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What rationale would work? Unfolding the role of learners' attitudes and motivation in predicting learning engagement and perceived learning outcomes in MOOCs

Xiaomei Wei[1*], Nadira Saab[1] and Wilfried Admiraal[2]

*Correspondence:
x.wei@iclon.leidenuniv.nl

[1] ICLON, Leiden University Graduate School of Teaching, Leiden University, Kolffpad 1, 2333 BN Leiden, The Netherlands
[2] Centre for the Study of Professions, Oslo Metropolitan University, St. Olavs Plass, PO Box 4, 0130 Oslo, Norway

Abstract

The aim of this study is to gain insight into the interplay between attitudes, motivation, learning engagement, and perceived learning outcomes in massive open online courses (MOOCs). An online survey was administered to 232 MOOC learners. This study provided comprehensive explanations for individual differences in learning engagement and perceived learning outcomes in MOOCs with a modified model of the expectancy-value theory of achievement motivation. The structural equation modeling revealed that attitudes served as a precursor of participation in MOOCs that significantly influenced self-efficacy, intrinsic value, and task effort cost; self-efficacy and intrinsic value were positively associated with both learning engagement and perceived learning outcomes, while attitudes toward MOOC learning was positively related to perceived learning outcomes only. Furthermore, the mediation analyses highlighted that intrinsic value was a powerful mediator, which positively influenced the effects of attitudes and self-efficacy on learning engagement and perceived learning outcomes. The moderation analyses discovered that task effort cost moderated the effects of attitudes on learning engagement and perceived learning outcomes. Curriculum designers and instructors could benefit from this study to understand what rationales drive individuals to be engaged in MOOC learning and to reach greater perceived learning outcomes in MOOCs.

Keywords: Massive open online courses, Attitudes toward MOOC learning, Motivation, Learning engagement, Perceived learning outcomes, The expectancy-value theory

Introduction

Massive open online courses (MOOCs) have extended the accessibility and sustainability of tertiary education. MOOCs have become one of the popular online learning formats and their proliferation has attracted many learners who, by participating in a MOOC, can connect with global learners online. Yet progressively more learners drop out during the course and only a small proportion of learners complete course learning (Cagiltay et al., 2020). Risen attention has been paid to how to facilitate learning engagement (Joksimović et al., 2018; Kuo et al., 2021), which is confirmed to be critical to succeeding in MOOC learning and reducing the dropout ratio (Wang et al., 2019). Previous MOOC studies have also determined that attitudes and motivation significantly explained course completion (Dalipi et al., 2018; Zhou, 2016). Attitudes toward MOOC learning were a significant predictor of learners' continuance intention and actual behavior toward course completion (Altalhi, 2021; Wu & Chen, 2017). Furthermore, prior studies confirmed that the relatively high dropout rates were inextricably related to the motivation that MOOC learners have (Badali et al., 2022; Watted & Barak, 2018). Learners' motivation for participation in MOOCs is diverse, and individual learning success is not restricted to course completion and high course grades. Even though researchers discovered that MOOC learners vary in engagement (e.g., Kang, 2020; Khalil & Ebner, 2017; Li & Baker, 2018), they did not reveal what rationales drive individuals to be engaged or disengaged in MOOC learning. Course grades and course completion rates are useful to quantify learning outcomes, but they are not always adequate to demonstrate the full picture of individual learning outcomes in MOOC learning (Stephens-Martinez et al., 2014). Learners' perception of learning outcomes might provide a lens for understanding the extent to which individuals perceive they have learned something from MOOCs (Wei et al., 2021). The aforementioned attitudes-engagement relationship suggests that attitudes serve as the evaluative predisposition to planned behavior (Ajzen, 1985). Learners may decrease their engagement in MOOCs and even may not initiate participation if they do not have positive attitudes toward MOOC learning. Simultaneously, learners' engagement in MOOCs aligns with their self-determined motivation for MOOCs (Sicilia et al., 2015). As most learners participate in MOOCs with different attitudes and motivation, it is critical to investigate how attitudes and motivation are related to learning engagement and perceived learning outcomes.

Motivation and engagement in MOOCs have been thoroughly studied, yet little is known about the mechanism through which attitudes and motivational belief aspects work together to influence learning engagement and perceived learning outcomes in MOOCs. While existing MOOC studies have primarily focused on positive motivational values, less attention has been paid to negative motivational values, such as perceived cost. To examine MOOC learners' motivation multidimensionally, this study is designed to investigate both positive and negative motivational beliefs by adopting the expectancy-value theory of achievement motivation (Wigfield & Eccles, 2000), which concerns the expectancy and value aspects of motivational beliefs (i.e., self-efficacy, task value, and perceived cost). Task value and perceived cost beliefs concern the valuable and detracted characteristics of a course that influence learners' determinations to either engage or disengage with the course (Eccles et al., 1983). Part et al. (2020) and Flake et al. (2015) have argued that, for a multidimensional presentation of individuals' motivational process, examining the benefits of robust predictors (i.e., self-efficacy, and task value) to educational outcomes is not enough, being aware of the negative effects of perceived cost is also essential. The weighting and role of the components of task value and perceived cost to influence academic outcomes vary in individuals and contexts (Eccles & Wigfield, 2020; Perez et al., 2019). However, considering the bi-direction of motivational beliefs, it is not clear the direct and indirect effects of task value and perceived cost on learners to be engaged in a MOOC. Given the context of teaching–learning asynchronously and learners' self-determined learning in MOOCs, there is a need to identify the role of task value and perceived cost in learning engagement and perceived learning outcomes. Based on previous MOOC studies, considering the significance of attitudes in the attitudes-engagement relationship mentioned above, together with the motivation-engagement relationship in MOOC learning, it suggests that attitudes may play a role in motivation. Attitudes are integrated into the expectancy-value model to bridge the connection between attitudes and motivational beliefs. Therefore, firstly, the current study estimates the extent to which attitudes, self-efficacy, task value, and perceived cost directly influence learning engagement and perceived learning outcomes. Secondly, we examine the indirect effects of task value and perceived cost in the relationships between attitudes/self-efficacy and learning engagement/perceived learning outcomes. The findings will benefit MOOC researchers and practitioners in understanding the mechanism of attitudes and motivational beliefs working together, and the role of task value and perceived cost in learning engagement and perceived learning outcomes in MOOCs.

Theoretical framework

To further reveal individual MOOC learning, we first review studies on learning engagement and perceived learning outcomes. Next, we elaborate on how motivation and attitudes are associated with learning engagement and perceived learning outcomes. Motivation is a complicated construct, because it broadly concerns the reasons or goals related to making choices, persistence, and performance on achievement tasks (Littlejohn et al., 2016). Learners who attend MOOCs are driven by a variety of reasons, which cannot be solely interpreted by a single motivational belief. The expectancy-value theory of achievement motivation concerns expectancy and value aspects of motivation (i.e., self-efficacy, task value, and perceived cost; Wigfield & Eccles, 2000), which can provide comprehensive explanations for understanding MOOC learners' engagement and perceived learning outcomes.

Learning engagement and perceived learning outcomes

Learning engagement

Learning engagement is defined as the exertion of one's physical and psychological ongoing effort during the learning process to realize academic achievement or learning goals (Oh et al., 2017). It is important to be addressed in online learning as it is positively associated with academic achievement (Vayre & Vonthron, 2019). Learning engagement comprises three aspects: cognitive, behavioral, and emotional engagement (Fredricks et al., 2004). Cognitive engagement refers to learners exerting mental effort in MOOCs, which concerns employing high-order learning strategies and metacognitive self-regulation strategies, and aiming at acquiring content knowledge and mastering skills (Kuo et al., 2021; Reeve & Tseng, 2011). Behavioral engagement is presented as learners' involvement in MOOC learning activities (e.g., course materials, video lectures, discussion forums, course assessments), on-task attention, and investment of effort within the learning process (Kang, 2020; Reeve & Tseng, 2011). Moreover, emotional engagement is regarded as learners expressing emotional feelings about their MOOC learning, such as interest, curiosity, enjoyment, and enthusiasm, which show the extent of positive evaluation on what they have learned (Skinner et al., 2008).

Perceived learning outcomes

In line with previous MOOC research, a multi-dimension perspective was adopted to consider perceived learning outcomes (i.e., cognitive, behavioral, and affective outcomes), which can provide more information on individual perceptions of knowledge and skills gained in MOOCs (Wei et al., 2023). Cognitive outcomes are defined as the acquisition of content knowledge and intellectual skills from MOOCs (Lan & Hew, 2020). Behavioral outcomes refer to the capabilities of applying knowledge and skills in MOOC learning, such as study skills, and self-regulated learning skills (Min & Foon, 2019). Furthermore, affective outcomes refer to learners' satisfaction with the learning gains and appreciation of the interaction with instructors and peers (Hew et al., 2020; Li, 2019).

The expectancy-value theory

The expectancy-value theory of achievement motivation (Eccles et al., 1983; Wigfield & Eccles, 2000) provides a theoretical perspective to examine multiple aspects of motivation, in terms of self-efficacy, task value, and perceived cost. Prior expectancy-value studies have confirmed that self-efficacy and task value are positively associated with multiple outcomes (i.e., academic outcomes, engagement, and attrition), for example in STEM disciplines (Perez et al., 2019), but perceived cost has not been receiving full attention (Eccles & Wigfield, 2020). Moreover, different motivational beliefs hold differentiated weights and relations to outcomes, which vary in developmental time (i.e., Kosovich et al., 2017; Perez et al., 2019) and context (i.e., Nuutila et al., 2018). Yet, it is still unclear whether motivational beliefs differ in their prediction ability and relations to learning engagement and perceived learning outcomes in MOOCs. In the current study, considering the benefits and cost of motivational beliefs in MOOC learning, the expectancy-value theory provides a lens to understand and intervene individuals' learning engagement and perceived learning outcomes.

The expectancy-value model comprises three major components in terms of expectancy (i.e., self-efficacy), task value, and perceived cost. All these three components are hypothesized to predict performance, choice, effort, and persistence (Wigfield & Eccles, 2000). Self-efficacy is one way to examine individual expectancy for learning and performance, which refers to one's confidence in capabilities of being well-performed and expectancy of being successful in tasks (Bandura & Wessels, 1994). Task value is described as the perceived valuable characteristics of the MOOC that influence learners making a choice to engage, perform, and persist in the task. It incorporates three indicators: (1) intrinsic value, which refers to individuals enjoying and being interested in the MOOC: (2) attainment value, which refers to doing well in the MOOC, which is vital to fulfilling individuals self-identity; and (3) utility value, which refers to achieving individuals' short-term or future goals related to the MOOC (Wigfield & Eccles, 2000). Perceived cost is conceptualized as the detracted characteristics of the task that affect learners' engagement in course learning. It comprises three indicators: (1) task effort cost, which refers to the anticipated time and effort investment required to succeed in the task or course; (2) loss of valued alternatives, which refers to completing the task or course keeps individuals away from other valued activities; and (3) emotional cost, which refers to the negative psychological states that are related to the potential failure or struggle in the task or course (Wigfield & Cambria, 2010).

Self-efficacy

According to Bandura (1993) and Zimmerman (2000), self-efficacy is a vital contributor of cognitive (e.g., personal goal setting, strategy use), motivational (e.g., motivation, task value), affective (e.g., stress, anxiety), and selection (e.g., activity choice) processes. Self-efficacy can influence one's own self-regulated learning behavior and academic accomplishment. In the context of university students attending compulsory courses, for example, Fryer and Ainley (2019) discovered that self-efficacy was positively associated with task value. Nevertheless, as learners are voluntarily to attend a MOOC, few studies have examined the extent to which self-efficacy affects task value and perceived cost in MOOCs.

Within the online learning environment, it has been confirmed that self-efficacy has a significant influence on learning (e.g., Tseng et al., 2020; Vayre & Vonthron, 2017). In a MOOC study by Kuo et al. (2021), it was found that general Internet-based learning self-efficacy (i.e., general belief of one's ability can master Internet-related activities) had a significant influence on behavioral and emotional engagement. Moreover, they discovered that functional Internet-based learning self-efficacy (i.e., specific belief of one's internet skills can complete online tasks) was significantly associated with cognitive and emotional engagement. Min and Foon (2019) discovered that these MOOC learners who expressed low self-efficacy reported their worries on cognitive (i.e., comprehension monitoring), behavioral (i.e., effort expended), emotional (i.e., anxiety, boredom) engagement. In addition, Jung and Lee (2018) found that academic self-efficacy was significantly linked with learning engagement (i.e., cognitive, behavioral, and emotional engagement) in MOOCs.

Researchers have pointed out that self-efficacy is a vital predictor of perceived learning outcomes in MOOCs. For example, in the study of Rabin et al. (2020), MOOC learners' self-efficacy was negatively related to their perceived barriers to satisfaction. Meanwhile, it was positively and significantly correlated with the perceptions of using self-regulated learning strategies. Furthermore, Ghazali et al. (2020) had set up a four-dimension of MOOC-efficacy (i.e., information searching, making queries, MOOC learning, MOOC usability). They identified that MOOC-efficacy had a positive influence on perceived learning outcomes, such as learners' willingness to peer interaction and collaboration, knowledge and skills construction, self-regulated learning skills, etc.

Task value

Concerning the role of task value in online learning, several studies have pictured that task value is an effective predictor associated with learning engagement. For example, when teachers perceived that the learning activities were valuable for teaching practice and professional development, they were more likely behaviorally engaged in the online professional learning communities (Zhang & Liu, 2019). In MOOC settings, there is evidence that task value effectively facilitates learning engagement. Findings in studies by Liu et al. (2023) and Tang and Chaw (2019) showed that intrinsic interest, attainment, and utility value positively predicted behavioral engagement in MOOC learning. MOOC learners with positive perceptions of the task in the course they attend were actively engaged in learning. Perceived usefulness (i.e., utility value) was a robust factor related to learning engagement (i.e., cognitive, behavioral, and emotional engagement) in MOOCs (Jung & Lee, 2018). In the discussion forums, Tang et al. (2018) indicated that intrinsically motivated learners who perceive the MOOC as interesting and enjoyable were more willing to longitudinally persist in behavioral engagement in forum activities than their counterparts. Moreover, intrinsic interest toward a MOOC was found to positively impact psychological engagement (i.e., cognitive, and emotional engagement; Sun et al., 2019). These studies suggest that the more learners are intrinsically motivated, the greater their cognitive, behavioral, and emotional engagement in MOOC learning.

In online learning, previous studies (Artino, 2008, 2009) discovered that task value (i.e., intrinsic, attainment, and utility value) positively influenced university students' perceived learning outcomes in terms of course satisfaction, continuing motivation, and the use of self-regulated learning strategies. Similarly, in the online university environment in South Korea, self-efficacy and task value significantly predicted both learner satisfaction and achievement scores (Joo et al., 2013). Moreover, Lee et al. (2020a) examined perceived effectiveness as learners' perceived learning outcomes of a MOOC, which was an indicator to measure satisfaction with online learning. Influential factors, such as self-efficacy, and task value, affected successful MOOC learners' perceived effectiveness. Particularly, the task value had a statistically significant effect on perceived effectiveness of learners who have fully completed the MOOC. With asynchronous instruction in MOOCs, how task value directly and indirectly impacts the perception of learners who have learned something needs further exploration.

Perceived cost

In the emerging research, researchers suggested that perceived cost was negatively linked with learning engagement in online learning (e.g., Santosa, 2015) and academic outcomes in offline learning (e.g., Perez et al., 2019). For example, Santosa (2015) examined how perceived cost influenced learning engagement with online tutorial activities. In that case, students perceived a high level of cost (e.g., reading materials make students feel like wasting time), which resulted in disengagement with online tutorial activities. Prior studies demonstrated that perceived cost was negatively associated with perceived learning outcomes in online settings. For example, researchers reported that perceived cost was a significant predictor of Chinese college student's perception of adopting online learning (Chen et al., 2021) and the adoption of e-training in the Nigerian civil service (Zainab et al., 2017). Researchers have investigated the role of perceived cost in online learning, however, the knowledge of how perceived cost directly and indirectly shapes learning engagement and perceived learning outcomes in MOOCs is still unclear.

Attitudes

Attitudes refer to learners' general beliefs of favorability and benefits of learning in MOOCs. Prior research highlights that attitude is one of the powerful determinants of continuance intentions to MOOC participation (e.g., Al-Rahmi et al., 2021; Joo et al., 2018). Attitudes toward MOOC learning might have effects on motivation and participation, because continuance intentions are consistent with personal motivation for MOOC participation and indicate individual willingness to continued participation. To our knowledge, in online learning context only a few studies examined how attitudes influence learners' motivation, learning engagement, and perceived learning outcomes. For example, in online distance education, Prior et al. (2016) conducted an investigation of postgraduate students to identify to what extent attitudes, digital literacy and self-efficacy impact their online learning behavior. The findings showed that positive attitudes had a significant influence on self-efficacy. Ma and Lee (2019) discovered some learner-related barriers, in which lack of positive attitudes toward learning in MOOCs hindered learning engagement. Moreover, pertaining to perceived learning outcomes, it was found that positive attitudes toward learning in MOOCs contributed to satisfaction (Albelbisi, 2020), as well as the improvement in self-regulated learning skills (Albelbisi & Yusop, 2019). According to Prior et al. (2016), positive attitudes contributed to self-efficacy in online learning. To further build the knowledge of the role of attitudes in MOOC learning, in the current study attitudes toward MOOC learning is regarded as the antecedent of the self-efficacy, task value, perceived cost, learning engagement, and perceived learning outcomes.

Aim of this study

The present study aims to make contributions to the insight into how attitudes and motivation impact learning engagement and perceived learning outcomes in MOOCs. The expectancy-value theory offers a theoretical perspective to examine motivational beliefs (i.e., self-efficacy, task value, and perceived cost; Eccles et al., 1983), which is employed to construct the theoretical framework for measured variables in this study. We propose a research model that involves attitudes, self-efficacy, task value, and perceived cost to explain learning engagement and perceived learning outcomes in MOOCs (see Fig. 1). Although we do know that attitudes and motivation explain course completion in MOOC learning, not yet known is how attitudes, motivation, learning engagement, and perceived learning outcomes relate. Therefore, we first examine the relationships between independent variables (i.e., attitudes, self-efficacy, task value, and perceived cost) and dependent variables (i.e., learning engagement, and perceived learning

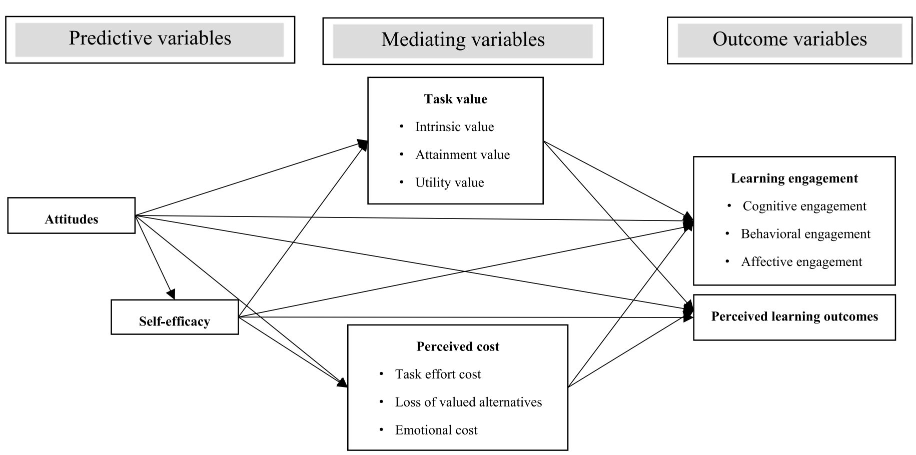

Fig. 1 The proposed research model

outcomes) in MOOCs. Next, we estimate the indirect effects of task value and perceived cost on the relationships between attitudes/self-efficacy and learning engagement/perceived learning outcomes. Since previous studies discovered that the role of task value and perceived cost differed in contexts, we examine the mediating and moderating effects of task value and perceived cost in our research mode. To fulfill the aim of this study, we have formulated the main research question: How do attitude and achievement motivation affect learners' learning engagement and perceived learning outcomes in MOOCs? This main research question is split into the following sub-questions to be addressed:

Firstly, we probe the relationships between every two latent variables presented in the research model (See Fig. 1).

RQ1: How are attitudes related to (a) self-efficacy, (b) task value, (c) perceived cost, (d) learning engagement, and (e) perceived learning outcomes in MOOCs?

RQ2: How is self-efficacy related to (a) task value, (b) perceived cost, (c) learning engagement, and (d) perceived learning outcomes in MOOCs?

RQ3: How is task value related to (a) learning engagement and (b) perceived learning outcomes in MOOCs?

RQ4: How is perceived cost related to (a) learning engagement and (b) perceived learning outcomes in MOOCs?

Task value and perceived cost were introduced by Eccles et al. (1983) as mediators that influence achievement-related outcomes. Yet, recent empirical research has documented that task value and perceived cost played either mediator or moderator to achievement-related outcomes (e.g., Edwards & Taasoobshirazi, 2022; Guo et al., 2015; Perez et al., 2019). These findings are contradictory to the roles of task value and perceived cost on achievement-related outcomes that are hypothesized in Eccles et al. (1983)'s expectancy-value model. To clarify the extent to which indirect effects task value and perceived cost have in MOOC learning, we examine their mediating and moderating roles in the proposed research model. Based on the hypotheses of mediators in the original expectancy-value model, we first came up with RQ 5 and RQ 6 to estimate the mediating effects of task value and perceived cost on learning engagement and perceived learning outcomes (See Fig. 1).

RQ5: How does task value mediate the relationships between attitudes, self-efficacy on the one hand, and learning engagement, on the other hand?

RQ6: How does perceived cost mediate the relationships between attitudes, self-efficacy, on the one hand, and perceived learning outcomes, on the other hand?

If there are no significant results of mediation analyses coming out, moderation analyses will be performed to estimate whether task value and perceived cost play a moderating role in learning engagement and perceived learning outcomes (See Fig. 2).

RQ7: How does task value moderate the relationships between attitudes, self-efficacy on the one hand, and learning engagement, on the other hand?

RQ8: How does perceived cost moderate the relationships between attitudes, self-efficacy, on the one hand, and perceived learning outcomes, on the other hand?

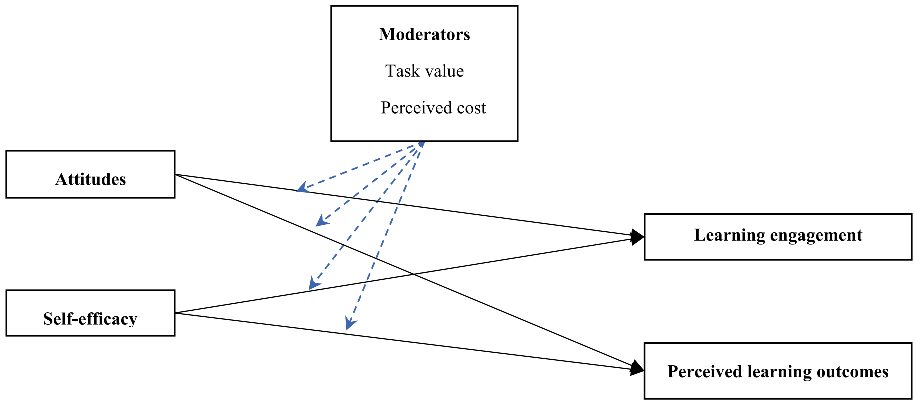

Fig. 2 The proposed moderation model

Table 1 Demographic and descriptive statistics of participants ($n = 232$)

Measures	Items	Frequency	Percentage (%)
Gender	Female	165	71.1
	Male	67	28.9
Age	≤ 22	181	78.0
	23–25	41	17.7
	≥ 25	10	4.3
Academic degree	Undergraduate students	177	76.3
	Graduate students	45	19.4
	Ph.D. students	0	0
	Other	10	4.3
Discipline of the MOOC learners recently attended	Natural science	12	5.2
	Humanities & Social science	149	64.2
	Medical science	27	11.6
	Agricultural science	2	0.9
	Engineering & Technology science	42	18.1
Types of MOOCs	Credit course	160	69
	Non-credit course	72	31

Methods

Procedure and participants

Data has been collected by administering an online questionnaire with university students who attended MOOCs during the academic year 2020–2021. The questionnaire has been piloted with 15 Chinese university students who attended MOOCs in the fall semester of 2020–2021. Then we administered the questionnaire to learners by Qualtrics using a convenience sampling method. We recruited participants in two universities in China, who reported they attended MOOCs during the academic year. Learners accessed the online questionnaires through an anonymous hyperlink or QR code. At the beginning of the questionnaire, participants were informed about the research purpose and terms of participation. All participants gave consent to the terms to indicate that they were willing to participate in the investigation voluntarily. The Research Ethics Committee has approved the current research. The data were collected in 2021. It took participants about 10–15 min to complete the questionnaire. Ultimately, the final sample of this study comprises 232 online learners who attended MOOCs during the academic year 2020–2021. Table 1 displays the demographic information of the participants.

Measuring instruments

The questionnaire that we adopted for data collection comprises all variables involved in the research model. All measuring items were adapted and modified from existing scales to fit the MOOC learning context. Furthermore, forward–backward translation procedures were employed to assure the equivalence of semantic and content of the questionnaires between English and Chinese version (Behling & Law, 2000; Brislin, 1986). Apart from demographic items, participants rated all items on a five-point Likert scale.

Attitudes

Attitudes toward learning in MOOCs was assessed with six items, which were adapted from Admiraal et al. (2017). Attitudes refer to the general belief of favorability and benefits of learning in MOOCs. Example items are "Learning in MOOCs makes my study more satisfying" and "I feel more motivated when I am learning in MOOCs", answered on a five-point Likert scale, anchoring from 1 (*Does not apply at all*) to 5 (*Does apply to a great deal*).

Self-efficacy

In order to examine learners' self-efficacy toward learning in MOOCs, the scale Self-efficacy of Pintrich et al. (1991) was adapted to match the MOOC learning context. Self-efficacy states learners' competence beliefs to be well-performed and expectancy of success in MOOC tasks. The scale includes eight items that focus on the self-appraisal of learners of their capabilities to accomplish tasks as well as their confidence to master what was taught in MOOCs. For example, items are "I'm confident I can do an excellent job in MOOCs" and "Considering the difficulty of MOOCs and my skills, I think I can do well in MOOCs". Participants scored all eight items on a five-point Likert scale, ranging from 1 (Very untrue for me) to 5 (Very true for me).

Task value

The scale Task value with 15 items was based on Perez et al. (2019) and was adapted to assess the task value for the MOOC that learners attended. The scale comprises three subscales including intrinsic value (7 items), attainment value (4 items), and utility value (4 items). Intrinsic value refers to how learners are interested in the MOOC with example items such as "This MOOC is interesting to me" and "Compared to other courses, I like this MOOC very much". Attainment value aims to explain that how learners think about doing well in the MOOC is important for themselves. Example items are "Being good at solving problems in this MOOC is important to me" and "Being someone who does well at this MOOC is important to me". Finally, utility value intends to capture the perception that the MOOC they attended is useful for their future with example items such as "This MOOC is useful for what I want to do after I graduate" and "What I am learning in this MOOC is useful because they will help me in the future". Participants rated all 15 items on a five-point Likert scale anchored with 1 (Strongly disagree) to 5 (Strongly agree).

Perceived cost

Perceived cost toward learning in a MOOC was measured with the scale of Perceived cost from Flake et al. (2015). The scale examines three aspects of cost in terms of task effort cost (5 items), loss of valued alternatives (5 items), and emotional cost (6 items). Task effort cost refers to the perception of how much time and effort would be invested to complete tasks in a MOOC. For example, items are "I have to put too much energy into this MOOC" and "This MOOC takes up too much time". Loss of valued alternatives assesses the extent to which doing tasks in a MOOC occupies one's time or energy to do other valued things or activities. Example items are "I have to sacrifice too much to be in this MOOC" and "This MOOC requires me to give up too many other activities I value". Emotional cost examines the negative appraisal of emotional and psychological state that results from doing tasks in the MOOC. For example, items are "This MOOC is too exhausting" and "This MOOC makes me feel too anxious". All 16 item questions were formatted on a five-point Likert scale, scoring from 1 (Strongly disagree) to 5 (Strongly agree).

Learning engagement

Three aspects of learning engagement were measured by adapting the scales of *Cognitive Engagement* and *Behavioral Engagement* from Reeve and Tseng (2011), and the scale of *Emotional Engagement* from Skinner et al. (2008). Cognitive engagement assesses the use of cognitive learning strategies and meta-cognitive self-regulation strategies when learners were studying the MOOC. For example, items are "When I study this MOOC, I try to connect what I am learning with my own experiences" and "If what I am learning is difficult to understand, I change the way I learn the material". Behavioral engagement examines behavior when learners were studying the MOOC with example items such as "I study this MOOC carefully" and "I work hard when I start something new in this MOOC". Emotional engagement is conceptualized as the positive emotional states toward the course when learners were studying the MOOC with example items such as "I enjoy learning new things in this MOOC" and "When I study this MOOC, I feel curious about what I am learning". Participants scored all 18 items on a five-point Likert scale which ranges from 1 (Strongly disagree) to 5 (Strongly agree).

Perceived learning outcomes

We assessed perceived learning outcomes using the adapted version of the scale *Course Outcomes* from Paechter et al. (2010), which was adopted in Wei et al. (2023). Perceived learning outcomes are composed of three sub-aspects including cognitive (3 items), behavioral (3 items), and affective outcomes (3 items). Cognitive outcomes refer to the extent to which learners mastered the content knowledge after they learned the course with an example item such as “I have understood the content and concepts in the subject matter of this MOOC”. Behavioral outcomes assess the extent to which learners gained the skills after they learned the course with an example item such as “I have developed skills on how to apply the knowledge in this MOOC”. Affective outcomes measure the extent to which learners appreciated what they learned from the MOOC with an example item such as “I am pleased with what I learned in this MOOC”. Participants responded to all 9 items on a five-point Likert scale which ranges from 1 (Strongly disagree) to 5 (Strongly agree).

Data analysis

The current study implemented structural equation modeling (SEM) analysis with maximum likelihood estimation (MLE) to explore the relationships among measured variables (Kline, 2015). Four steps of data analysis were employed.

First, exploratory factor analysis (EFA) was performed using IBM SPSS 25.0 to explore the underlying structure of task value, perceived cost, and learning engagement, separately. The values of Kaiser–Meyer–Olkin (KMO) Measure of Sampling Adequacy and Bartlett’s Sphericity Test indicated that the EFA was appropriate to be carried out (Kaiser, 1974; Tobias & Carlson, 1969). We performed principal component analysis (PCA) with Direct Oblimin rotation and looked for eigenvalues greater than 1.0. The items with factor loading values lower than 0.4 or cross-loadings above 0.4 were removed (Ferguson & Cox, 1993).

Second, we adopted confirmatory factor analysis (CFA) utilizing Mplus 8.3 to verify the measurement model. Based on the results of CFA, we obtained the descriptive statistics and relevant parameters of discriminant validity (i.e., the Pearson correlations, the square root of the average variance extracted), convergent validity (i.e., Composite reliability, the average of variance extracted, and standardized factor loading), and internal reliability (i.e., Cronbach’s alpha) of the constructs used in the measurement model (Kline, 2015).

Third, to answer RQ1 to RQ4, we implemented structural equation modeling (SEM) analysis with maximum likelihood estimation (MLE) to verify the structural model (Kline, 2015). The following fit indices were used to report an acceptable model fit for both measurement model and structural model: chi-square (χ^2), chi-square divided by degrees of freedom ($\chi^2/df < 3$), the comparative fit index (CFI > 0.900), the Tucker-Lewis index (TLI > 0.900; Garver & Mentzer, 1999), the root mean square error of approximation (RMSEA $\leq$ 0.080, 95% CI), and the standardized root mean square residual (SRMR $\leq$ 0.080; Hu & Bentler, 1999).

Four, to answer RQ5 and RQ6, mediation analyses were carried out through bias-corrected bootstrapping of 5000 samples with a 95% confidence interval (Preacher & Hayes, 2008). Furthermore, to answer RQ7 and RQ8, moderation analyses were performed through bias-corrected bootstrapping of 5000 samples with a 95% confidence interval (Preacher & Hayes, 2008).

Results

Measurement validation

Separate EFAs were performed with attitudes, self-efficacy, task value, perceived cost, learning engagement, and perceived learning outcomes. First, after the separate EFAs, one component was extracted from each factor following: attitudes (6 items) with a total of 64.52% variance explained, self-efficacy (8 items) with a total of 51.72% variance explained, perceived learning outcomes (9 items) with a total of 59.96% variance explained. Second, fifteen task value items were entered into an EFA, yielding two components: (1) intrinsic value (7 items), and (2) attainment & utility values (8 items). These two factors explained 68.08% of the total variance. Third, regarding perceived cost, two items with low loading values were removed, and fourteen items in total from task effort cost (4 items), loss of valued alternatives (4 items), and emotional cost (6 items) yielded one component, with a total of 65.44% variance explained. Fourth, concerning learning engagement, a total of 18 items from cognitive engagement (8 items), behavioral engagement (5 items), and emotional engagement (5 items) were falling into one component, which explained 54.99% of the total variance.

To further verify the measurement model, we performed CFA to examine the corresponding relationship between factors and measurement items. After performing CFA, the subscale attainment & utility values, loss of valued alternatives, and emotional cost were removed from further analyses as they were not supported in the measurement model. Finally, the CFA confirmed a total of six latent variables namely attitudes, self-efficacy, intrinsic value, task effort cost, learning engagement, and perceived learning outcomes, and 31 observable indicators in total. Table 2 shows the overview of measurement instruments. Figure 3 presents the measurement model as the revised research model after CFA. The goodness-of-fit indices for the measurement model indicated a good fit with the data, $\chi^2 = 830.328$, $df = 419$, $\chi^2/df = 1.982$, CFI = 0.910, TLI = 0.900, RMSEA = 0.065, SRMR = 0.053.

Table 6 in Appendix A shows the means, standard deviations, and values of discriminant validity of the constructs in the measurement model. For each latent variable, the square root of the average variance extracted is greater than the Pearson correlation between any two latent variables, which confirmed the appropriate discriminant validity of all constructs (Fornell & Larcker, 1981). Table 7 in Appendix A shows that the convergent validity and internal reliability of all constructs were acceptable. The standardized factor loadings of all items were ranging from 0.655 to 0.883, and all items showed statistical significance at the $p < 0.001$ level. Values of composite reliability of all latent variables were above 0.900, and values of average of variance extracted of all latent variables were greater than 0.900. Furthermore, the internal reliability of all latent variables was supported by Cronbach's alpha values which range from 0.792 to 0.932, indicating all constructs have an appropriate internal consistency (Nunnally & Bernstein, 1994). All measuring instruments utilized in the current study are displayed in Table 8 in Appendix B.

Structural model

To answer RQ1 to RQ4, we implemented SEM to examine the relationships among latent variables. The goodness-of-fit indices for the structural model indicated a good fit with the data, $\chi^2 = 1.441$, $df = 1$, $\chi^2/df = 1.441$, CFI = 0.999, TLI = 0.991, RMSEA = 0.044, SRMR = 0.015. Figure 4 and Table 3 display the relationships between every two latent variables, and the strength of the path coefficients. Concerning RQ1, we found that attitudes were positively and significantly associated with

Table 2 The overview of measurement instruments

Variables	Measured factors	No. of items used	Factors kept after CFA	No. of item kept after CFA	Example of items	Source
Attitudes	Attitudes	6	Attitudes	3	I feel more motivated when I am learning in MOOCs.	Admiraal et al. (2017)
Self-efficacy	Self-efficacy	8	Self-efficacy	4	I'm confident I can do an excellent job in MOOCs.	Pintrich et al. (1991)
Task value						
	Intrinsic value	7	Intrinsic value	4	This MOOC is interesting to me.	Perez et al. (2019)
	Attainment value	4			–	
	Utility value	4			–	
Perceived cost						
	Task effort cost	5	Task effort cost	4	I have to put too much energy into this MOOC.	Flake et al. (2015)
	Loss of valued alternatives	5			–	
	Emotional cost	6			–	
Learning engagement						
	Cognitive Engagement	8	Cognitive Engagement	5	When I study this MOOC, I try to connect what I am learning with my own experiences.	Reeve and Tseng (2011); Skinner et al. (2008)
	Behavioral Engagement	5	Behavioral Engagement	4	I study this MOOC carefully.	
	Emotional Engagement	5	Emotional Engagement	3	When I study this MOOC, I feel curious about what I am learning.	
Perceived learning outcomes	Perceived learning outcomes	9	Perceived learning outcomes	4	I have understood the content and concepts in the subject matter of this MOOC.	Paechter et al. (2010)

Participants responded to all items on five-point Likert scales

self-efficacy ($\beta = 0.649$, $p < 0.001$), intrinsic value ($\beta = 0.340$, $p < 0.001$) and perceived learning outcomes ($\beta = 0.140$, $p < 0.05$), and showed a negative effect on task effort cost ($\beta = -0.190$, $p < 0.05$), but had a non-significant effect on learning engagement ($\beta = 0.072$, $p = 0.235$). Concerning RQ2, self-efficacy was to be found positively and significantly related to intrinsic value ($\beta = 0.409$, $p < 0.001$), learning engagement

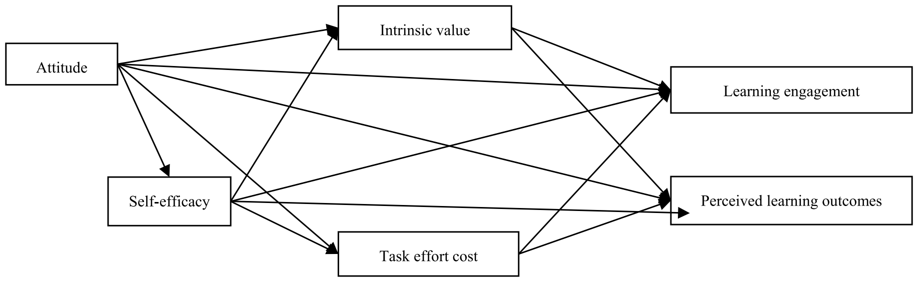

Fig. 3 The revised research model

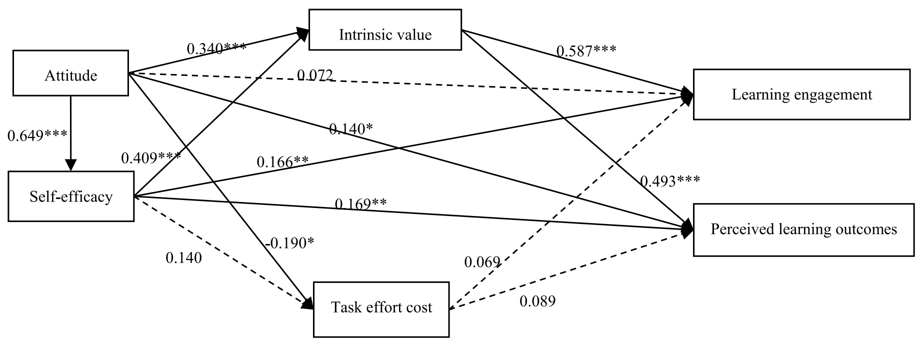

Fig. 4 The structural model. The full line indicates a significant relationship between two latent variables. The dotted line indicates a non-significant relationship between two latent variables. ***$p<0.001$. **$p<0.01$. *$p<0.05$

Table 3 Path coefficients of the structural model

Paths		*B*	SE
Independent variables	**Dependent variables**		
AT	→ SE	0.649***	0.048
	→ IV	0.340***	0.069
	→ TE	− 0.190*	0.096
	→ LENG	0.072	0.061
	→ PLO	0.140*	0.063
SE	→ IV	0.409***	0.062
	→ TE	0.140	0.102
	→ LENG	0.166**	0.063
	→ PLO	0.169**	0.061
IV	→ LENG	0.587***	0.059
	→ PLO	0.493***	0.063
TE	→ LENG	0.069	0.050
	→ PLO	0.089	0.046

AT = Attitudes, SE = Self-efficacy, IV = Intrinsic value, TE = Task effort cost, LENG = Learning engagement, PLO = Perceived learning outcomes. B indicates the strength of the path coefficients. ***$p<0.001$. **$p<0.01$.*$p<0.05$

($\beta = 0.166$, $p < 0.01$), and perceived learning outcomes ($\beta = 0.169$, $p < 0.01$), but it showed a non-significant association with task effort cost ($\beta = 140$, $p = 0.171$). When it comes to RQ3 and RQ4, the results entailed that intrinsic value had a positive and significant effect on learning engagement ($\beta = 0.587$, $p < 0.001$) and perceived learning outcomes ($\beta = 0.493$, $p < 0.001$). However, task effort cost non-significantly predicted learning engagement ($\beta = 0.069$, $p = 0.165$) and perceived learning outcomes ($\beta = 0.089$, $p = 0.054$).

Mediated relations

To examine the mediating effects of task value and perceived cost (RQ5 and RQ6), mediation analyses were performed through bias-corrected bootstrapping of 5000 samples with a 95% confidence interval. Table 4 depicts to what extent mediating variables carry the indirect effects of an independent variable on a dependent variable on each mediation path.

Regarding RQ5, the results indicated that attitudes showed slightly direct effect ($\beta = 0.144$, $p < 0.05$, 95% *CI* [0.023, 0.288]) and statistically significant indirect effect ($\beta = 0.385$, $p < 0.001$, 95% *CI* [0.301, 0.510]) on learning engagement. Self-efficacy had both a significant direct effect ($\beta = 0.197$, $p < 0.01$, 95% *CI* [0.088, 0.335]) and a significant indirect effect ($\beta = 0.385$, $p < 0.001$, 95% *CI* [0.295, 0.501]) on learning engagement. To be specific, intrinsic value significantly mediated the relationship between attitudes and learning engagement ($\beta = 0.393$, $p < 0.001$, 95% *CI* [0.316, 0.510]) as well as the relationship between self-efficacy and learning engagement ($\beta = 0.384$, $p < 0.001$, 95% *CI* [0.292, 0.497]), respectively. However, task effort cost failed to play

Table 4 Bias-corrected bootstrapped confident intervals of the total, direct and indirect effects among latent variables

Mediation path		***B***	**SE**	**95% CI for indirect effect**	
(INV → MV → DV)				**BootLLCI**	**BootULCI**
AT → LENG	Total effect	0.529***	0.057	0.414	0.655
	Total direct	0.144*	0.057	0.023	0.288
	Total indirect:	0.385***	0.047	0.301	0.510
	Specific 1: AT → IV → LENG	0.393***	0.045	0.316	0.510
	Specific 2: AT → TE → LENG	− 0.008	0.009	− 0.036	0.005
SE → LENG	Total effect	0.582***	0.053	0.472	0.711
	Total direct	0.197**	0.057	0.088	0.335
	Total indirect:	0.385***	0.047	0.295	0.501
	Specific 1: SE → IV → LENG	0.384***	0.046	0.292	0.497
	Specific 2: SE → TE → LENG	0.001	0.006	− 0.007	0.028
AT → PLO	Total effect	0.541***	0.055	0.424	0.673
	Total direct	0.214***	0.059	0.109	0.384
	Total indirect:	0.327***	0.047	0.237	0.450
	Specific 1: AT → IV → PLO	0.337***	0.044	0.254	0.451
	Specific 2: AT → TE → PLO	− 0.010	0.010	− 0.038	0.006
SE → PLO	Total effect	0.571***	0.052	0.468	0.708
	Total direct	0.231***	0.056	0.116	0.389
	Total indirect:	0.340***	0.045	0.254	0.450
	Specific 1: SE → IV → PLO	0.339***	0.043	0.257	0.448
	Specific 2: SE → TE → PLO	0.001	0.006	− 0.008	0.023

INV = Independent variable, MV = Mediating variable, DV = Dependent variable, AT = Attitudes, SE = Self-efficacy, IV = Intrinsic value, TE = Task effort cost, LENG = Learning engagement, PLO = Perceived learning outcomes. B indicates the strength of the indirect effect. ***$p < 0.001$. **$p < 0.01$. *$p < 0.05$

the mediating role in the relationship between attitudes and learning engagement ($\beta = -0.008$, $p = 0.393$, 95% CI [− 0.036, 0.005]), neither in the relationship between self-efficacy and learning engagement ($\beta = 0.001$, $p = 0.856$, 95% CI [− 0.007, 0.028]).

Regarding RQ6, it was found that both direct ($\beta = 0.214$, $p < 0.001$, 95% CI [0.109, 0.384]) and indirect effect ($\beta = 0.327$, $p < 0.001$, 95% CI [0.237, 0.450]) of attitudes on perceived learning outcomes were significant. Moreover, self-efficacy had both significant direct ($\beta = 0.231$, $p < 0.001$, 95% CI [0.116, 0.389]) and significant indirect effect ($\beta = 0.340$, $p < 0.001$, 95% CI [0.257, 0.448]) on perceived learning outcomes. When looking at the specific mediation paths, the results documented that the relationship between attitudes and perceived learning outcomes was significantly mediated only through intrinsic value ($\beta = 0.337$, $p < 0.001$, 95% CI [0.254, 0.451]), and the indirect effect of intrinsic value between self-efficacy and perceived learning outcomes showed statistical significance ($\beta = 0.339$, $p < 0.001$, 95% CI [0.257, 0.448]). Nevertheless, the indirect effect of self-efficacy on learning engagement ($\beta = 0.010$, $p = 0.001$, 95% CI [− 0.007, 0.028]) and perceived learning outcomes ($\beta = 0.001$, $p = 0.840$, 95% CI [− 0.008, 0.023]) through task effort cost were non-significant.

Moderated relations

We performed moderation analyses to all paths. Since the non-significant mediating effects of task effort cost were found on all mediation paths, we speculated that the interaction effects between task effort cost and other variables might exist. To verify this hypothesis, moderation analyses were implemented with task effort cost as the moderator and intrinsic value as the covariate variable for all these paths. The results in Table 5 show that attitudes by task effort cost is an interaction variable that significantly influenced learning engagement ($\beta = -0.092$, $p = 0.005$, 95% CI [− 0.155, − 0.029]) and perceived learning outcomes ($\beta = -0.075$, $p = 0.036$, 95% CI [− 0.146, − 0.005]). Attitudes were also found to be a positive predictor of learning engagement ($\beta = 0.442$, $p < 0.001$, 95% CI [0.231, 0.653]) and perceived learning outcomes ($\beta = 0.403$, $p < 0.001$, 95% CI [0.169, 0.638]). Specifically, the results suggest that the lower the task effort cost, the stronger the correlations of attitude with learning engagement and perceived learning outcomes in MOOC learning (See Figs. 5 and 6). However, the interaction variable of self-efficacy by task effort cost shows non-significant relationships with learning engagement and perceived learning outcomes, which indicates there are no moderating effects

Table 5 Results of moderation analyses of task effort cost

	Learning engagement				Perceived learning outcomes			
			95% CI for main & moderating effects				95% CI for main & moderating effects	
Dependent variables	***B***	**SE**	**BootLLCI**	**BootULCI**	**B**	**SE**	**BootLLCI**	**BootULCI**
Attitudes	0.442***	0.107	0.231	0.653	0.403***	0.119	0.169	0.638
Self-efficacy	0.424***	0.122	0.183	0.665	0.420**	0.138	0.148	0.692
Attitudes × task effort cost	− 0.092**	0.032	− 0.155	− 0.029	− 0.075*	0.036	− 0.146	− 0.005
Self-efficacy × task effort cost	− 0.058	0.038	− 0.133	0.017	− 0.071	0.043	− 0.156	0.013

Moderator = Task effort cost, Covariate = Intrinsic value. ***$p < 0.001$. **$p < 0.01$. *$p < 0.05$

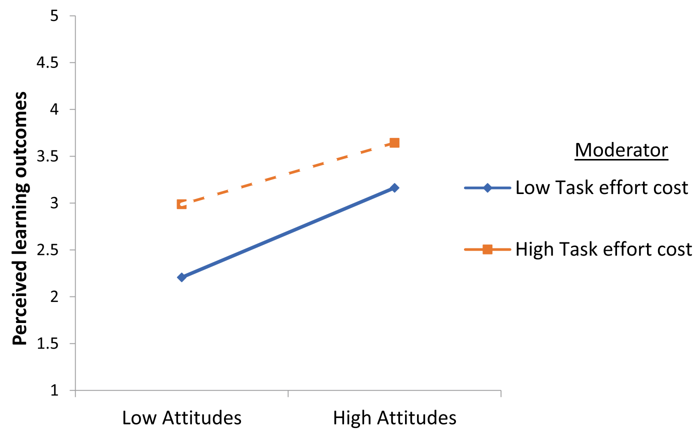

Fig. 5 Moderating effect of the task effort cost on the relationship between attitudes and learning engagement

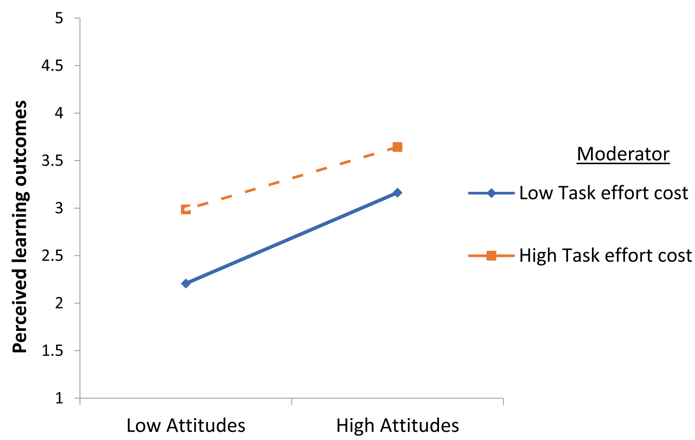

Fig. 6 Moderating effect of the task effort cost on the relationship between attitudes and perceived learning outcomes

of task effort cost on the relationship between self-efficacy, learning engagement, and perceived learning outcomes.

Discussion

In the current study, we examined the relationships between attitudes/motivation and learning engagement/perceived learning outcomes in MOOC learning. Specifically, we estimated how attitudes, self-efficacy, task value, and perceived cost relate to (1) learning engagement and (2) perceived learning outcomes, (3) the mediating role of task value and perceived cost in the relationships between attitudes/self-efficacy and learning engagement/perceived learning outcomes, and (4) the moderating role of task effort cost in the relationships between attitudes/self-efficacy and learning engagement/perceived learning outcomes. The current study makes several contributions to the literature on MOOC learning. First, self-efficacy and intrinsic value were found to be the two significant factors that related to participants' engagement in MOOC learning. Second, self-efficacy and intrinsic value were found to be also positively associated with perceived learning outcomes in MOOCs. Third, attitudes served as the precursor of participation in MOOCs, which extended knowledge about attitudes being a vital factor to impact self-efficacy, intrinsic value, task effort cost, and perceived learning outcomes. Fourth, we have shown a mediating role of intrinsic value in the relationships between attitudes/self-efficacy and learning engagement/perceived learning outcomes, highlighting the critical mediating role of intrinsic value in MOOC learning. Fifth, we contribute to the literature that the relationships between attitude and learning engagement/perceived learning outcomes vary in task effort cost. The main findings are summarized and discussed below.

Attitudes as the precursor of participation in MOOCs

The strong relationship between attitudes and self-efficacy suggests that MOOC learners with positive attitudes toward MOOC learning are more likely to demonstrate a higher level of self-efficacy for MOOC learning. Similarly, Prior et al. (2016) conducted a study with participants who enrolled in online distance courses at high costs offered by a business school, and they discovered that attitudes were a positive significant predictor of self-efficacy. Compared with Prior et al. (2016), our investigation approached learners who attended MOOCs for free or at affordable cost, and the effect of attitudes on self-efficacy was even stronger. This strong relationship between attitudes and self-efficacy, together with the significant relationship of attitudes with intrinsic value (positive) and task effort cost (negative) suggest that attitudes served as the precursor of motivational beliefs in MOOC context. Moreover, as in Albelbisi (2020), attitudes were also significantly associated with perceived learning outcomes.

The importance of self-efficacy for learning in MOOCs

The importance of self-efficacy for the extent in which participants are engaged in learning and perceived that they have learned relevant knowledge and skills is confirmed in this study. This importance of self-efficacy in learning engagement (Jung & Lee, 2018; Min & Foon, 2019) and perceived learning outcomes (Lee et al., 2020b; Rabin et al., 2020) was already established in previous work. But what the current study adds is the strong relationship between self-efficacy and intrinsic value. This finding suggests that self-efficacious MOOC learners are more motivated to undertake academic tasks in MOOCs.

The substantial direct and mediating effects of intrinsic value on learning in MOOCs

The strong association between intrinsic value and learning engagement aligns with the results of previous studies (Liu et al., 2023; Sun et al., 2019) indicating that intrinsic value is a positive incentive for learning engagement in MOOCs. Corresponding with the results of Artino's prior work in online learning (Artino, 2008, 2009), the more learners were motivated by intrinsic value, the greater their perceived learning outcomes. In addition to these significant associations, the current study highlights the powerful effects of intrinsic value on learning engagement and perceived learning outcomes, which suggests that learners' intrinsic value might effectively contributes to greater learning engagement and perceived learning outcomes in MOOCs.

The results of mediation analyses revealed that intrinsic value had substantial mediating effects on the relationships between attitude and self-efficacy, on the one hand, and learning engagement and perceived learning outcomes, on the other, in MOOC learning. Thus, it means that learners who are with positive attitudes and are self-efficacious show relatively greater learning engagement and perceived learning outcomes because they are more internally interested in the MOOC. The mediation results highlight that within the asynchronous learning environment in MOOCs, intrinsic value is substantially influential in fostering learning engagement and perceived learning outcomes.

Task effort cost as a moderator in the relationship between attitudes, learning engagement, and perceived learning outcomes in MOOCs

The non-significant correlation between task effort cost and learning engagement contradicts the results of Santosa (2015), who discovered a negative relationship between task effort cost and learning engagement in online tutorial activities. Within a different context from our study, where self-paced teaching and learning occur asynchronously, and the content delivered online, in that study students who perceived a relatively high level of effort cost to be paid were more likely to be less engaged with online tutorial activity. However, Santosa (2015) implemented a laboratory experiment with a single online tutorial activity regarding reading course materials instead of a MOOC with a series of learning activities. In our model, intrinsic value (positive) might take away the direct effect (negative) of task effort cost on learning engagement as its substantial direct and mediating effects on learning engagement. Possibly, one explanation might be that learners' perceptions of interest and enjoyment in a MOOC affect whether they perceive this MOOC as too effortful. In addition, the current study found a non-significant association between task effort cost and perceived learning outcomes. There is no other research that has investigated this correlation in MOOCs, but Perez et al. (2019) investigated the relationship of task effort cost with learning outcomes in an undergraduate biology course on campus. Perez et al. (2019) indicated that task effort cost was a negative contributor to final biology grades, which confirms the negative association between task effort cost and learning outcomes in the campus context. Unlike the study of Perez et al. (2019), we asked students to self-report their subjective perceptions of what they have learned something from a MOOC other than course grades. The findings of Perez et al. (2019) and the current study suggested that task effort cost can directly reveal the individual difference in course grades, but it cannot validly and solely explain individual subjective perceptions of learning outcomes. For these MOOC learners in our study, the effect of task effort cost needs to be considered under the interaction we discovered between subjective belief and task effort cost in relation to learning engagement and perceived learning outcomes. Task effort cost manifests the negative incentive of a MOOC, however, how it correlates to learning engagement and perceived learning outcomes still needs further exploration.

The findings of moderation analyses imply that at a low task effort cost, MOOC learners with positive attitudes are more engaged with academic tasks and have greater perceived learning outcomes, compared to the other learners. Perceiving a high task effort cost can disrupt the contribution of positive attitudes to learning engagement and perceived learning outcomes. The moderation analyses extend the knowledge of the moderating role of task effort cost in influencing individual perceptions of MOOC learning. For example, the main effect of task effort cost was confirmed in the study of Zielinski et al. (2019) that learners who perceived high-cost more frequently reported barriers that impact their learning engagement and success in a MOOC. Our findings indicate that task effort cost is a critical aspect of the motivational beliefs that would influence MOOC learners' participation. What the current study adds to the literature is that the effects of attitudes on learning engagement and perceived learning outcomes vary with task effort cost.

Practical implications

Based on the main findings of this research, we offer three practical implications for stimulating learning engagement and perceived learning outcomes in MOOCs, which are elaborated below.

Firstly, it is essential to encourage learners to have positive attitudes toward learning in MOOCs since positive attitudes support self-efficacy and intrinsic value, which in turn further fosters learning engagement and perceived learning outcomes. To this end, for example, cultivate MOOC learners' sense of community, encouraging learners to interact with peers and instructors through peer review assignments, collaborative coursework, and discussion forums. For example in MOOC discussion forums, Ramesh et al. (2014) discovered that learners' attitudes have changed to be positive when their posts get responded to and resolved in discussion forums. Positive interactions in the learning community can be effective to make MOOC learners feel more connected and sustain their motivation to learn the course.

Second, self-efficacy is a modifiable and task-oriented set of beliefs (Margolis & McCabe, 2003), therefore, we recommend curriculum instructors and designers support learners' efficacy expectations of performance resulting in them feeling more confident and motivated in MOOC learning. According to Bandura (1977) self-efficacy can be modified through several methods, such as performance accomplishments, vicarious experience, and verbal persuasion. First, performance accomplishments can raise learners' perceived mastery expectations. In learning tasks of a MOOC, instructors can offer learners successive levels of challenges from easy to difficult, which enables learners to acquire new subject knowledge built on their mastered knowledge. Learners would perceive the cumulated accomplishments when they address these challenges successfully, which could benefit learners to become self-efficacious for onward learning tasks. Second, vicarious experiences, or observing others perform a task or achieve a goal, can be a powerful tool in enhancing students' self-efficacy. In the sharing section, it is suggested to encourage MOOC learners to share experiences in how to overcome difficulties with sustained effort to complete learning tasks or achieve learning goals, together with clear outcomes of their success stories, such as credit recognition, professional development, and earned promotions. These exemplifications might be helpful in inspiring learners to see their own possibilities of succeeding in MOOC learning. Third, verbal persuasion, or receiving encouragement and constructive positive feedback from others, can be helpful to progressively enhance learners' performance capabilities. In the peer review assessments of a MOOC, the instructors embed well-designed rubrics that could guide learners in providing peers with effective feedback.

Third, one suggestion to motivate MOOC learners through intrinsic value could be to apply need supportive teaching (Leenknecht et al., 2017) that focuses on learners' psychological needs for autonomy, competence, and relatedness. To support MOOC learners' autonomy, for example, goal setting can be adopted to encourage individuals to formulate personal goals and enable them to choose valuable learning activities to shape learning paths. The need for competence refers to learners' experience of the effectiveness of competence growth, which is similar to learners' efficacy expectations. The proposals mentioned above for enhancing self-efficacy are also practical to fulfill the need for competence. Meanwhile, considering problem-centeredness for MOOC learning activities could be an effective principle to enhance learners' feelings of competence. Specifically, introducing learning activities with problem complexity-differentiation might cultivate learners' competence in multiple aspects, such as factual knowledge, procedural knowledge and competence, performance, and application of knowledge and skills. Furthermore, the sense of relatedness can be enhanced through teacher-learner and learner-learner interactions, such as supported and trained peer activities, and structured interaction and communication in MOOC discussion forums.

Limitations and future research

Despite that the current study has gained insight into factors impacting learning engagement and perceived learning outcomes in MOOCs, several limitations of the study should be mentioned. Firstly, we collected quantitative data on perceived influential factors, learning engagement, and perceived learning outcomes via structured questionnaires. To understand the individual differences in learning engagement and perceived learning outcomes more thoroughly, future research could consider gathering additional qualitative data from focus group interviews or in-depth interviews. The interviews aim to reveal detailed explanations to understand the results and explore new points through open-ended questions. That allows researchers to take a closer look at individual perceptions of MOOC learning.

Second, the data collected of this study could not fully support all hypothesized relationships in the proposed research model (Fig. 1). We could not gain insight into how the subfactors of task value (i.e., attainment value, and utility value) and perceived cost (i.e., loss of valued alternatives, and emotional cost) affect learning engagement and perceived learning outcomes, because these subfactors dropped from the original research model after EFA and CFA. Our findings of mediation and moderation analyses suggest that motivational beliefs play different roles in influencing learning in MOOCs. Future MOOC research might adopt a mixed method, i.e., survey investigation (quantitative) and interviews (qualitative), to add more empirical evidence on what roles of other aspects of task value and perceived cost play in influencing learning engagement and perceived learning outcomes.

Third, although this study estimated the correlations between influential factors and learning engagement and perceived learning outcomes, it cannot reveal the causal relationships between independent and dependent variables. Future studies may adopt an experimental design to examine the causal relationships between independent variables (i.e., attitudes, and motivation) and dependent variables (i.e., learning engagement, and perceived learning outcomes).

Fourth, attitudes and motivation were measured at the same time as the measurement of the other variables, which examined MOOC learners' retrospective view of the learning in MOOCs. We could not capture the attitudes and motivation at the time when MOOC learners started learning the course. Perez et al. (2019) found dynamic relationships among motivational beliefs of expectancy-value over the entire course period, and the interplay of these motivational beliefs was related to the final biology grades. A meaningful direction for future MOOC research could be employing longitudinal approaches to examine the dynamic relationships among motivational beliefs over the course period and how these relationships influence learning engagement and perceived learning outcomes.

Conclusions

The current study addressed the gap in the literature on how attitudes and self-efficacy influence learning engagement and perceived learning outcomes in MOOCs, and the mediating role of intrinsic value and the moderating role of task effort cost in these relationships. Firstly, this study established that MOOC learners' attitudes and self-efficacy did have significant and positive effects on their learning engagement and perceived learning outcomes. Second, the findings highlight the considerable importance of intrinsic value in MOOC learning as it powerfully meditated the relationships between attitudes and self-efficacy on the one hand, and learning engagement and perceived learning outcomes on the other hand. Third, task effort cost was a significant moderator, which influenced the strength of the effects of attitudes on learning engagement and perceived learning outcomes. Based on our findings, we suggest cultivating MOOC learners' sense of community through peer review assignments, collaborative coursework, and discussion forums, which would be helpful for promoting positive attitudes toward MOOC learning. Moreover, aiming at enhancing MOOC learners' self-efficacy, curriculum instructors and designers can employ methods such as performance accomplishments, vicarious experience, and verbal persuasion to make them feel more confident and motivated in MOOC learning. Finally, fulfilling MOOC learners' psychological needs for autonomy, competence, and relatedness through need-supportive teaching can be an effective way to arouse intrinsic value.

Appendix A

See Table 6 and Table 7.

Table 6 Descriptive statistics and discriminant validity

Construct	Mean	SD	Skewness	Kurtosis	AVE	AT	SE	IV	TE	LE	PLO
AT	3.529	0.818	− 0.751	0.397	0.957	**0.978**					
SE	3.700	0.628	− 1.028	2.367	0.936	0.351	**0.967**				
IV	3.563	0.778	− 0.790	1.312	0.950	0.349	0.327	**0.975**			
TE	2.981	0.834	0.056	− 0.326	0.953	− 0.066	0.010	0.008	**0.976**		
LENG	3.752	0.565	− 0.920	3.216	0.944	0.213	0.218	0.287	0.035	**0.972**	
PLO	3.745	0.606	− 0.663	1.580	0.952	0.211	0.203	0.255	0.036	0.226	**0.976**

AT = Attitudes, SE = Self-efficacy, IV = Intrinsic value, TE = Task effort cost, LENG = Learning engagement, PLO = Perceived learning outcomes. Boldface elements on the diagonal are the square root of the average variance extracted

Table 7 Convergent validity and internal reliability

Constructs	Parameters of significant test		Composite reliability	Average of Variance Extracted	Cronbach's a
	Factor loading	Measurement error			
AT			0.985	0.957	0.807
AT1	0.764***	0.034			
AT2	0.782***	0.031			
AT3	0.883***	0.024			
SE			0.983	0.936	0.792
SE5	0.700***	0.041			
SE6	0.738***	0.037			
SE7	0.779***	0.033			
SE8	0.725***	0.038			
IV			0.987	0.950	0.897
IV1	0.818***	0.024			
IV3	0.690***	0.039			
IV4	0.819***	0.027			
IV7	0.745***	0.034			
TE			0.988	0.953	0.835
TE2	0.813***	0.030			
TE3	0.797***	0.031			
TE4	0.785***	0.032			
TE5	0.783***	0.032			
LENG			0.952	0.944	0.932
CE2	0.692***	0.036			
CE3	0.760***	0.030			
CE6	0.731***	0.032			
CE7	0.734***	0.032			
CE8	0.794***	0.026			
BE1	0.822***	0.023			
BE2	0.697***	0.036			
BE4	0.703***	0.035			
BE5	0.655***	0.039			
EE1	0.770***	0.029			
EE2	0.749***	0.031			
EE3	0.688***	0.037			
PLO			0.988	0.952	0.862
PLO1	0.726***	0.034			
PLO3	0.826***	0.025			
PLO4	0.809***	0.027			
PLO7	0.725***	0.034			

AT = Attitudes, SE = Self-efficacy, IV = Intrinsic value, TE = Task effort cost, LENG = Learning engagement, CE = Cognitive engagement, BE = Behavioral engagement, EE = Emotional engagement, PLO = Perceived learning outcomes. ***$p < 0.001$

Appendix B

See Table 8.

Table 8 Items assessed for each variable

Variable	No.	Item
Attitudes	AT1	Learning in MOOCs makes my study more satisfying.
	AT2	I like learning in MOOCs.
	AT3	I feel more motivated when I am learning in MOOCs.
	AT4	Because of learning in MOOCs, my study becomes more efficient.
	AT5	Learning in MOOCs in an effective way enhances my learning productivity.
	AT6	Learning in MOOCs improves my academic performance.
Self-efficacy	SE1	I believe I can learn a lot in MOOCs.
	SE2	I'm certain I can understand the most difficult material presented in MOOCs.
	SE3	I'm confident I can learn the basic concepts taught in MOOCs.
	SE4	I'm confident I can understand the most complex material presented in MOOCs.
	SE5	I'm confident I can do an excellent job in MOOCs.
	SE6	I expect to do well in MOOCs.
	SE7	I'm certain I can master the skills being taught in MOOCs.
	SE8	Considering the difficulty of MOOCs and my skills, I think I can do well in MOOCs.
Task value		
Intrinsic value	IV1	This MOOC is interesting to me.
	IV2	I find studying for this MOOC is interesting.
	IV3	Compared to other courses, I like this MOOC very much.
	IV4	I am fascinated by this MOOC.
	IV5	I enjoy this MOOC.
	IV6	This MOOC is exciting to me.
	IV7	I like this MOOC.
Attainment value	AV1	Being good at solving problems in this MOOC is important to me.
	AV2	Compared to other courses, doing well in this MOOC is important to me.
	AV3	Being someone who does well at this MOOC is important to me.
	AV4	Doing well at this MOOC is an important part of who I am.
Utility value	UV1	This MOOC is useful for what I want to do after I graduate.
	UV2	This MOOC will be important when I get a job or go to graduate school.
	UV3	This MOOC will be useful for me later in life.
	UV4	What I am learning in this MOOC is useful because they will help me in the future.
Cost		
Task effort cost	TE1	This MOOC demands too much of my time.
	TE2	I have to put too much energy into this MOOC.
	TE3	This MOOC takes up too much time.
	TE4	This MOOC is too much work.
	TE5	This MOOC requires too much effort.
Loss of valued alternatives	LV1	I have to sacrifice too much to be in this MOOC.
	LV2	This MOOC requires me to give up too many other activities I value.
	LV3	Taking this MOOC causes me to miss out on too many other things I care about.
	LV4	I can't spend as much time doing the other things that I would like because I am taking this MOOC.
	LV5	I pay attention to this MOOC.

Table 8 (continued)

Variable	No.	Item
Emotional cost	EC1	I worry too much about this MOOC.
	EC2	This MOOC is too exhausting.
	EC3	This MOOC is emotionally draining.
	EC4	This MOOC is too frustrating.
	EC5	This MOOC is too stressful.
	EC6	This MOOC makes me feel too anxious.
Learning engagement		
Cognitive engagement	CE1	When doing coursework in this MOOC, I try to relate what I'm learning to what I already know.
	CE2	When I study this MOOC, I try to connect what I am learning with my own experiences.
	CE3	I try to make all the different ideas fit together and make sense when I study this MOOC.
	CE4	I make up my own examples to help me understand the important concepts I study in this MOOC.
	CE5	Before I begin to study this MOOC, I think about what I want to get done.
	CE6	When I'm working on my coursework in this MOOC, I stop once in a while and go over what I have been doing.
	CE7	As I study this MOOC, I keep track of how much I understand, not just if I am getting the right answers.
	CE8	If what I am learning in this MOOC is difficult to understand, I change the way I learn the material.
Behavioral engagement	BE1	I study this MOOC carefully.
	BE2	I try hard to do well in this MOOC.
	BE3	When I start a new topic in this MOOC, I learn it very carefully.
	BE4	I work hard when I start something new in this MOOC.
	BE5	I pay attention to this MOOC.
Emotional engagement	EE1	I enjoy learning new things in this MOOC.
	EE2	When I work on something in this MOOC, I feel interested.
	EE3	When I study this MOOC, I feel curious about what I am learning.
	EE4	This MOOC is fun.
	EE5	When I work on something in this MOOC, I get involved.
Perceived learning outcomes	PLO1	I have understood the content and concepts in the subject matter of this MOOC.
	PLO2	I have learned the knowledge taught in the subject matter of this MOOC.
	PLO3	This MOOC expands my knowledge of the subject.
	PLO4	I have developed skills on how to apply the knowledge in this MOOC.
	PLO5	I have developed the skills of communication and cooperation in this MOOC.
	PLO6	I have developed the skills of self-regulated learning in this MOOC.
	PLO7	I am pleased with what I learned in this MOOC.
	PLO8	I am appreciated the interaction with the instructor in this MOOC.
	PLO9	I am appreciated the interaction with peer students in this MOOC.

Note: Participants scored all items on Five-point Liker scales: Attitudes（1 - Completely inapplicable to 5 - Completely Applicable), Self-efficacy（1 - Very untrue of me to 5 - Very true of me), Task value (1 - Strongly Disagree to 5 - Strongly Agree), Cost (1 - Strongly Disagree to 5 - Strongly Agree), Learning engagement (1 - Strongly Disagree to 5 - Strongly Agree), Perceived learning outcomes (1 - Strongly Disagree to 5 - Strongly Agree)

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Author contributions

XW: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing—original draft, Writing—review and editing, Visualization, Funding acquisition, Project administration. NS: Conceptualization, Methodology, Formal analysis, Writing—review and editing, Supervision, Project administration. WA: Conceptualization, Methodology, Formal analysis, Writing—review and editing, Supervision, Project administration.

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Declarations

Competing interest

The authors declare that they do not have any competing interests.

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