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Do learners share the same perceived learning outcomes in MOOCs? Identifying the role of motivation, perceived learning support, learning engagement, and self-regulated learning strategies

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ABSTRACT

The aim of this study was to examine how motivation, perceived learning support, learning engagement, and self-regulated learning strategies relate to learners' perceived learning outcomes of massive open online courses (MOOCs). An online survey was administered to 546 participants from four MOOCs. Seven types of reasons for attending MOOCs were identified, ranging from intrinsic to extrinsic motivation. One-way MANOVA revealed that learners with autonomous motivation demonstrate higher scores on perceived learning outcomes than learners with controlled motivation. In addition, multiple regression analysis methods showed that course design, interaction with instructors and peers, engagement in learning activities, and applying cognitive and metacognitive learning strategies significantly explain differences in perceived learning outcomes. Furthermore, mediation analyses demonstrated that cognitive and metacognitive learning strategies significantly mediated the relationships between motivation, perceived learning support, and learning engagement on the one hand and perceived learning outcomes on the other. Finally, practical implications are discussed and future research directions are recommended.

1. Introduction

Massive open online courses (MOOCs) offer learners ample opportunities to access courses covering a wide range of disciplines within tertiary education for free or at affordable costs. The openness of MOOCs attracts a diversity of learners, and its flexibility enables learners to engage in a series of learning activities, such as video lectures, discussion forums, and peer review and to fulfill their learning goals without any restrictions of time and place (Baturay, 2015). Unlike conventional campus education, learning in MOOCs is generally more learner-determined, and the motivation of learners is more diverse. Aiming at pursuing full course completion or high academic achievement is not the predominant motivation for all learners (Littlejohn, Hood, Milligan, & Mustain, 2016), therefore, course completion rates and academic achievement are fairly low (Henderikx, Kreijns, & Kalz, 2017; Rabin, Kalman, & Kalz, 2019). Retention (e.g., course completion, attrition, and dropout rates) and academic outcomes have been primarily examined as the proxy of learning outcome variables (Deng, Benckendorff, & Gannaway, 2019), which perhaps does not reveal the real picture of individual learning gains from MOOCs. A recent MOOC review study found that increasing attention focuses on perceived learning outcomes (Wei, Saab, & Admiraal, 2021), which might be a better perspective to investigate how individuals value their learning gains to interpret learner-determined learning in MOOCs.

Previous studies on MOOC learning have determined that several important factors in terms of motivation, perceived learning support, learning engagement, and self-regulated learning strategies significantly explained learning outcomes in a MOOC (e.g., Albelbisi, Yusop, & Salleh, 2018; Handoko, Gronseth, McNeil, Bonk, & Robin, 2019; Hood & Littlejohn, 2016a). As one of the antecedents of participation, motivation refers individuals' learning goals, which then drive them to reach their intended achievement. Yet whatever learners' motivation is, perceived learning support, such as structured course design and effective interactions with instructors and peer learners, contributes to successful online learning (Albelbisi et al., 2018; Brophy, 2000; Narciss, Proske, & Koerndle, 2007). Pre-prepared video lectures and learning materials create an asynchronous space where it is challenging to offer learners adequate learning support by providing access to synchronous

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instructions and interaction with instructors and peers (Oh, Chang, & Park, 2020). Therefore during this self-paced learning process, being engaged in a MOOC is essential to understand knowledge and master skills. Learning engagement was found to be significantly and negatively correlated with dropout (e.g., De Freitas, Morgan, & Gibson, 2015), and positively to course grades (e.g., Lan & Hew, 2020). In lacking instructors' direct monitoring, learners' self-regulation is crucial when interacting with pre-prepared video lectures and learning tasks. The use of self-regulated learning strategies shapes personalized learning paths, and learners with a higher level of capability in self-regulated learning are more likely to complete courses and achieve better academic outcomes (e.g., Min & Nasir, 2020). Given learners are required to self-regulate their learning in the asynchronous learning environment of MOOCs, it is necessary to examine the role of self-regulated learning in influencing perceived learning outcomes. Considering the diverse learning needs of learners and the learner-determined learning process in MOOCs, more research is required to better understand the interplay between learner motivation, perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. Therefore, to gain insights into the mechanics of perceived value for learners, firstly, the current study investigates to what extent motivation impacts perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. Furthermore, we examine the mediating role of self-regulated learning strategies in the relationships between motivation, perceived learning support, learning engagement, on the one hand, and perceived learning outcomes, on the other hand.

2. Literature review

Previous studies have identified that motivation, perceived learning support, learning engagement, and self-regulated learning strategies are vital factors to succeed in MOOC learning (e.g., Hood & Littlejohn, 2016a). Aiming at clarifying how factors influence learners' perceived learning outcomes, we begin with the antecedents of participation. Learners who sign up for MOOCs differ in personal motivation, which mobilizes, directs, and impacts their learning behavior and perceived learning outcomes (Deci & Ryan, 2000; Wei, Saab, & Admiraal, 2021). During the learning process, perceived learning support, learning engagement, and self-regulated learning determine how the process of learning develops and results in learners' perceived learning outcomes (Paechter, Maier, & Macher, 2010; Pintrich, 1999; Pintrich & De Groot, 1990; Pintrich, Smith, Garcia, & McKeachie, 1991; Wei, Saab, & Admiraal, 2021). All explanatory variables mentioned above will be elaborated below.

2.1. Motivation

Motivation is defined as the impetus to activate a person toward performing a behavior or actions (Ryan & Deci, 2000). According to Deci and Ryan (1985b), intrinsic motivation and extrinsic motivation are distinguished based on the reasons or goals for doing something, which indicates that individuals are mobilized to act by distinct motivational orientations ranging from internalization to behavioral regulation. Intrinsic motivation drives one's performance to respond to the personal inherent motivational resources (e.g., interest, pleasure, and enjoyment). Extrinsic motivation refers to taking actions for reasons that are induced by exogenous demands or others, comprising four underlying regulations varying from a low to a high degree of autonomy: external regulation (e.g., rewards and punishment), introjected regulation (e.g., senses of guilt and shame), identified regulation (e.g., personal importance), and integrated regulation (e.g., personal identified values and needs; Deci, Eghrari, Patrick, & Leone, 1994; Ryan & Connell, 1989; Ryan & Deci, 2002). Following the controlled-to-autonomous continuum, three motivational profiles emerged: impersonal (i.e., amotivation), controlled (i.e., introjected and external regulation), and autonomous motivation (i.e., intrinsic, integrated, and identified regulation; Deci & Ryan, 1985a, 1987). Learners are driven by diverse motivation to attend MOOCs, such as personal enjoyment, satisfying curiosity, the acquisition of knowledge and skills gains, educational achievement, professional advancement, personal development, relevance to career, and social connection (Littlejohn et al., 2016; Luik et al., 2019; Milligan & Littlejohn, 2017; Watted & Barak, 2018). These prior studies further suggested that motivation for participation in MOOCs is more personalized and goes beyond just succeeding in course completion and academic grades. Several studies show that autonomous motivation (e.g., initial interest, curiosity, development of knowledge and expertise) positively predicted satisfaction, the intention to use MOOCs, and the use of self-regulated learning skills (Littlejohn et al., 2016; Maya-Jariego, Holgado, González-Tinoco, Castaño-Muñoz, & Punie, 2020; Pozón-López, Higueras-Castillo, Muñoz-Leiva, & Liébana-Cabanillas, 2021). In a study by Semenova (2020), more learners who are intrinsically motivated (e.g., personal interest, curiosity, and enjoyment) completed the particular MOOC compared to university-affiliated learners, who are externally motivated by earning a certificate. Additionally, Rabin, Henderikx, Yoram, and Kalz (2020) pointed out that learners with extrinsic motivation show less tolerance to barriers faced in MOOCs. There were more possibilities for learners driven by external rewards to face barriers when attending a MOOC. For example, these learners were confronted with barriers related to inadequate prior knowledge of learning content and reduced abilities to cope with technical problems in online learning, which were negative to learner satisfaction. The above-mentioned studies suggest that learners' motivation for attending a MOOC can be diverse from extrinsic motivation to intrinsic motivation. The underlying regulations of extrinsic and intrinsic motivation vary from a low to high degree of autonomy, which generates learner profiles of motivation namely impersonal, controlled, and autonomous motivation (Deci & Ryan, 1985a, 1987). Based on prior findings, a further focus on the learning of learners with shared quality of motivation is needed to characterize learner profiles of motivation and how motivation predicts individual perceived learning outcomes in MOOCs.

2.2. Perceived learning support

Perceived learning support refers to learners' perceptions of receiving learning support from course instruction, instructors, and peers when learning in a MOOC. Perceived learning support can be structured by four components: course design, interaction with instructors, interaction with peer students, and learner autonomy (Paechter et al., 2010).

The quality of course design is a factor that facilitates learning outcomes in MOOCs. Specifically, participants are more likely to engage in learning actively and meaningfully if curriculum content and learning materials are well structured for coherent learning (Brophy, 2000). Explicit illustration of instructional objects and required effort helps learners to realize learning outcomes efficiently in MOOCs (Barman, Naimi-Akbar, & Jansson, 2019; Pilli & Admiraal, 2017). Moreover, a user-friendly platform has a positive influence on learner perceptions of course satisfaction (Joo, So, & Kim, 2018). Interactions between instructors and learners or among learners (e.g., in discussion forums, peer-review tasks, or group work) may benefit learners' construction of knowledge and social connections and communication. Instructors can offer learners pedagogical, social, managerial, and technical online support, which contributes to the construction, processing, and enhancement of knowledge as well as engaging participants in learning (Berge, 1995; Hew, 2016). Learners' mutual interactions in discussion forums, providing peer-review feedback, cooperation in group work, and exchanging individual information significantly predict learning performance (Huisman, Admiraal, Pilli, van de Ven, & Saab, 2018; Kurucay, 2015; Kurucay & Inan, 2017). As these studies indicated, both learner-learner and learner-instructor interactions have positive consequences for learning outcomes. Concerning learner autonomy, MOOCs enable learners to be flexible in terms of time and space, as well as to take decisions for a personalized learning pace and learning strategies (Littlejohn et al., 2016). Furthermore, learners can decide to use ample learning opportunities, such as practices, application, and test attempts, which are beneficial for learners to reach better individual learning outcomes (e.g., Abbakumov, Desmet, & Van den Noortgate, 2020; Margaryan, Bianco, & Littlejohn, 2015).

2.3. Learning engagement

Existing studies of learner engagement in MOOCs have revealed that learners' engagement with learning activities (e.g., video lectures, discussion forums, peer review, course assessments) influences their learning outcomes. Studies that adopted educational data mining and learning analytics showed that participants were more actively engaged in learning activities, such as discussion forums, assignment submissions, and video lectures, they could achieve better grades and higher course completion rates (Tang, Xing, & Pei, 2018; Tseng, Tsao, Yu, Chan, & Lai, 2016; Wise & Cui, 2018). Similar findings have been found by researchers who utilized other quantitative methods to measure learning engagement (e.g., Bonafini, Chae, Park, & Jablokow, 2017; Chiu & Hew, 2018; Crossley, Paquette, Dascalu, McNamara, & Baker, 2016). Their findings revealed that the number of videos watched, course pages viewed, posts/comments in discussion forums, and assignment submissions strongly predicted course completion and academic achievement. Similar findings have been found for learners who were engaged in peer-review activities (Elizondo-Garcia & Gallardo, 2020; Yurdabakan, 2016).

2.4. Self-regulated learning strategies

Self-regulated learning has been conceptualized and interpreted in various theories and models (Panadero, 2017). Following Pintrich's model, self-regulated learning refers to learners employing cognitive (i.e., rehearsal, elaboration, organization, and critical thinking), metacognitive (i.e., planning, monitoring, and regulating), and resource management strategies (i.e., time and study environment, effort regulation, peer learning, and help seeking) to regulate learning on their own (Pintrich & De Groot, 1990). In the online learning environment, researchers highlighted that it is essential for learners to engage in self-regulated learning (e.g., Jansen, van Leeuwen, Janssen, Conijn, & Kester, 2020), which significantly relates to learning outcomes. For example, in a study by Cheng and Chau (2013), students' self-regulated learning capabilities were examined in a language program. The findings showed that five strategies (i.e., elaboration, organization, critical thinking, metacognitive self-regulation, and peer learning) were positively correlated with the scores of e-Portfolio achievement. Broadbent and Poon (2015) reviewed 12 studies published between 2004 and 2014 and concluded that self-regulated learning strategies, such as critical thinking, metacognition, time management, and effort regulation, significantly predicted the academic outcomes of online learning. According to prior research, several self-regulated learning strategies were identified as predictors of learning outcomes in MOOC learning, namely goal setting, help-seeking, effort regulation, and time management (Kizilcec, Pérez-Sanagustín, & Maldonado, 2016; Littlejohn et al., 2016; Milligan & Littlejohn, 2016; Nawrot & Doucet, 2014). Moreover, Lee, Watson, and Watson (2020) discovered that time management, environmental structuring, and metacognitive activities were positively related to perceived learning outcomes of MOOC completers. Additionally, Magen-Nagar and Cohen (2017) examined high school students' applied self-regulated learning in a MOOC. The findings indicated that self-regulated learning strategies played a mediating role between motivation and perceived academic achievement.

2.5. Perceived learning outcomes

Previous studies have distinguished three domains of learners' perceived learning outcomes, including cognitive, behavioral, and affective outcomes (Wei, Saab, & Admiraal, 2021; Yu, Tian, Vogel, & Kwok, 2010). With respect to cognitive learning, participants have generally perceived content knowledge and intellectual skill increments and benefits from the MOOC they have studied (Y.-H. Chen & Chen, 2015; Jung & Lee, 2020; Kim, Watson, & Watson, 2016; Lan & Hew, 2020; Li, 2019). Behavioral learning outcomes refer to perceived actual behavior toward the application of knowledge and skills (Kraiger, Ford, & Salas, 1993; Simonson, 1979). For example, Rodriguez and Armellini (2017) reported that participants perceived an increase in their capabilities after completing a Study Skills MOOC. The affective learning outcomes concern attitudes, motivational tendencies, emotional feelings, satisfaction, and appreciation of the learning experience (Kraiger et al., 1993; Otto et al., 2019; Wei, Saab, & Admiraal, 2021; Yu et al., 2010). For example, participants exhibited that they were highly satisfied with supportive peer interactions (de Lima & Zorrilla, 2017).

2.6. Aim of this study

The aim of this exploratory research study is to examine the interplay between motivation, perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. We propose a research model that involves all variables measured to explain individual perceived learning outcomes in MOOCs (see Fig. 1). In the research model, we categorize variables measured into predictive variables (i.e., motivation, perceived learning support, and learning engagement), mediating variables (i.e., self-regulated learning strategies), and outcome variables (i.e., perceived learning outcomes; Albelbisi et al., 2018; Deng et al., 2019; Hood & Littlejohn, 2016b). Motivation stimulates a person to perform or act in academic activities. Connecting learner motivation to perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes contributes to the understanding of how motivation drives individual learning in MOOCs. Prior studies suggested that perceived learning support, learning engagement, and self-regulated learning strategies are significant contributors to academic outcomes. However, full course completion and high academic achievement are not the predominant motivation for all learners, and MOOCs are suffering from low rates of course completion and low levels of academic achievement. Perceived learning outcomes instead of course completion or achievement might provide better understanding of how these factors influence individual learning from MOOCs. As mentioned above, self-regulated learning plays a critical role in directly impacting successful MOOC learning (e.g., Jansen et al., 2020), and self-regulated learning strategies played a mediating role between motivation and perceived academic achievement of high school students (Magen-Nagar & Cohen, 2017). However, not known is that the extent to which self-regulated learning strategies are related to perceived learning outcomes in MOOCs. In the current study, therefore, we firstly investigated the primary motivation of learners taking MOOCs using qualitative data and examined how learner motivation is related to perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. With this, we hope to gain insights into how individual motivation explains perceived learning and perceived learning outcomes. Second, we examine the mediating role of self-regulated learning strategies in relationship between motivation, perceived learning support, learning engagement, on the one hand, and perceived learning outcomes, on the other hand. Given self-regulated learning is critical to successful learning in the asynchronous learning environment of MOOCs, we hope to identify the extent to which motivation, perceived learning support, and learning engagement influence perceived learning outcomes through self-regulated learning strategies. We expect this study to benefit researchers and practitioners to further understand

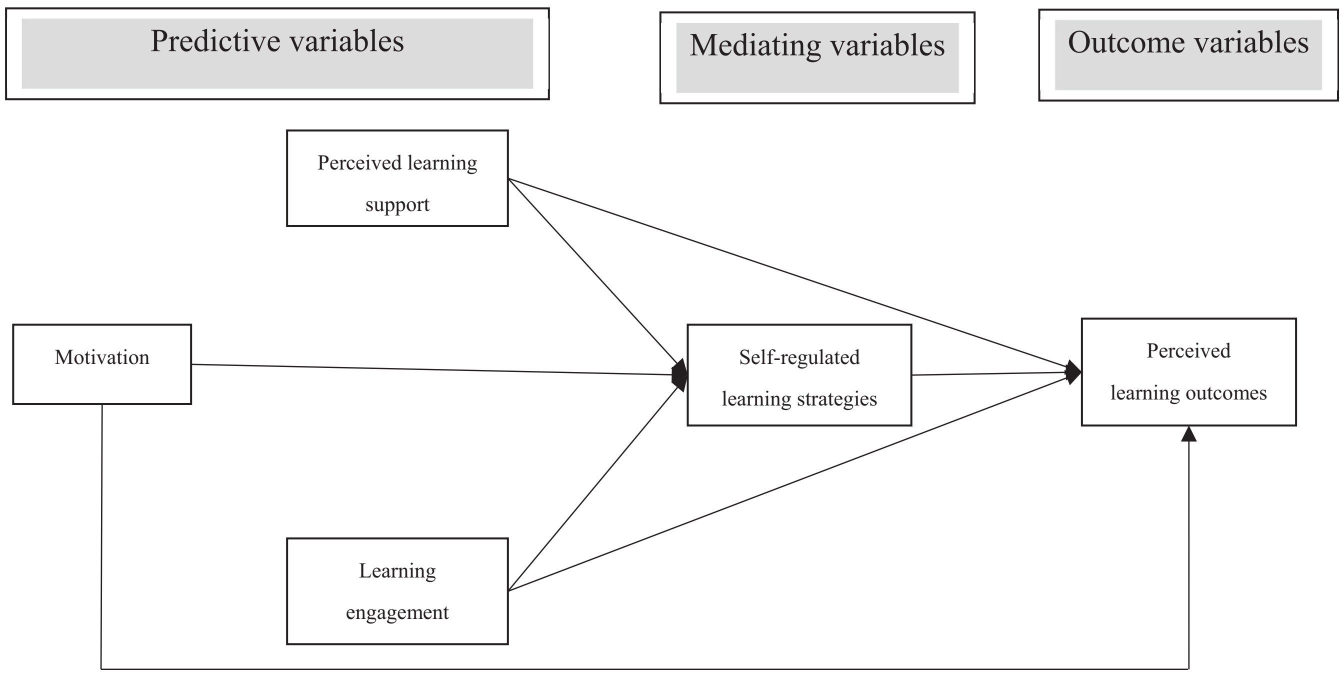

Fig. 1. The proposed research model for predicting perceived learning outcomes in MOOCs.

perceived learning outcomes in MOOCs, as well as to become aware of the importance of self-regulated learning strategies in MOOCs. The research questions proposed to drive this study are as follows:

RQ1: What motivates learners to participate in MOOCs?

RQ2: How is motivation related to perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes in MOOCs?

RQ3: How do self-regulated learning strategies mediate the relationships between motivation, perceived learning support, and learning engagement, on the one hand, and perceived learning outcomes, on the other hand.

3. Methods

3.1. Course context

This study conducted an online survey with the learners of the Chinese University MOOC platform (https://www.icourse163.org/). This platform is one of the authoritative platforms that collaborates with universities and institutions, and the courses cover diverse disciplinary fields in higher education. Four free MOOCs offered by two Chinese universities were used as the sampling pool to approach participants, and participation in the investigation was voluntary. These courses belong to the fields of humanities and social sciences. These four courses were also delivered as components of the on-campus curriculum. The detailed characteristics of these four MOOCs are presented in Table 1. All of them were running during the fall semester of 2020 and lasted 11 to 17 weeks. Each course embraces similar components, such as modules, video lectures, unit tests, discussion forums, peer-reviewed assignments, final exams, and recommended learning materials. Each test or exam is allowed to be attempted multiple times, and course assessments differ in the proportion that makes up the final course grades. In each course, learners who obtain a certificate of qualification have to reach 60% for their final grades, and learners who receive a certificate of excellence have to obtain 80% or 85% for their final grades.

3.2. Participants and procedures

Participants in four MOOCs provided by the Chinese University MOOC platform received online questionnaires. First, based on the research design, a questionnaire tool was developed by adapting prior instruments, which comprised the target factors aiming to address the research questions. Second, a piloting test was conducted with 11 Chinese university students who had MOOC experience to offer feedback on the instruments. Their comments contributed to the further improvement of the survey tool. Finally, a convenience sampling method was

Table 1
Curriculum design features of the four MOOCs.

Course feature	MOOC1	MOOC2	MOOC3	MOOC4
Length	11 weeks	11 weeks	14 weeks	17 weeks
Modules	11	5	8	15
Video lectures	67	56	44	74
Course assessments	Unit tests (30%) Discussion forum (10%) Assignments (10%) Final exam (50%)	Unit tests (30%) Discussion forum (10%) Assignments (10%) Final exam (50%)	Unit tests (45%) Discussion forum (10%) Final exam (45%)	Unit tests (30%) Discussion forum (10%) Assignments (10%) Final exam (50%)
Attempts/test	2 times / test	2 times / test	2 times / test	3 times / test
Recommended learning materials	Yes	Yes	Yes	Yes
Certificate types	Qualification (60%), Excellence (80%)	Qualification (60%), Excellence (80%)	Qualification (60%), Excellence (85%)	Qualification (60%), Excellence (85%)

utilized for data collection, and the online survey was delivered by Qualtrics. We sent invitation letters to instructors who were running MOOCs in the 2020–2021 fall semester through the first author's network and received responses from four instructors who were willing to support the data collection. Starting in the last three weeks of each MOOC, the instructors distributed an anonymous hyperlink or QR code for the questionnaire created by Qualtrics via email and WeChat to learners. Participants were informed about the research purpose and gave consent to the terms; participation was voluntary. The current research was approved by the research ethics committee. It took about 10–15 min to complete the questionnaire. Data collection occurred between November 27, 2020 and January 7, 2021. Ultimately, the final sample of this study comprised 546 online learners from four distinct MOOCs. The demographic information and descriptive statistics of the participants is presented in Table 2.

To check if the relatively low response rates from MOOC1 and MOOC2 influence the findings, we performed the same data analysis on the data from four courses and the data without MOOC1 and MOOC2. The results from both analyses do not influence the results for all RQs. In MOOC1 and MOOC2, learners with intrinsic motivation or extrinsic motivation for participation in MOOCs, which shows the population is diverse. Furthermore, concerning the curriculum design of these four MOOCs (Table 1), they have shared characteristics on modules, pre-prepared lectures, types of course assessments, formative assessments, suggestions of recommended learning materials, and types of certificate. In this study learners were undergraduate, graduate, and Ph.D. students (Table 2), who were engaging in their higher education studies. Focusing on individual learning in these four MOOCs, the small population in these two courses is still valuable for the current study to research individual perceived learning and perceived learning outcomes. Therefore, we decided to keep all data to address the RQs.

3.3. Measuring instruments

The questionnaire tool was composed of all the variables described in the research model. In addition to demographic items, all measuring items were adapted from previous scales and studies. Participants gave responses to items on a 5-point Likert scale or a 6-point Likert scale. For each measure, wording modifications to the items were employed to fit the target research contexts. Furthermore, two open questions aimed to collect qualitative data and gain deeper insights into the motivation of participants' learning in MOOCs. In order to guarantee the semantic accuracy and equivalence of instruments, forward–backward translation procedures were applied between the English and Chinese versions (Behling & Law, 2000).

3.3.1. Motivation

The qualitative data gathered from two open questions aimed at mapping out learner primary motivation for attending MOOCs (e.g., "What are the reasons for your participation in this MOOC?"). Two rounds of data analyses were conducted to develop the motivation coding scheme. Firstly, we adopted content analysis (Hsieh & Shannon, 2005) to distinguish the primary reasons for participating in MOOCs with 546 texts coded independently by two researchers. The discrepancies in codings were discussed and resolved. Two researchers reached an agreement on all codings of the primary reasons for participation. After the first round of coding, eight reason categories emerged: 1 = Personal interests, 2 = Earning credits, 3 = Teacher's requirements, 4 = Personal interest & earning credits, 5 = To supplement knowledge, 6 = Self-development, 7 = Easy access to learning resources, and 8 = Nothing reported. Second, based on self-determination theory (Deci & Ryan, 1985c; Ryan & Deci, 2000), these eight different reasons were clustered into three types of motivation: 1) autonomous motivation regarding intrinsic motivation and well-internalized extrinsic motivation (i.e., intrinsic regulation, integrated regulation, and identified regulation), 2) controlled motivation comprising introjected and external regulation, and 3) combined motivation, which is the combination of autonomous and controlled motivation. Amotivation was not found. The authors discussed all coded information and reached an agreement concerning the final coding results. Table 3 displays the coding scheme used to measure the motivation of participants who attended the four MOOCs.

Table 2
Demographic and descriptive statistics of participants in four MOOCs ($n = 546$).

Measures	Items	MOOC1	MOOC2	MOOC3	MOOC4	Total frequency (percentage)
Enrollment number		1749	3176	1667	4666	
Valid responses to the questionnaire		20 (3.7%)	23 (4.2%)	139 (25.4%)	364 (66.7%)	546 (100%)
Gender	Female	12 (2.2%)	11 (2.0%)	106 (19.4%)	320 (58.6%)	449 (82.2%)
	Male	8 (1.5%)	12 (2.2%)	33 (6.0%)	44 (8.1%)	97 (17.8%)
Age	≤ 22	19 (3.5%)	23 (4.2%)	138 (25.3%)	279 (51.1%)	459 (84.1%)
	23–25	0	0	1 (0.2%)	73 (13.3%)	74 (13.5%)
	26–28	0	0	0	8 (1.5%)	8 (1.5%)
	≥ 29	1 (0.2%)	0	0	4 (0.7%)	5 (0.9%)
Academic degree	Undergraduate students	19 (3.5%)	23 (4.2%)	139 (25.4%)	216 (39.6%)	397 (72.7%)
	Graduate students	0	0	0	148 (27.1%)	148 (27.1%)
	Ph.D. students	0	0	0	1 (0.2%)	1 (0.2%)
Prior MOOC experience	Yes, I do, and I have completed at least one course.	11 (2.0%)	17 (3.1%)	91 (16.7%)	309 (56.6%)	428 (78.4%)
	Yes, I do, but I have not completed any courses.	4 (0.73%)	4 (0.73%)	29 (5.3%)	31 (5.7%)	68 (12.5%)
	No, I do not have any.	5 (0.9%)	2 (0.4%)	19 (3.5%)	24 (4.4%)	50 (9.2%)
Prior knowledge of the subject	Not at all	9 (1.6%)	12 (2.2%)	37 (6.8%)	44 (8.1%)	102 (18.7%)
	A little	6 (1.1%)	6 (1.1%)	53 (9.7%)	127 (23.3%)	192 (35.2%)
	Somewhat	5 (0.9%)	4 (0.7%)	32 (5.9%)	153 (28.0%)	194 (35.5%)
	A fair amount	0	1 (0.2%)	14 (2.5%)	37 (6.8%)	52 (9.5%)
	A great deal	0	0	3 (0.55%)	3 (0.55%)	6 (1.1%)

Table 3
Reasons for learners' participation and motivation types ($n = 546$).

Reasons of participation	Frequency	Percent (%)	Motivation types					
Reason category			Intrinsic motivation	Extrinsic motivation				Amotivation
			(a) Intrinsic regulation	(b) Integrated regulation	(c) Identified regulation	(d) Introjected regulation	(e) External regulation	(f) Non-regulation
1. Personal interest	52	9.5	*					
2. Earning Credits	234	42.8					*	
3. Teacher's requirements	44	8.1					*	
4. Personal interest & earning credits	25	4.6	*				*	
5. To supplement knowledge	75	13.7			*			
6. Self-development	61	11.2			*			
7. Easy access to learning resources	37	6.8			*			
8. Nothing reported	18	3.3						

Note: * Reason is further categorized into motivation types.

3.3.2. *Perceived learning support*

Perceived learning support in MOOCs was examined by adapting the scale *Students' Experiences* employed in e-learning courses (Paechter et al., 2010). Our scale *Perceived learning support* offers an interpretation of learners' perceptions of the learning support they received during the course (from course instruction, instructors, and peers). Four subscales were included in the scale: (1) *Course design* measures learners' overview of the course organization, the ease of using the learning platform, and the cost–benefit of efforts and learning outcomes (e.g., "The course and learning materials are coherently organized and well structured"); (2) *Interaction with instructors* refers to how instructors offer support and instruction to learners during course learning (e.g., "The instructor interacted with students in the discussion forums"); (3) *Interaction with peer students* aims at measuring whether learners have opportunities for information exchange and interaction in peer communication (e.g., "I could exchange information and knowledge easily and quickly with peer students"); (4) *Learner autonomy* refers to the opportunities learners have to control and regulate their learning process (e.g., "I could individually decide the use of learning strategies and the pace of learning"). This scale included a total of 15 items that participants rated on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*).

3.3.3. *Learning engagement*

Ten items were developed to measure learners' engagement with learning activities in MOOCs, such as watching video lectures, discussion forums, and peer learning, based on the studies of Bonafini et al. (2017), Chiu and Hew (2018), and Lan and Hew (2020). Learners reported learning activities in which they frequently participate, such as watching videos, course assessments, and discussion forums (Lan & Hew, 2020). The number of videos watched as well as the number of viewings, votes, and comments in discussion forums explain a positive association with participants' academic achievement (Bonafini et al., 2017; Lan & Hew, 2020). Based on the previous studies, we developed a 10-item scale that aims to assess the frequency of learners engaged in learning activities (e.g., "I reflected on the peer feedback to improve coursework in peer review"). Learners gave responses on a 5-point Likert scale anchored on 1 (*never*) to 5 (*very often*).

3.3.4. *Self-regulated learning strategies*

Self-regulated learners' strategies toward learning in MOOCs were measured by adapting the *Self-Regulated Learning Strategies* scale, which belongs to *the Motivated Strategies for Learning Questionnaire (MSLQ)* (Pintrich et al., 1991; C.-H. Wang, Shannon, & Ross, 2013). The scale comprises four indicators that assess learners' application of strategies in terms of cognitive thinking processes, metacognitive self-regulation, and resource management in dealing with their learning in MOOCs: (1) *elaboration* concerns how learners build the connection between what they learn with prior knowledge and integrate the new information with what they already know (e.g., "I try to relate ideas in this subject to those in other courses whenever possible"); (2) *critical thinking* measures learners' application of prior knowledge to new circumstances and the critical evaluation of what they learn in MOOCs (e.g., "I often find myself questioning things I hear or read in this MOOC to decide if I find them convincing"); (3) *metacognitive self-regulation* refers to learners employing metacognitive strategies in learning activities in MOOCs, including planning, monitoring, and regulating (e.g., "When watching video lectures and reading course materials for this MOOC, I make up questions to help focus my watch and reading"); and (4) *time and study environment management* assesses to what extent learners are able to schedule, plan, and manage their study time and arrange the settings where they work on learning (e.g., "I make sure that I keep up with the weekly sessions and assignments for this MOOC"). This scale included 26 items that participants scored on a 6-point Likert scale, ranging from 1 (*very untrue for me*) to 6 (*very true for me*).

3.3.5. *Perceived learning outcomes*

Perceived learning outcomes were assessed by adapting the *Course Outcomes* scale (Paechter et al., 2010). Three subscales aimed at measuring learners' general perceptions regarding the aspects of learning outcomes in MOOCs, each of which has three items: (1) *cognitive outcomes* include the extent to which learners perceive they master the knowledge delivered by MOOCs (e.g., "I have understood the video lectures and course materials taught in this MOOC"); (2) *behavioral outcomes* assess learners' perceptions of skills acquired from the course learning (e.g., "I have developed skills on how to apply the knowledge in this MOOC"); (3) *affective outcomes* refer to how learners are satisfied with what they have learned and their appreciation of interactions with instructors and peers (e.g., "I am pleased with what I learned in this MOOC"). All nine items are scored on a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*).

3.4. *Data analysis*

To address the research questions proposed in the current study, both quantitative and qualitative data analysis were applied. The data analysis was implemented with the statistical tools IBM SPSS 25.0 and PROCESS v3.5.

Prior to the data analysis, exploratory factor analysis(*EFA*)was performed to explore the latent structure of perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. The appropriateness of EFA was verified by the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The KMO values of perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes were 0.940, 0.888, 0.963, and 0.943, respectively, which were all above 0.5. This means that the sampling was adequate (Kaiser, 1974). The χ^2 values of Bartlett's Sphericity Test for perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes were 5066.61 ($p < 0.001$, $df = 66$), 3102.09 ($p < 0.001$, $df = 45$), 10,996.86 ($p < 0.001$, $df = 325$), and 4287.53 ($p < 0.001$, $df = 36$), respectively. Principal component analysis (PCA) with direct oblimin rotation was performed on each concept to extract the components with eigenvalues >1.0 and remove the items with factor loading values lower than 0.4 or cross-loadings above 0.4 (Ferguson & Cox, 1993). The results of PCA showed that perceived learning support encompassed three subscales: course design, interaction with instructors and peers, and learner autonomy. Learning engagement included two indicators: engagement in learning activities and engagement in course assessments. Two components were extracted from 26 items of self-regulated learning strategies: cognitive and metacognitive learning strategies and time management. Table 4 shows the overview of measurement instruments. Table 5 depicts the descriptive statistics, Cronbach's alphas, and Pearson's correlations for the measured variables. Fig. 2 displays the final research model after the EFA and content analysis. Four-step analytical procedures undertaken for data analysis are elaborated on below.

First, to address RQ 1, content analysis was implemented to code the qualitative data of motivation and to portray what motivates participants to take MOOCs. Only the primary motivation of learners was coded to answer RQ1.

Second, to address RQ 2, we implemented one-way MANOVA with IBM SPSS 25.0 to examine how learner motivation is related to perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. Anchored on coding results, qualitative data of motivation were transformed to a categorical variable, which consisted of three subgroups, namely 1) autonomous motivation, 2) controlled motivation, and 3) combined motivation. A one-way MANOVA was performed after the transformation of motivation. The multivariate normality, linearity, multicollinearity, and homogeneity of variances' covariance matrices among the dependent variables were checked, and the results met the preliminary assumptions of MANOVA. The Levene test of homogeneity of variances ($p > 0.05$) verified that the implementation of the MANOVA procedure was appropriate (Schultz, 1985). Post hoc multiple comparisons utilizing the Scheffé method were performed to examine differences in dependent variables among three motivational profiles.

Third, as to RQ3, we first implemented multiple regression analysis with the enter method was carried out to explain the relationships between factors and perceived learning outcomes. The prior assumptions of multiple regression, such as multivariate normality, linearity, and the homogeneity of standardized residual variance, were checked to verify the proposed model (Osborne & Waters, 2002). Next, to identify the mediating role of self-regulated learning strategies, a mediating analysis was adopted with PROCESS v3.5, utilizing the percentile bootstrap method with a 95% confidence interval of 5000 samples (Preacher & Hayes, 2008). Particularly, dummy coding was utilized to present the multi-categorical motivation, and a multi-categorical mediation analysis was carried out with an autonomous motivation reference category (Hayes & Little, 2018). Once, at least one relative indirect effect occurred, which supports the claim that the mediator mediates the effect of motivation on perceived learning outcomes (Hayes & Little, 2018).

4. Results

4.1. Motivation of learners' participation in MOOCs

Table 6 summarizes the primary motivation of learners who participated in the MOOCs. There were seven emerging themes in total coded from the qualitative data, except for 18 attendees who did not report anything regarding their motives for taking MOOCs. Table 6 displays the descriptive statistics of coded motivation in detail and the examples of illustrative quotes of each motivation type ($n = 528$). Seven themes were further categorized into three motivational profiles, namely autonomous motivation (n = 225, 41.2%), controlled motivation (n = 278, 50.9%), and combined motivation (n = 25, 4.6%). In the controlled motivation group, which had the largest proportion of participants, the most frequently coded motivation was *Earning credits*, indicating that it was mandatory for learners to attend the MOOCs to fulfill the credit requirement (n = 234, 42.8%). Some participants expressed that the *Teacher's requirements* motivated them to be involved in the courses (n = 44, 8.1%). Both credits and teacher's requirements were external motives for learners to attend a MOOC.

In the autonomous motivation group (Table 6), participants exhibited other motives for taking MOOCs. One prevalent motivator was *To supplement knowledge* (n = 75, 13.7%), learners expressed that they gained and improved content knowledge from course learning.

Table 4
The overview of measurement instruments.

Variables	Measured factors	No. of item used	Factors kept after CPA	No. of item kept CPA	Scales	Source
Motivation		2		2	Open-ended questions	Deci and Ryan (1985c)
Perceived learning support	Course design	3	Course design	3	6-point Likert scale	Paechter et al. (2010)
	Interaction with instructors	4	Interaction with instructors and peers	8		
	Interaction with peer students	4				
	Learner autonomy	4		2		
Learning engagement		10	Engagement in learning activities	6	5-point Likert scale	Bonafini et al. (2017); Chiu and Hew (2018); Lan and Hew (2020).
			Engagement in course assessments	3		
Self-regulated learning strategies	Elaboration	6	Cognitive & meta-cognitive learning strategies	23	6-point Likert scale	Pintrich et al. (1991); Wang et al. (2013)
	Critical thinking	5				
	Metacognitive self-regulation	8				
	Time and study environment management	7	Time management	3		
Perceived learning outcomes	Cognitive outcomes	3	Perceived learning outcomes	9	6-point Likert scale	Paechter et al. (2010)
	Behavioral outcomes	3				
	Affective outcomes	3				

Table 5
Descriptive statistics, Cronbach's alphas, and Pearson's correlations for the measured variables ($n = 546$).

Measurement variables	Number of items	Mean	Std. Deviation	Pearson's Correlation							Cronbach's alpha
				1	2	3	4	5	6	7	
Perceived learning support											
1. CD	3	4.680	0.810	1							0.796
2. INSP	8	4.495	0.854	0.780**	1						0.938
3. LA	2	4.719	0.897	0.673**	0.588**	1					0.705
Learning engagement											
4. ELA	6	3.220	0.915	0.328**	0.463**	0.292**	1				0.910
5. ECA	3	4.236	0.727	0.385**	0.427**	0.324**	0.499**	1			0.795
Self-regulated learning strategies											
6. CMLS	23	4.392	0.753	0.592**	0.636**	0.461**	0.574**	0.442**	1		0.969
7. TM	3	3.379	1.047	0.060	0.031	−0.020	−0.097*	0.162**	−0.142**	1	0.745
Perceived learning outcomes											
8. PLO	9	4.478	0.802	0.609**	0.650**	0.451**	0.539**	0.423**	0.823**	−0.053	0.951

Notes. CD = course design, INSP = interaction with instructors and peers, LA = learner autonomy, ELA = engagement in learning activities, ECA = engagement in course assessments, CMLS = cognitive and metacognitive learning strategies, TM = time management, PLO = perceived learning outcomes.
** Correlation is significant at the 0.01 level (2-tailed).
* Correlation is significant at the 0.05 level (2-tailed).

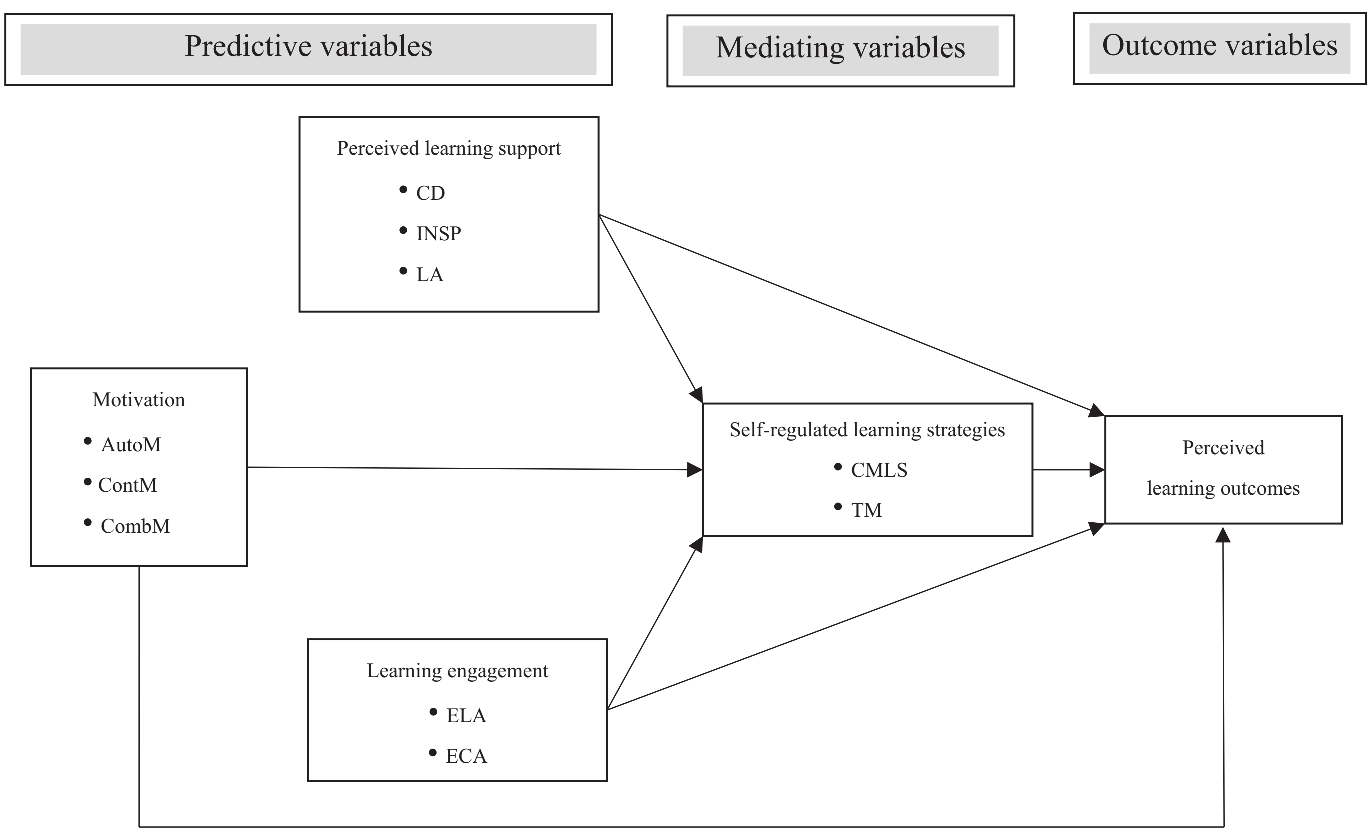

Fig. 2. The final research model for predicting perceived learning outcomes in MOOCs.
Note: In the research model, motivation is a categorical variable, and other constructs are all continuous variables. AutoM = autonomous motivation, ContM = controlled motivation, CombM = combined motivation, CD = course design, INSP = interaction with instructors and peers, LA = learner autonomy, ELA = engagement in learning activities, ECA = engagement in course assessments, CMLS = cognitive and metacognitive learning strategies, TM = time management.

Furthermore, the reason for developing proficient skills and capabilities in the subject they study and making preparation for their future career was labeled as *Self-development* ($n = 61$, 11.2%). In addition to the aforementioned two motives, a small number of participants regarded MOOCs as an extension of campus education resources. Other participants indicated that the factor that mostly stimulated them to enroll in the MOOCs was *Easy access to learning resources* ($n = 37$, 6.8%). They could get access to any curriculum free of charge or at an affordable cost without any restriction of time and place. Moreover, we also discovered that *Personal interests* was a facilitating factor for learners to attend MOOCs ($n = 52$, 9.5%). These participants were intrinsically motivated to follow courses. Additionally, a small number of participants

Table 6
Results of motivation for learners' participation in MOOCs (n = 528).

Motivation types	Reason for participation	Frequency	Percent (%)	Example of illustrative quotes
Autonomous motivation		225	41.2	
Intrinsic regulation	Personal interests	52	9.5	"*I took this course because I was interested in issues related to education in various countries.*" (Learner 413) "*The course I attended was attractive.*" (Learner 39)
Identified regulation	To supplement knowledge	75	13.7	"*MOOCs offer ample opportunities for self-regulated learning, and I could acquire subject knowledge taught in the courses.*"(Learner 189) "*I was taking advantage of fragmented time to study in a MOOC to expand theoretical knowledge upon the topic.*" (Learner 218) "*Learn more professional knowledge regarding teaching techniques and art in classroom scenario.*" (Learner 103)
	Self-development	61	11.2	"*As a teacher student, learning something new related to curriculum and instruction in this course could be a benefit for the improvement of my professional competence.*" (Learner 180) "*I will be a teacher in my future career, so I am looking forward to acquiring more practical skills for teaching that could be applied in classroom settings, as well as the approaches to improve classroom efficiency.*" (Learner 84)
	Easy access to learning resources	37	6.8	"*It was quite convenient and easy to approach curriculum resources, which could fulfill the learning demand myself.*" (Learner 299) "*While studying in class, I have missed some important content introduced on the slides, so I went to this online course to review video lectures and take notes.*" (Learner 265)
Controlled motivation		278	50.9	
		234	42.8	
External regulation	Earning Credits			"*The MOOC I attended was a compulsory course, and I had to obtain the credits.*" (Learner 491) "*We were required to take online courses, and the MOOC I took was one of the elective courses arranged by the college.*" (Learner 18)
	Teacher's requirement	44	8.1	"*The tutor asked us to learn this course on the MOOC platform.*" (Learner 111) "*We have to take online courses at home that required by instructors due to the Covid-19 pandemic.*" (Learner 389)
Combined motivation		25	4.6	
Intrinsic regulation & External regulation	Personal interests & Earning credits	25	4.6	"*It was obligatory to take a MOOC for course credits, but also I was interested in this course.*" (Learner 413) "*This course was one of the elective courses, and I was also interested in issues relevant to education.*" (Learner 12)

illustrated that they participate in MOOCs with a combined motivation, namely *Personal interests & earning credits* ($n = 25$, 4.6%). Learners in this group exhibited both intrinsic and extrinsic motivation for MOOC learning.

4.2. Relationship between motivation and perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes

In Table 7, the descriptive statistics of dependent variables are presented for each motivational profile. A statistically significant MANOVA was observed, Wilks' Lambda = 0.889, $F = 3.905$, $p < 0.001$, partial $\eta^2 = 0.057$. Results of multivariate tests indicate that there were statistically significant differences among three motivational profiles in regard to perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. In Table 8, the results of tests of between-subjects effects confirmed the significant differences among motivational profiles in course design (F (2, 525) = 9.779, $p < 0.001$, partial $\eta^2 = 0.036$), interaction with instructors and peers (F (2, 525) = 8.702, $p < 0.001$, partial $\eta^2 = 0.032$), learner autonomy (F (2, 525) = 6.041, $p = 0.003$, partial $\eta^2 = 0.022$), cognitive and metacognitive learning (F (2, 525) = 15.889, $p < 0.001$, partial $\eta^2 = 0.057$), time management (F (2, 525) = 3.678, $p = 0.026$, partial $\eta^2 = 0.014$), and perceived learning outcomes (F (2, 525) = 11.659, $p < 0.001$, partial $\eta^2 = 0.043$). However, there were non-significant differences to be found among motivational profiles in engagement in learning activities (F (2, 525) = 2.682, $p = 0.069$, partial $\eta^2 = 0.010$) and engagement in course assessments (F (2, 525) = 0.137, $p = 0.872$, partial $\eta^2 = 0.001$), respectively.

Regarding perceived learning support, the Scheffé post hoc tests were carried out and identified the statistically significant mean

Table 7
Descriptive statistics of one-way MANOVA of motivation on dependent variables among learner motivational profiles ($n = 528$).

Dependent variable	Autonomous motivation			Controlled motivation			Combined motivation		
	N	Mean	Std. Deviation	N	Mean	Std. Deviation	N	Mean	Std. Deviation
CD	225	4.865	0.789	278	4.550	0.796	25	4.680	0.819
INSP	225	4.673	0.862	278	4.359	0.835	25	4.460	0.701
LA	225	4.873	0.894	278	4.595	0.894	25	4.780	0.936
ELA	225	3.328	0.925	278	3.139	0.903	25	3.233	0.918
ECA	225	4.244	0.759	278	4.230	0.695	25	4.307	0.608
CMLS	225	4.599	0.711	278	4.255	0.739	25	4.129	0.631
TM	225	3.502	1.114	278	3.261	0.973	25	3.533	0.923
PLO	225	4.669	0.803	278	4.341	0.773	25	4.289	0.690

Notes: CD = course design, INSP = interaction with instructors and peers, LA = learner autonomy, ELA = engagement in learning activities, ECA = engagement in course assessments, CMLS = cognitive and metacognitive learning strategies, TM = time management, PLO = perceived learning outcomes.

Table 8
Results of tests of between-subjects effects of motivation on dependent variables among learner motivational profiles (n = 528).

Dependent variable	Type III Sum of Squares	df	Mean square	F	Sig.	Partial eta squared
CD	12.328	2	6.164	9.779**	< 0.001	0.036
INSP	12.304	2	6.152	8.702**	< 0.001	0.032
LA	9.698	2	4.849	6.041*	0.003	0.022
ELA	4.475	2	2.238	2.682	0.069	0.010
ECA	0.142	2	0.071	0.137	0.872	0.001
CMLS	16.589	2	8.294	15.889**	< 0.001	0.057
TM	7.855	2	3.927	3.678*	0.026	0.014
PLO	14.264	2	7.132	11.659**	< 0.001	0.043

Note: CD = course design, INSP = interaction with instructors and peers, LA = learner autonomy, ELA = engagement in learning activities, ECA = engagement in course assessments, CMLS = cognitive and metacognitive learning strategies, TM = time management, PLO = perceived learning outcomes.
** Between-subjects effects are significant at the 0.001 level.
* Between-subjects effects are significant at the 0.05 level.

differences of course design ($p < 0.001$), interaction with instructors and peers ($p < 0.001$), and learner autonomy ($p = 0.003$), which lay between groups of autonomous motivation and controlled motivation. Specifically, the autonomous motivation group reported higher scores of course design ($M = 4.865$, $SD = 0.789$), interaction with instructors and peers ($M = 4.673$, $SD = 0.862$), and learner autonomy ($M = 4.873$, $SD = 0.894$) compared to controlled motivation ($M = 4.550$, $SD = 0.796$; $M = 4.359$, $SD = 0.835$; $M = 4.595$, $SD = 0.894$, respectively), using Scheffé post hoc comparisons all with $p < 0.05$.

Concerning learning engagement, learners with autonomous motivation ($M = 3.328$, $SD = 0.925$) showed higher scores of engagement in learning activities than groups with controlled motivation ($M = 3.139$, $SD = 0.903$) and combined motivation ($M = 3.233$, $SD = 0.918$). Furthermore, the controlled motivation group ($M = 4.307$, $SD = 0.608$) rated the highest scores of engagement in course assessments, followed by autonomous motivation ($M = 4.244$, $SD = 0.759$) and combined motivation ($M = 4.230$, $SD = 0.695$). However, the post hoc test showed that there were no significant differences in engagement in learning activities and engagement in course assessments to be found among three groups, respectively, using Scheffé post hoc comparisons all with $p > 0.05$.

When we looked at self-regulated learning strategies, according to the results of the post hoc tests, learners with autonomous motivation showed significant differences in cognitive and metacognitive learning strategies compared to groups with controlled motivation ($p < 0.001$) and combined motivation ($p = 0.009$), respectively, using Scheffé post hoc comparisons all with $p < 0.05$. Regarding time management, a significant difference was found between groups with autonomous and controlled motivation ($p = 0.035$), using Scheffé post hoc comparisons with $p < 0.05$. To be Specific, the autonomous motivation group ($M = 4.599$, $SD = 0.711$) reported higher scores of cognitive and metacognitive learning strategies than controlled motivation ($M = 4.255$, $SD = 0.739$) and combined motivation ($M = 4.129$, $SD = 0.631$). Moreover, the combined motivation group ($M = 3.533$, $SD = 0.923$) had higher scores of time management compared to the groups with autonomous motivation ($M = 3.502$, $SD = 1.114$) and controlled motivation ($M = 3.261$, $SD = 0.973$). Regarding time management, a significant difference was found between groups with autonomous and controlled motivation ($p = 0.035$), using Scheffé post hoc comparisons with $p < 0.05$.

Lastly, the results of the post hoc tests on perceived learning outcomes showed that the significant difference lies between autonomous motivation and controlled motivation ($P < 0.001$). The autonomous motivation group ($M = 4.669$, $SD = 0.803$) showed higher scores of perceived learning outcomes than groups of controlled motivation ($M = 4.341$, $SD = 0.773$).

4.3. The mediating role of self-regulated learning strategies

4.3.1. Relationships between perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes

In order to examine the mediating role of self-regulated learning strategies, we firstly performed the regression analyses on independent variables (i.e., perceived learning support, learning engagement, self-regulated learning strategies) and perceived learning outcomes. The regression standardized residual and the scatterplot indicated that the multivariate normality, linearity, and homogeneity of the standardized residual variance were verified. As Table 9 displays, the Durbin-Watson value ($DW = 1.917$) approached 2, which illustrates that no obvious correlation was to be found between the residuals (Theil & Nagar, 1961). Regarding the presence of multi-collinearity, the rules of thumb for conventional thresholds statistically significant are tolerance value <0.1 and a variance inflation factor (VIF) value >10 (O'brien, 2007). The tolerance values (ranging from 0.301 to 0.881) and variance inflation factor (VIF) values (ranging from 1.135 to 3.328) revealed that the regression model did not suffer multi-collinearity problems. In sum, the research data in this example met the assumptions of applying multiple linear regression.

In Table 9, we see that the seven independent variables in the regression model had a significant predictive ability for the dependent variable ($F(7, 538) = 191.316$, $R^2_{Adjusted} = 0.710$, $p < 0.001$), explaining 71% of the variance in learning outcomes. Four independent variables showed statistically significant relationships with perceived learning outcomes. To be specific, cognitive and metacognitive learning strategies had the strongest positive relationship with perceived learning outcomes ($\beta = 0.641$, $p < 0.001$), followed by interaction with instructors and peers ($\beta = 0.124$, $p = 0.002$), course design ($\beta = 0.114$, $p =$

Table 9
Multiple regression analysis results of factors affecting perceived learning outcomes ($n = 546$).

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	0.173	0.150		1.159	0.247					
	CD	0.113	0.042	0.114*	2.714	0.007	0.609	0.116	0.063	0.301	3.328
	INSP	0.116	0.038	0.124*	3.046	0.002	0.650	0.130	0.070	0.323	3.093
	LA	−0.016	0.028	−0.018	−0.554	0.580	0.451	−0.024	−0.013	0.530	1.888
	ELA	0.074	0.027	0.084*	2.736	0.006	0.539	0.117	0.063	0.564	1.774
	ECA	0.001	0.032	0.001	0.040	0.968	0.423	0.002	0.001	0.643	1.556
	CMLS	0.682	0.037	0.641**	18.444	<0.001	0.823	0.622	0.426	0.441	2.266
	TM	0.026	0.019	0.034	1.393	0.164	−0.053	0.060	0.032	0.881	1.135
ANOVA	$R = 0.845$, $R^2 = 0.713$, $R^2_{Adjusted} = 0.710$										
	$F = 191.316$, $p < 0.001$, Durbin-Watson = 1.917										

Note: CD = course design, INSP = interaction with instructors and peers, LA = learner autonomy, ELA = engagement in learning activities, ECA = engagement in course assessments, CMLS = cognitive and metacognitive learning strategies, TM = time management, PLO = perceived learning outcomes.

** The coefficient is significant at the 0.001 level.

* The coefficient is significant at the 0.05 level.

0.007), and engagement in learning activities (β = 0.084, *p* = 0.006). No significant relationships were found with learner autonomy (β = −0.018, *p* = 0.580), engagement in course assessments (β = 0.001, *p* = 0.968), and time management (β = 0.034, *p* = 0.164), respectively.

4.3.2. Self- regulated learning strategies as a mediator

Table 10 shows the results of mediating effects of self-regulated learning strategies on each mediation path. Mediation paths are visualized in Figs. 3, 4, and 5. In the multi-categorical mediation analysis with respect to learner motivation, the autonomous motivation group was chosen as the reference group. In the path of M → CMLS → PLO, compared to the autonomous motivation group, controlled motivation (β = −0.302, *SE* = 0.057, 95% *CI* [−0.416, −0.193]) and combined motivation (β = −0.413, *SE* = 0.120, 95% *CI* [−0.642, −0.167]) exerted a significant negative indirect relationship with perceived learning outcomes. The results indicated that cognitive and metacognitive learning strategies mediated the relationship between learner motivation and perceived learning outcomes. For the other self-regulation scale, namely time management, no significant indirect effect on perceived learning could be found in controlled motivation (β = 0.011, *SE* = 0.015, 95% *CI* [−0.013, 0.046]) and combined motivation (β = −0.002, *SE* = 0.017, 95% *CI* [−0.043, 0.029]), compared to the autonomous motivation group.

Regarding the indirect effects of perceived learning support on perceived learning outcomes, the results showed that the statistically significant indirect effects of course design (β = 0.418, *SE* = 0.036, 95% *CI* [0.350, 0.491]), interaction with instructors and peers (β = 0.410, *SE* = 0.034, 95% *CI* [0.346, 0.479]), and learner autonomy (β = 0.321, *SE* = 0.034, 95% *CI* [0.255, 0.388]) on perceived learning outcomes were mediated through cognitive and metacognitive learning strategies. Time management failed to play a mediation role in that path. When we come to learning engagement and its link to perceived learning outcomes, cognitive and metacognitive learning strategies significantly mediated the relationship between engagement in learning activities and perceived learning outcomes (β = 0.385, *SE* = 0.033, 95% *CI* [0.323, 0.450]), but time management again showed non-significance (β = 0.000, *SE* = 0.005, *p* = 0.980, 95% *CI* [−0.010, 0.014]). Furthermore, the indirect effect of engagement in course assessments on perceived learning outcomes was strongly mediated through cognitive and metacognitive learning strategies (β = 0.385, *SE* = 0.040, 95% *CI* [0.309, 0.463]), and time management played a marginal mediation role (β = −0.022, *SE* = 0.009, 95% *CI* [−0.039, −0.006]).

5. Discussion

The current research examined the relationships between factors and perceived learning outcomes in MOOCs and thus provides several contributions to the literature. Firstly, this exploratory study offers an understanding of the interactions between motivation, perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes in MOOCs. As Hood and Littlejohn (2016b) and Deng et al. (2019) have highlighted that it was significant to measure perceptions of individual learning in MOOCs, our findings contribute to the knowledge on key teaching and learning factors related to perceived learning outcomes. The mediation analysis corroborates the findings by Magen-Nagar and Cohen (2017), who discovered that self-regulated learning strategies played a mediating role in the relationship between motivation and a sense of achievement. Unlike the research context in the study by Magen-Nagar and Cohen (2017), which was rooted in MOOCs for secondary school students, our research was carried out in higher education, which adds knowledge to the literature in that perceived learning support and learning engagement had significant and powerful indirect influences on perceived learning outcomes through self-regulated learning strategies. Second, the investigation of perceived learning outcomes extends the existing research regarding learning outcome variables (Broadbent & Poon, 2015; Pilli & Admiraal, 2017; Wei, Saab, & Admiraal, 2021), which offers an understanding of individuals' perceptions in learning were related to the extent to which learners have perceived learning outcomes in MOOC. Furthermore, we contribute to the literature concerning the connections between learner motivational profiles and perceived learning outcomes. An autonomous motivational profile is more advantageous than a controlled motivational profile for perceiving better learning outcomes, and a combined motivational profile was developed to be an adaptive group for potentially optimal learning. We adopted motivation profiles to category learners who have shared motivation orientation, which is helpful to identify individual differences in perceived learning outcomes (Ratelle, Guay, Vallerand, Larose, & Senécal, 2007). The main findings are summarized and discussed below.

5.1. Motivation for attending MOOCs

Seven types of primary motivation were identified. The findings reveal that individuals differ in their primary motivation for taking MOOCs, ranging from intrinsic to extrinsic motivation, which is in line with prior studies (e.g., Littlejohn et al., 2016; Luik et al., 2019; Milligan & Littlejohn, 2017; Watted & Barak, 2018). In the present study the majority of learners were undergraduate and graduate students engaged in their higher education studies. The MOOC courses that they were obligated to attend related to the field of their academic programs. The finding that these students were primarily driven by pursuing educational benefits and that the motivation was extrinsic is similar to the results of Brooker, Corrin, De Barba, Lodge, and Kennedy (2018) and Z. Chen et al. (2015).

Table 10
Percentile bootstrap confidence intervals of the indirect effects (n = 546).

Mediation path (IV → MV → DV)	B	SE	95% CI for indirect effect BootLLCI	BootULCI
Motivation				
M → CMLS →PLO				
Specific 1: AutoM → CMLS → PLO (reference)				
Specific 2: ContM → CMLS → PLO	−0.302**	0.057	−0.416	−0.193
Specific 3: CombM → CMLS → PLO	−0.413**	0.120	−0.642	−0.167
M → TM → PLO				
Specific 1: AutoM → TM → PLO (reference)				
Specific 2: ContM → TM → PLO	0.011	0.015	−0.013	0.046
Specific 3: CombM → TM → PLO	−0.002	0.017	−0.043	0.029
Perceived learning support				
CD → PLO				
Direct effect	0.185**	0.029	0.128	0.241
Indirect effect:				
Specific 1: CD → CMLS → PLO	0.418**	0.036	0.350	0.491
Specific 2: CD → TM → PLO	−0.005	0.005	−0.017	0.004
INSP→ PLO				
Direct effect	0.200**	0.028	0.145	0.256
Indirect effect:				
Specific 1: INSP → CMLS → PLO	0.410**	0.034	0.346	0.479
Specific 2: INSP→ TM → PLO	−0.002	0.004	−0.010	0.007
LA → PLO				
Direct effect	0.082**	0.024	0.034	0.130
Indirect effect:				
Specific 1: LA → CMLS → PLO	0.321**	0.034	0.255	0.388
Specific 2: LA → TM → PLO	0.001	0.003	−0.004	0.010
Learning engagement				
ELA → PLO				
Direct effect	0.087**	0.026	0.036	0.137
Indirect effect:				
Specific 1: ELA → CMLS → PLO	0.385**	0.033	0.323	0.450
Specific 2: ELA → TM → PLO	0.000	0.004	−0.008	0.011
ECA → PLO				
Direct effect	0.081**	0.030	0.023	0.140
Indirect effect:				
Specific 1: ECA → CMLS → PLO	0.385**	0.040	0.309	0.463
Specific 2: ECA → TM → PLO	−0.022**	0.009	−0.039	−0.006

Note: IV = independent variable, MV = mediating variable, DV = dependent variable, M = motivational profile, AutoM = autonomous motivation, ContM = controlled motivation, CombM = combined motivation, CD = course design, INSP = interaction with instructors and peers, LA = learner autonomy, ELA = engagement in learning activities, ECA = engagement in course assessments, CMLS = cognitive and metacognitive learning strategies, TM = time management, PLO = perceived learning outcomes. B indicates the strength of the indirect effect.

** $p < 0.001$.

5.2. Motivation that relates to perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes

Based on the shared characteristics of the seven types of primary motivation, three motivational profiles were further identified, namely autonomous, controlled, and combined motivation.

First, learners with autonomous motivation demonstrated higher scores on perceived learning support, self-regulated learning strategies, and perceived learning outcomes than learners with controlled motivation. The results align with the findings of previous studies showing the positive effects of autonomous motivation (Littlejohn et al., 2016; Pozón-López et al., 2021; Zhou, 2016). The results suggested that autonomous learners were more likely to succeed in MOOC learning. In the MOOC context characterized by openness, flexibility, and fewer restrictions, autonomous motivation is more powerful to drive learners to attend MOOCs, and it shows more advantages than controlled motivation in contributing to better MOOC learning. The finding that motivation was not significant related to learners' engagement in learning activities and course assessments is partially in line with the results of the studies carried out by Williams, Stafford, Corliss, and Reilly (2018) and Lan and Hew (2020). In the study of Lan and Hew (2020), motivation had no effect on the frequency of the engagement with some learning activities and assessments, such as quiz submissions, reading forum messages, and doing course readings, although both completers and non-completers were motivated by autonomous and controlled motivation. In addition to the behavioral engagement in this study, we suggest to further investigate the relationship of motivation with cognitive and affective engagement in learning activities and course assessments.

Second, a combined motivational profile emerged, which supports the idea that learners can have both autonomous and controlled motivation for the same learning situation (Deci & Ryan, 2000; Ratelle et al., 2007; Vansteenkiste, Sierens, Soenens, Luyckx, & Lens, 2009). Within the campus context, according to Ratelle et al. (2007) and Vansteenkiste et al. (2009), considering the quality and quantity of the motivation, the combined motivational profile can be further grounded into sub-profiles (i.e., high autonomous and controlled, high autonomous and low controlled, low autonomous and high controlled, low autonomous and controlled). They found that these sub-profile groups were associated with different aspects of optimal learning. In the present study, the combined motivation group was motivated by personal interests and earning credits to enroll in MOOCs. However, in the current study, compared to learners with controlled motivation, learners with combined motivation showed no significant differences in perceived learning support, learning engagement, self-regulated learning strategies, and perceived learning outcomes. There were only 25 participants who expressed combined motivation, which was far less than the number of participants in the autonomous and controlled groups. One explanation for not finding significant differences might be that the small number of learners in this group cannot provide enough empirical evidence. These findings suggest that in the online context more research is necessary to explore how subtypes of combined motivation affect learners' perceptions of the learning process and learning outcomes. Focusing on the quality and quantity of motivation could lead to identifying adaptive motivational groups and offering support to the potential adaptive motivational groups to be autonomous with respect to optimal learning in MOOCs.

5.3. Self-regulated learning strategies, perceived learning support, and learning engagement that relate to perceived learning outcomes

Self-regulated learning strategies, in terms of cognitive and metacognitive learning strategies (i.e., elaboration, critical thinking, and metacognitive self-regulation), are positively related to perceived learning outcomes. This finding is in accordance with the results of Cheng and Chau (2013). The findings from the mediation analysis demonstrated that cognitive and metacognitive learning strategies significantly mediated the relationships between perceived learning support and learning engagement on the one hand, and perceived learning outcomes on the other. Similarly, a study by Magen-Nagar and Cohen (2017) showed that self-regulated learning strategies play a mediating role between motivation and the perceived academic achievement in MOOCs. Particularly, in the current study, we found that the direct influences of perceived learning support and learning engagement on perceived learning outcomes had significantly increased when cognitive and metacognitive learning strategies as the mediator. The results of mediation analysis highlight that self-regulated learning

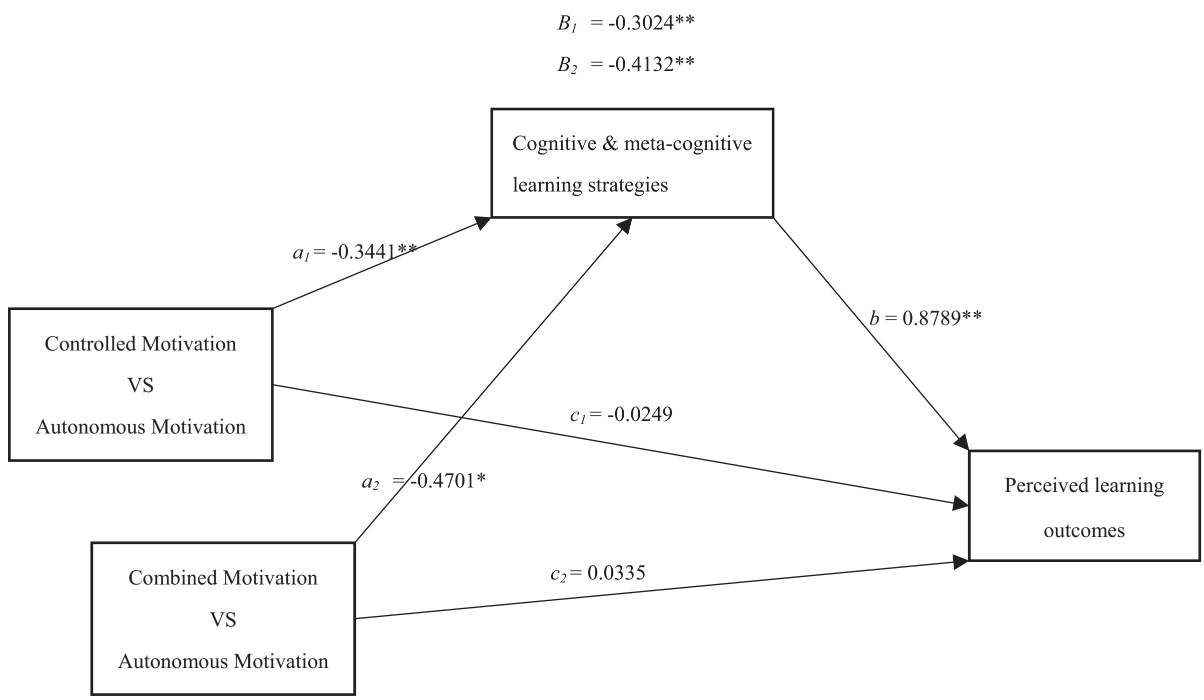

Fig. 3. Mediation path: Motivation → Cognitive & meta-cognitive learning strategies → Perceived learning outcomes.
Note: X = Motivation (categorical variable); *Mediator* (M) = Cognitive & meta-cognitive learning strategies; Y = Perceived learning outcomes; a = Coefficient of X on M, b = Coefficient of M on Y, c = = Coefficient of X on Y, B = Relative indirect effect of X on Y = a * b. Autonomous motivation is regarded as reference. ** $p < 0.001$. * $p < 0.05$.

strategies were powerfully influential in shaping perceived learning outcomes in the asynchronous learning environment of MOOCs without instructors' direct monitoring. It seems that learners with abilities to use cognitive and metacognitive learning strategies are more likely to stimulate themselves to involve in MOOC learning and perceive a higher level of learning outcomes. The finding that time management strategies showed a non-significant relationship with perceived learning outcomes contradicts the results of Lee et al. (2020). One explanation might be that the majority of learners in this study were university students who had to invest time in MOOC learning to complete the requirements of their academic programs. The external restrictions are probably more powerful than time management strategies in driving students to learn in MOOCs. In the study of Lee et al. (2020), the courses enabled participants to complete all sessions at a personal preferred pace, and the authors reported that time management was significantly related to perceived learning outcomes.

With respect to the perceived learning support, the outcome that interaction with instructors and peers significantly explained differences in perceived learning outcomes is in agreement with the results of study conducted by Kurucay and Inan (2017). The result that course design was strongly related to perceived learning outcomes can be confirmed in a prior study carried out by Joo et al. (2018). The finding that learner autonomy did not significantly relate to perceived learning outcomes partially contradicts the findings presented by Paechter et al. (2010). In the latter's study, researchers only found that the flexibility of choosing learning strategies and learning paces had a positive association with the acquisition of personal competence. The relationship of learner autonomy with perceived learning outcomes requires further empirical exploration.

When it comes to learning engagement, the finding that engagement in learning activities (e.g., discussion forums, peer review) was significantly linked to perceived learning outcomes corresponds with the results of X. Wang, Yang, Wen, Koedinger, and Rosé (2015) and Elizondo-Garcia and Gallardo (2020). The outcome that engagement in course assessments was a non-significant predictor of perceived learning outcomes contradicts the results of Tseng et al. (2016), which indicated that participants who actively engaged in assessments report better final grades and higher course completion rates than their counterparts. The findings of Tseng et al. (2016) and the current study suggested that there might be a gap between course completion/grades and perceived learning outcomes. The frequency of behavioral engagement in course assessments can reveal that learners differ in the level of course completion and course grades, but it cannot validly explain how active learners have obtained better perceived learning outcomes. More empirical studies are needed to measure how engagement in course assessment contributes to perceived learning outcomes.

5.4. Practical implications

Based on the main outcomes of the current study, in order to facilitate perceived learning outcomes of learners in MOOCs, we come up with three practical implications for curriculum designers and instructors below.

Since autonomous motivation has a positive effect on perceived learning outcomes, it is critical to offer participants autonomy support to cater to personal needs. For example, to create an autonomy-supportive climate (Deci & Ryan, 1987), curriculum designers and instructors could provide supplementary learning materials that are well-organized to expand the content of the video lectures. That would make it possible for learners who are internally motivated to choose valuable learning materials to fulfill further learning needs.

Considering learners who are externally motivated to attend MOOCs, need supportive teaching (Stroet, Opdenakker, & Minnaert, 2013) could be suggested to curriculum designers and instructors to stimulate learners to be more autonomously motivated and actively engage in MOOCs, as self-determination theory states that offering contextual support to satisfy inherently psychological needs for competence, relatedness, and autonomy can benefit the process of internalization (Deci, Vallerand, Pelletier, & Ryan, 1991). For example, to enhance perceived competence, the content of learning materials differing in

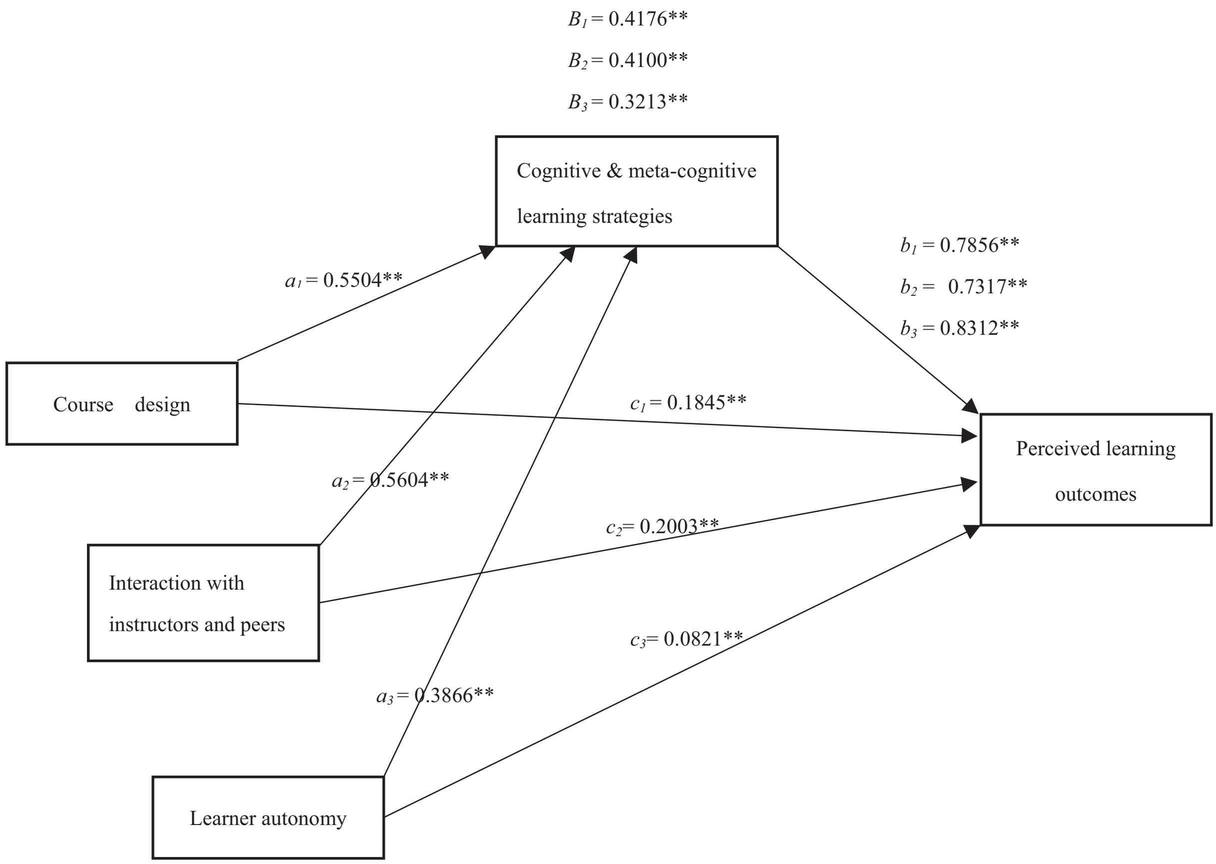

Fig. 4. Mediation path: Perceived learning support → Cognitive & meta-cognitive learning strategies → Perceived learning outcomes.
Note: X = Course design, Interaction with instructors and peers, and Learners autonomy; *Mediator* (M) = Cognitive & meta-cognitive learning strategies; Y = Perceived learning outcomes; a = Coefficient of X on M, b = Coefficient of M on Y, c = Coefficient of X on Y, B = Indirect effect of X on Y = a * b. ** $p < 0.001$.

difficulty and complexity should be considered, which could support learners to gradually challenge themselves to obtain sophisticated knowledge and skills. One suggestion for learners to feel like being autonomy supported could be for curriculum designers and instructors to pay attention to optimizing courses' coherence and structure. Moreover, regarding the need for relatedness, curriculum designers and instructors can offer learners pedagogical, social, managerial, and technical online tutorial support that could promote more learner-content, learner-learner, and instructor-learner interaction (Berge, 1995; Hew, 2016).

Given that self-regulated learning strategies have powerful and positive effects on perceived learning outcomes in MOOCs, we highly recommend that curriculum designers and instructors employ approaches to support learners' self-regulated learning. It could be effective to implement interventions based on the four phases of self-regulated learning, including forethought, monitoring, control, and reflection (Pintrich, 1999; Wong et al., 2019). Therefore, we suggest embedding self-regulated learning strategies into learning content and integrating self-regulated learning activities into curriculum design (Jansen et al., 2020), which could help learners to improve self-regulated learning in MOOCs.

5.5. Limitations and future research

There are a few limitations to the present study. Firstly, Learner motivation has been measured with two open items asking for learners' reason to participate. To investigate the motivation of learners more thoroughly, in-depth interviews could be helpful to gain further information on how learners are motivated to attend MOOCs. In that case, learners are able to provide more explanations and more detailed information about their reasons to participate in a particular MOOC.

Second, the correlated relationships between factors and perceived learning outcomes have been examined, which cannot further reveal the potential causal relationship between independent and dependent variables. An experimental design is needed to examine the causal relationship between motivation, perceived learning support, learning engagement, and self-regulated learning strategies on the one hand and perceived learning outcomes on the other.

Third, learning engagement only covered the behavioral aspect in this study, which perhaps does not sufficiently interpret the multi-dimensional engagement of MOOC learners. We could further examine other types of engagement, such as cognitive, emotional, social, and agentic engagement, to extend the evidence for the impact of learners' engagement on perceived learning outcomes (Bond, Buntins, Bedenlier, Zawacki-Richter, & Kerres, 2020; Büchele, 2021; Deng, Benckendorff, & Gannaway, 2020). Additionally, user data is a gigantic potential resource to explore the learning processes, which could visualize the learning engagement through data mining and learning analytic techniques (Wei, Saab, & Admiraal, 2021). Understanding how multi-dimensional engagement can affect perceived learning outcomes is a meaningful direction to be explored in the future. We have not related perceived learning outcomes to actual academic outcomes, which might mean that we could not offer evidence to explain how the actual academic learning outcomes are presented in the perceived learning outcomes. The relationships between perceived learning, perceived learning outcomes, and actual learning outcomes need to be further examined.

Lastly, we only paid attention to learner factors that affect perceived learning outcomes. Benefiting from the previous review work (Deng et al., 2019; Hood & Littlejohn, 2016b; Pilli & Admiraal, 2017), it is necessary to examine variables related to teaching contexts, such as

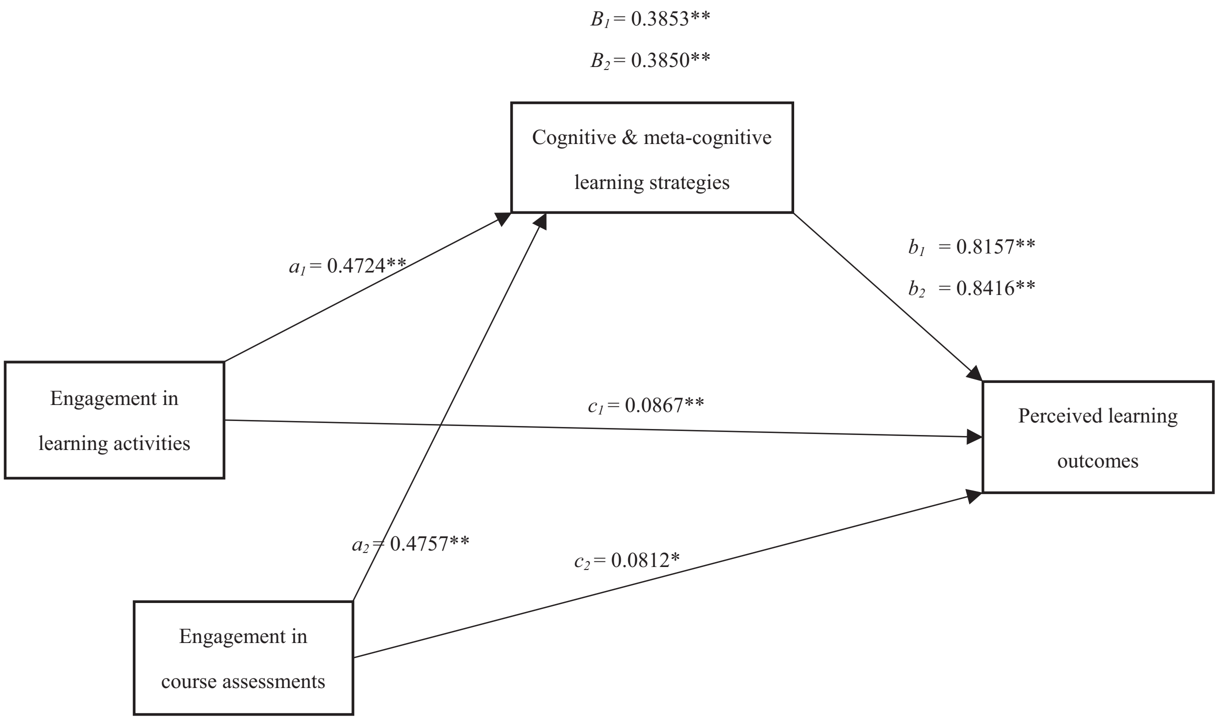

Fig. 5. Mediation path: Learning engagement → Cognitive & meta-cognitive learning strategies → Perceived learning outcomes.
Note: X = Engagement in learning activities, and Engagement in course assessments; *Mediator* (M) = Cognitive & meta-cognitive learning strategies; Y = Perceived learning outcomes; a = Coefficient of X on M, b = Coefficient of M on Y, c = Coefficient of X on Y, B = Indirect effect of X on Y = a * b. ** $p < 0.001$. * $p < 0.05$.

instructor characteristics and course features, which are critical to guarantee the quality of learning outcomes from MOOCs. Future research could extend our findings, examining the interactivity of learner variables and teaching context variables that influence perceived learning outcomes.

6. Conclusion

The present study addressed the gap in the literature on how motivation, perceived learning support, and learning engagement relate to perceived learning outcomes in MOOCs and the importance of self-regulated learning strategies as a mediator of these relationships. Firstly, learners varied in their motivation for participation in MOOCs, and university students seemed to be more motivated by pursuing educational benefits. Second, compared with controlled and combined motivation groups, learners with autonomous motivation reported higher scores for course design, interaction with instructors and peers, learner autonomy, engagement in learning activities, cognitive and metacognitive learning strategies, and perceived learning outcomes. Third, several factors in terms of cognitive and metacognitive learning strategies, interaction with instructors and peers, and engagement in learning activities were significantly and positively associated with perceived learning outcomes, whereas time management, learner autonomy, and engagement in course assessments showed non-significant correlations to perceived learning outcomes. Fourth, cognitive and metacognitive learning strategies were powerful mediator, which had positively and significantly increased the effects of perceived learning support and learning engagement on perceived learning outcomes. Based on our findings, we recommended MOOC curriculum instructors and designers to create an autonomy-supportive climate in instruction to cater to personal needs. Need supportive teaching (Stroet et al., 2013) could be an effective method to stimulate learners to be more autonomously motivated and actively engage in MOOCs, which could satisfy the individual needs for competence, relatedness, and autonomy. Furthermore, it could be helpful to embed self-regulated learning interventions into curriculum design and learning content to promote perceived learning outcomes.

CRediT authorship contribution statement

Xiaomei Wei: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Funding acquisition, Project administration. **Nadira Saab:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision, Project administration. **Wilfried Admiraal:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision, Project administration.

Declaration of Competing Interest

None.

Data availability

Only the research project members can access the stored data.

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