement, and their relationships with efficacy beliefs,” *Anxiety, Stress, and Coping*, vol. 20, no. 2, pp. 177–196, 2007.

[36] Y. Jung and J. Lee, “Learning engagement and persistence in massive open online courses (MOOCS),” *Computers & Education*, vol. 122, pp. 9–22, 2018.

[37] W. Schaufeli, “Applying the Job Demands-Resources model: a ‘how to’ guide to measuring and tackling work engagement and burnout,” *Organizational Dynamics*, vol. 46, no. 2, pp. 120–132, 2017.

[38] D. Xanthopoulou, A. Bakker, E. Demerouti, and W. Schaufeli, “Reciprocal relationships between job resources, personal resources, and work engagement,” *Journal of Vocational Behavior*, vol. 74, no. 3, pp. 235–244, 2009.

[39] Y. Guo, “The influence of academic autonomous motivation on learning engagement and life satisfaction in adolescents: the mediating role of basic psychological needs satisfaction,” *Journal of Education and Learning*, vol. 7, no. 4, pp. 254–261, 2018.

[40] L. Molinari and C. Mameli, “Basic psychological needs and school engagement: a focus on justice and agency,” *Social Psychology of Education*, vol. 21, no. 1, pp. 157–172, 2018.

[41] S. Aggarwal, M. Lamba, K. Verma, S. Khuttan, and H. Gautam, “A preliminary investigation for assessing attention levels for massive online open courses learning environment using EEG signals:: an experimental study,” *Human Behavior and Emerging Technologies*, vol. 3, no. 5, pp. 933–941, 2021.

[42] F. Shahzad, G. Xiu, I. Khan, M. Shahbaz, M. U. Riaz, and A. Abbas, “The moderating role of intrinsic motivation in cloud computing adoption in online education in a developing country: a structural equation model,” *Asia Pacific Education Review*, vol. 21, no. 1, pp. 121–141, 2020.

[43] S. Z. Hasan, H. Ayub, A. Ellahi, and M. Saleem, “A moderated mediation model of factors influencing intention to adopt cryptocurrency among university,” *Human Behavior and Emerging Technologies*, vol. 2022, article 9718920, pp. 1–14, 2022.

[44] E. L. Deci and R. M. Ryan, “The “what” and “why” of goal pursuits: human needs and the self-determination of behavior,” *Psychological Inquiry*, vol. 11, no. 4, pp. 227–268, 2000.

[45] K. M. Sheldon, “Integrating behavioral-motive and experiential-requirement perspectives on psychological needs: a two process model,” *Psychological Review*, vol. 118, no. 4, pp. 552–569, 2011.

[46] S. Schneider, “Are there never too many choice options? The effect of increasing the number of choice options on learning with digital media,” *Human Behavior and Emerging Technologies*, vol. 3, no. 5, pp. 759–775, 2021.

[47] A. W. Oliveira, “Theorizing technology and behavior: introduction to special issue,” *Human Behavior and Emerging Technologies*, vol. 2, no. 4, pp. 302–306, 2020.

[48] R. M. Fuller and A. R. Dennis, “Does fit matter? The impact of task-technology fit and appropriation on team performance in repeated tasks,” *Information Systems Research*, vol. 20, no. 1, pp. 2–17, 2009.

[49] H. Coates, “The value of student engagement for higher education quality assurance,” *Quality in Higher Education*, vol. 11, no. 1, pp. 25–36, 2005.

[50] M. M. Handelsman, W. L. Briggs, N. Sullivan, and A. Towler, “A measure of college student course engagement,” *The Journal of Educational Research*, vol. 98, no. 3, pp. 184–192, 2005.

[51] S. Hu and G. D. Kuh, “Being (dis)engaged in educationally purposeful activities: the influences of student and institutional characteristics,” in *Paper presented at the American Educational Research Association Annual Conference*, pp. 10–14, Seattle, WA, USA, 2001, April.

[52] H. Coates, “A model of online and general campus-based student engagement,” *Assessment & Evaluation in Higher Education*, vol. 32, no. 2, pp. 121–141, 2007.

[53] J. A. Fredricks, P. C. Blumenfeld, and A. H. Paris, “School engagement: potential of the concept, state of the evidence,” *Review of Educational Research*, vol. 74, no. 1, pp. 59–109, 2004.

[54] E. L. Deci and R. M. Ryan, *Handbook of Self-Determination Research*, University Rochester Press, NY, 2002.

[55] R. P. Bagozzi and J. R. Edwards, “A general approach for representing constructs in organizational research,” *Organizational Research Methods*, vol. 1, no. 1, pp. 45–87, 1998.

[56] R. P. Bagozzi and T. F. Heatherton, “A general approach to representing multifaceted personality constructs: application to state self-esteem,” *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 1, no. 1, pp. 35–67, 1994.

[57] D. A. Sass and P. L. Smith, “The effects of parceling unidimensional scales on structural parameter estimates in structural equation modeling,” *Structural equation modeling*, vol. 13, no. 4, pp. 566–586, 2006.

[58] D. L. Bandalos, “The effects of item parceling on goodness-of-fit and parameter estimate bias in structural equation modeling,” *Structural Equation Modeling*, vol. 9, no. 1, pp. 78–102, 2002.

[59] R. B. Kline, “*Principles and practice of structural equation modeling*,” Guilford publications, Waikoloa, HI, USA, 2015.

[60] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of marketing research*, vol. 18, no. 1, pp. 39–50, 1981.

[61] R. S. Lazarus, "Cognition and motivation in emotion," *American psychologist*, vol. 46, no. 4, p. 352, 1991.

[62] W. Bao, "COVID-19 and online teaching in higher education: a case study of Peking University," *Human Behavior and Emerging Technologies*, vol. 2, no. 2, pp. 113–115, 2020.

[63] S. Hu, "Reconsidering the relationship between student engagement and persistence in college," *Innovative Higher Education*, vol. 36, no. 2, pp. 97–106, 2011.

[64] G. L. Lavigne, R. J. Vallerand, and P. Miquelon, "A motivational model of persistence in science education: a self-determination theory approach," *European Journal of Psychology of Education*, vol. 22, no. 3, pp. 351–369, 2007.

[65] Ø. Sørebø, H. Halvari, V. F. Gulli, and R. Kristiansen, "The role of self-determination theory in explaining teachers' motivation to continue to use e-learning technology," *Computers & Education*, vol. 53, no. 4, pp. 1177–1187, 2009.