Behaviour & Information Technology

ISSN: 0144-929X (Print) 1362-3001 (Online) Journal homepage: https://www.tandfonline.com/loi/tbit20

Discovering MOOC learner motivation and its moderating role

Yue Chen, Qin Gao, Quan Yuan & Yuanli Tang

To cite this article: Yue Chen, Qin Gao, Quan Yuan & Yuanli Tang (2019): Discovering MOOC learner motivation and its moderating role, Behaviour & Information Technology, DOI: 10.1080/0144929X.2019.1661520

To link to this article: https://doi.org/10.1080/0144929X.2019.1661520

Published online: 10 Sep 2019.

BEHAVIOUR & INFORMATION TECHNOLOGY
https://doi.org/10.1080/0144929X.2019.1661520

Discovering MOOC learner motivation and its moderating role

Yue Chen, Qin Gao, Quan Yuan and Yuanli Tang

Department of Industrial Engineering, Tsinghua University, Beijing, People's Republic of China

ABSTRACT

In massive open online courses (MOOCs), learners have diverse types of motivation. Learners with different motivations have different interaction behaviours, presence, and *learning* outcomes. However, scant research has investigated the moderating role of learner motivations in the associations between presence and *learning* outcomes. This study examined MOOC learner motivation and its moderating role by surveying 646 MOOC learners. By exploratory factor analysis, this study identified four types of motivation: interest in knowledge, curiosity and expansion, connection and recognition, and professional relevance. Based on motivation, the study clustered learners into high-motivation, low-motivation, and asocial learners. Both high-motivation and asocial learners reported strong interest in knowledge and professional relevance, but asocial learners reported the lowest level of connection and recognition among the three groups of learners. Despite the low social presence, the asocial learners still had high levels of cognitive and teaching presence and *learning* outcomes. In addition, learners with higher presence generally perceived higher cognitive *learning*, but asocial learners with higher social presence were less satisfied. The results highlight the impacts of specific types of motivation to enrol in MOOCs and suggest designing different environments for learners with different motivation types.

ARTICLE HISTORY
Received 25 January 2019
Accepted 25 August 2019

KEYWORDS
Motivation; presence; MOOCs; community of inquiry; interaction; satisfaction

1. Introduction

Learners obtain meaningful *learning* by interaction with content, teachers, and other learners in the *learning* community (Moore 1989). During interaction, learners develop feelings of being connected to a *learning* community and perceive educational presence, including cognitive, teaching, and social presence (Garrison, Anderson, and Archer 1999). Previous studies have shown significant associations between interaction, educational presence, and *learning* outcomes (Akyol and Garrison 2011; Baker 2010; Garrison and Arbaugh 2007; Jung and Lee 2018; Ke and Kwak 2013; Rovai 2002b).

Over the last few years, many people have learned from massive open online courses (MOOCs). One of the most popular local MOOC platforms, XuetangX, offers over 1900 courses and has over 16 million users (IBL News 2019). In MOOCs, besides interaction and presence, learners are strongly affected by their motivation. Motivation is the goal people pursue and the extent to which they desire to achieve the goal. MOOC learners can easily register or withdraw from a course without the complex procedures of traditional *learning*. Therefore, MOOC *learning* relies more on learners' motivation. Generally, learners with stronger overall motivation interact more with lecture videos (Barba, Kennedy, and Ainley 2016), participate in more community *learning* activities (Castaño, Maiz, and Garay 2015; Denker et al. 2018; Gillani and Eynon 2014; Yang 2014), and further develop higher cognitive, teaching, and social presence (Kilis and Yıldırım 2018; Kim 2015; Tao 2009). Many studies in MOOC contexts have shown positive associations between overall motivation and *learning* outcomes (Barba, Kennedy, and Ainley 2016; Wu and Bai 2018; Xiong et al. 2015).

However, in MOOCs, learners from diverse backgrounds have very different types of motivation, needs, and expectations of a course. Different types of motivation lead to various interactions, different engagement in *learning* (Brooker et al. 2018; Xiong et al. 2015), and different levels of presence (Angelaina and Jimoyiannis 2012; Goh et al. 2017; Ngoyi et al. 2014). Knowing more about what motivates learners to enrol in MOOCs and how these motivations affect their interactions and *learning* outcomes would enable educators to better design MOOC *learning* environments for learners with different motivations and needs.

To describe learners' motivations to enrol in MOOCs, some previous research determined items to describe motivation (e.g. Hew and Cheung 2014; Watted and

CONTACT Qin Gao gaoqin@tsinghua.edu.cn Department of Industrial Engineering,Tsinghua University, Beijing 100084, China.

Barak 2018) by bottom-up methods. To investigate the effects of these items conveniently, the researchers grouped them using qualitative analyses. However, these groups or structures lacked quantitative verification. A previous study (Kizilcec and Schneider 2015) collected 13 items of MOOC motivation through an open-ended survey and tried to verify a structure of the items by data-driven methods, but the research could not further extract a structure. The first aim of this study is to develop a quantitatively validated structure of MOOC learner motivation.

Because of the motivation diversity, more research is required about the experience of learners with different motivations and needs so that the *learning* environments and content can be designed to satisfy various learners' needs. To understand learners' expectations, previous research grouped learners based on their behaviours (e.g. video clicking stream) and further studied their behaviours or *learning* strategies (Arora et al. 2017; Khalil, Kastl, and Ebner 2016; Kizilcec, Piech, and Schneider 2013; Poquet et al. 2018). These behavioural data were objective, and the quantity was large since MOOCs usually involve thousands of learners. However, these data lacked direct and interpretable expressions from learners. The data also involved more examples of irrelevant behaviours and did not consider learners' offline *learning* behaviours.

To get more qualitative insights about learners' motivations, Barak, Watted, and Haick (2016) identified groups of learners with different motivations based on their emails and forum posts that contained motivational information. However, learners expressed little about their *learning* motivations in emails or forum posts. In addition, most communications aimed to solve *learning* problems rather than to express one's motivation. Some motivations were rarely mentioned in emails or posts. Therefore, it is worthwhile to identify learner groups through their self-reported motivations. The second aim of this study is to group learners based on their motivations and compare their interactions, presence, and *learning* outcomes.

In addition, some previous research has found positive associations between presence and *learning* outcomes in online contexts (e.g. Baker 2010; Ke and Kwak 2013). Regarding the associations between *learning* and social interaction or presence, however, some other studies obtained nonsignificant or even negative results (Cho and Tobias 2016; He 2013; Mackey and Freyberg 2010). Previous research has offered a possible explanation that these associations were affected by system or course aspects, such as system design and course content (He 2013). A recent study found that the association of social interaction and *learning* engagement was mediated by the extent to which learners' needs were satisfied (Fang et al. 2019). This need satisfaction was determined not only by the system or course but by the learners themselves. In other words, besides the system/course aspect, learners' motivations may moderate the associations between social presence and *learning* outcomes. Although the results of some studies have implied that motivation may affect the association of social presence with *learning* outcomes (e.g. Kizilcec and Schneider 2015; Zhang, Allon, and Mieghem 2017), little research has directly studied the moderating role of learners' motivations. The third aim of this study is investigating the moderating role of motivations by comparing learner groups by motivation in terms of the associations between presence and *learning* outcomes.

To achieve these aims, this study conducted a survey study with 646 valid responses from MOOC learners. We first identified types of motivation for enrolling in MOOCs. Based on these types of motivation, we then clustered learners into groups and compared their interactions, presence, and *learning* outcomes. Finally, we studied the associations between presence and *learning* outcomes in the different groups.

2. Literature review

2.1. Types of motivation for enrolling in MOOCs

Many researchers have studied how motivation affects *learning* experience and outcomes. Most have adopted overall motivation level or intrinsic/extrinsic motivation categorisation (Deci and Ryan 1985, 1991, 2002). Intrinsic motivation refers to inherent gratification from a task, whereas extrinsic motivation refers to external incentives beyond the task. This categorisation has been widely used in general *learning* contexts (Chen and Jang 2010; Everaert, Opdecam, and Maussen 2017; Giesbers et al. 2013; Salmon et al. 2017).

However, MOOC learners were found to have highly different types of motivation. Studies in the MOOC context obtained inconsistent results on the effects of intrinsic and extrinsic motivation. Some studies have found both intrinsic and extrinsic motivation positively affected engagement (Xiong et al. 2015) and continuance (Alraimi, Zo, and Ciganek 2015). Some studies have determined that intrinsic motivation positively affected interactions with videos (Barba, Kennedy, and Ainley 2016), the completion rate of a MOOC (Salmon et al. 2017), *learning* engagement (Fang et al. 2019), and attitude to MOOCs (Zhou 2016) but ignored extrinsic motivation or did not find its effects. One study demonstrated that neither intrinsic nor extrinsic motivation affected *learning* outcomes (Brooker et al. 2018). In Barba et al.'s study (2016), intrinsic motivation was also divided into value beliefs, individual interest, and mastery approach. These three constructs affected different aspects of interaction differently. Individual interest even had a small negative effect on final grade despite the positive effects of the other two constructs.

Therefore, it can be inferred that intrinsic or extrinsic motivation types were generalised and probably insufficient to study the effect of motivation in MOOCs. Some studies of interviews showed that learners with different specific motivations adopted different *learning* strategies (Gillani and Eynon 2014; Mukhtar, Muis, and Elizov 2018; Zheng et al. 2015). For example, extrinsic motivation included both wanting to supplement offline *learning* in school and wanting to obtain additional professional skills. If a learner wanted to supplement his or her offline *learning* by a MOOC, he or she would treat the MOOC as a modularised resource, be less likely to consider completing the whole course, and rarely discuss the course content with other learners (Zheng et al. 2015). If a learner wanted to obtain additional professional skills, he or she would use the forum of a MOOC for discussion more often (Gillani and Eynon 2014). In summary, even when the two specific motives were extrinsic motivation, they would lead to different *learning* strategies. This suggests that instead of intrinsic and extrinsic categories of motivation, a more detailed description of motivation is required for investigating its effects on MOOC *learning*.

Some researchers have investigated specific items of motivation for enrolling in MOOCs by bottom-up methods as shown in Table 1. We manually grouped these items into four themes: (1) to satisfy curiosity for knowledge and about the form of MOOCs; (2) to help a career or *learning*, such as to support *learning* in an offline school, to acquire new knowledge and potentially useful skills for the future, to obtain high-quality educational resources from famous universities and teachers, or to collect certifications; (3) for self-growth through flexible lifelong *learning* at any time and place; and (4) for social interaction, such as through *learning* with others and expanding social networks by making friends with other learners in the same course.

Similarly, most of these studies also grouped the items or developed structures for motivation by qualitative methods such as analysing interviews, but these structures lacked quantitative verification. To validate a structure, Kizilcec and Schneider (2015) developed a 13-item scale for measuring MOOC motivation and attempted to establish a structure by data-driven methods, such as factor analysis, but the research retained some problems. First, the results showed that six factors accounted for 30% of the variance. A quantitatively verified structure remains absent. Second, the motivation items were collected by responses to open-ended surveys from learners on three courses, which were not comprehensive enough. As mentioned above, previous studies have provided a comprehensive pool of motivation items. Based on this pool, a more complete structure can be established. Third, the response options were 'Applies' or 'Does not apply'. This dichotomous rating could reduce the resolution of data and the reliability and validity of the measurement (Preston and Colman 2000). The range of the scale needs to be increased.

To summarise, the first research question is:

> RQ1. What are the types of motivation to enroll in MOOCs verified by quantitative methods?

2.2. Grouping and comparing learners by motivation

Most relevant research grouped learners by their behaviours, such as interactions with video lectures, assessments (Kizilcec, Piech, and Schneider 2013), forum activity (Poquet et al. 2018), or both (Arora et al. 2017; Khalil, Kastl, and Ebner 2016). These objective data can be collected in a large amount without learners' active feedbacks, but from these data, we can hardly interpret learners' direct feelings and opinions. For example, some studies (Kim et al. 2014; Qu and Chen 2015) presented behavioural patterns of learners, but participants had a difficult time interpreting the data. In addition, these system log data also included irrelevant behaviours and missed learners' offline *learning* behaviours.

To get more qualitative insights about learners' motivations, Barak, Watted, and Haick (2016) grouped learners by inductive content analysis of their emails and forum posts that contained motivational information. However, learners expressed little about their *learning* motivation in emails or forum posts (only 144 out of 1600 messages and posts contained text regarding motivation). Most communications aimed to solve *learning* problems rather than to express one's motivation. Learners probably did not disclose much of their inner thoughts due to the needs of impression management (Ellison, Heino, and Gibbs 2006). Therefore, some motivations were rarely mentioned in emails or posts. In addition, to better understand the difference of needs and experiences among different learner groups, further comparisons were required about detailed aspects of *learning* such as interaction and presence, but previous research lacked further comparisons.

To summarise, it is necessary to identify learner groups with the consideration of their directly reported

Table 1. Motivation for *learning* in MOOCs from literature.

Study	Methods	Contexts	Items/Results
(Hew and Cheung 2014)	The authors reviewed 25 articles that applied interviews or surveys to determine learners' motivations to enrol in MOOCs.	Various courses and participants for the 25 articles	Why students sign up for MOOCs: • The desire to learn about a new topic or to extend current knowledge • Curiosity about MOOCs • Personal challenge • The desire to collect as many completion certificates as possible
(Huang and Hew 2017)	The authors conducted semi-structured interview to collect learners' views on the motivational design of MOOCs. Results suggested that although the interview participants were from different backgrounds, their reasons for *learning* and for sustaining *learning* were very similar.	11 participants from six countries. Various disciplines including business, health, archaeology, history, etc.	Factors influencing *learning*: • Relevance to work, mentioned by 8 participants; example: 'I am in business and so interested in any business related courses. It helped me synthesise some great new ideas already'. • Relevance to lifestyle, mentioned by 1 participant • Interest, mentioned by 3 participants; example: 'It was important to me because I am interested in history, archaeology and art'. • Credibility, mentioned by 1 participant
(Kizilcec and Schneider 2015)	Survey items were obtained by analysing responses to the open-ended question 'Why did you enroll in this course?' The responses were iteratively coded by MTurkers.	Thousands of responses from three different MOOCs (on topics in political science, computer science, and economics)	Online *Learning* Enrollment Intentions (OLEI) scale (Applies or not): • General interest in topic • Relevant to job • Relevant to school or degree program • Relevant to academic research • For personal growth and enrichment • For career change • For fun and challenge • To meet new people • To experience an online course • To earn a certificate/statement of accomplishment • Course offered by prestigious university/professor • To take with colleagues/friends • To improve my English skills
(Loizzo et al. 2017)	The authors studied learners' experience by observations and interviews. One of the researchers participated in the course as a teaching assistant.	12 adult learners with bachelor's and master's degrees enrolled in a four-week MOOC about human trafficking	Learners' motivations: • Content interest • To learn more about the topic • Professional development • Enjoyment • Information retrieval • Career planning • Social connection • Competition
(Milligan and Littlejohn 2017)	The authors analysed responses to an open-ended question: What was your primary motivation for taking this course?	970 learners in two MOOCs: Fundamentals of Clinical Trials and Introduction to Data Science	Learners' motivations: • Relevance to current role • Learning content • Relevance to future career • Interest in the topic • Other motivation (prestige, certification, MOOC study, zero cost, opportunity to learn in English)
(Salmon et al. 2017)	The authors conducted an online survey and interviews after the MOOC's completion.	155 responses to the survey and 29 interviewed learners from a Carpe Diem MOOC	Three dominant motivations to complete the MOOC: • To further existing knowledge • To acquire skills in the learning design process • To apply the learning design methodology in practice
(Shapiro et al. 2017)	The authors conducted interviews and sentiment analysis.	36 learners from two courses: Introduction to Chemistry, Data Analysis and Statistical Inference	Learners' motivations: • To gain knowledge • Relevance to current work, and career change or advancement • Convenience of MOOCs, high-quality course materials, and ease of understanding • Personal interest, fun, and hobby • Care about certificate, commitment, and confidence building Learners' motivations to complete a MOOC:

(*Continued*)

Table 1. Continued.

Study	Methods	Contexts	Items/Results
(Watted and Barak 2018)	The authors collected data from an online survey with an open-ended question 'Why are you taking the MOOC in Nanotechnology and Nanosensors', 116 forum posts, and 45 email messages. Data were analysed by a deductive and inductive analysis.	308 learners from a Nanotechnology and Nanosensor MOOC	• Educational: experience of online course, certificate, and school relevance • Personal: growth and enrichment, and general interest • Career: career change, research relevance, product development, professional competence
(Xu and Yang 2016)	The authors classified learners based on their activities in the platform such as whether they took exams and video-playing activities.	Thousands of learners involved in 10 courses of various subjects	Learners' motivations: • Certification earning • Video watching • Course sampling
(Yousef et al. 2015b)	The authors analysed responses to an open-ended question 'What are your goals/ objectives when participating in MOOCs?'	82 learners and 76 professors	Objectives of MOOC stakeholders • Blended learning (e.g. to enhance classroom learning) • Flexibility (e.g. to conveniently access resources) • High-quality content (e.g. to learn from the best universities) • Instructional design and learning methodologies (professors' aim) • Lifelong learning • Network learning • Openness (e.g. to learn free courses) • Student-centered learning (mainly professors' aim)
(Zheng et al. 2015)	The motivation items were determined through interviews and grounded theory.	18 MOOC learners from various countries and various disciplines	Motivation to join MOOCs: • Fulfilling current needs, including course complement and professional needs • Preparing for the future, including impressing potential employers and shaping a goal for college application • Satisfying curiosity • Connecting with people

motivations and further compare different groups. The second research question concerns grouping learners by motivation:

> RQ2. What groups of MOOC learners can be identified based on motivation, and how do their interactions, presence, and *learning* outcomes differ?

This study compares interactions, presence, and *learning* outcomes because they are necessary components of the *learning* process, and previous studies have examined the effects of motivation on these variables. First, interaction is a major component of formal *education*. Interaction in online *learning* includes student-content and student-instructor and student-student interactions (Moore 1989). Learners with higher overall motivation levels have higher behavioural intentions (Khan et al. 2018) and exhibit more interaction behaviours (Castaño, Maiz, and Garay 2015; Gillani and Eynon 2014; Yang 2014), such as video interactions (Barba, Kennedy, and Ainley 2016), communication (Denker et al. 2018), and forum discussion (Yang 2014). Learners with higher motivation also have higher *learning* engagement (Xiong et al. 2015) and social engagement (Barak, Watted, and Haick 2016). Besides the extent of motivation, types also affect interaction as mentioned in section 2.1 (Gillani and Eynon 2014; Mukhtar, Muis, and Elizov 2018; Zheng et al. 2015). For example, a previous study showed that both intrinsic and extrinsic motivation positively affected *learning* engagement, but social motivation did not (Xiong et al. 2015). Therefore, more research is required about how learners with different types of motivation interact in MOOCs.

Second, during interactions, learners develop their cognitive, teaching, and social presence. Overall motivation level has been found to be positively associated with cognitive, teaching, and social presence (Baker 2010; Kilis and Yıldırım 2018; Kim 2015; So and Brush 2008; Tao 2009). As elaborated above, different types of motivation bring different interactions. Presence is developed during interaction, and therefore different motivations potentially bring different presence levels.

Third, a higher overall motivation level has been found to be associated with superior *learning* outcomes. Learners with stronger motivation perceive higher usefulness of MOOCs (Wu and Chen 2017) and have higher final grades (Barba, Kennedy, and Ainley 2016), retention rates (Sujatha and Kavitha 2018; Xiong et al. 2015), and satisfaction (Keller 2010). Motivation also influences *learning* outcomes in terms of self-regulated *learning* (Littlejohn et al. 2016), which refers to thoughts, feelings, and actions that are planned and cyclically adapted to personal goals (Zimmerman 2000). More self-regulated *learning* behaviours are associated with a stronger interest in tasks (intrinsic motivation) (Niu 2019), more student-content interaction (Kizilcec, Pérez-Sanagustín, and Maldonado 2017), and superior *learning* outcome (Bernacki, Aguilar, and Byrnes 2011; Pardo, Han, and Ellis 2017). Therefore, this study also evaluates self-regulated *learning* to explain the effects of motivation on *learning* outcomes.

2.3. Association between presence on learning among learner groups

Cognitive and teaching presence have been found to promote *learning*. Higher cognitive presence is associated with higher cognitive *learning* and actual *learning* performance (Akyol and Garrison 2011; Yang et al. 2016). Higher teaching presence is associated with higher engagement (Jung and Lee 2018), satisfaction, cognitive *learning* (Ke and Kwak 2013; Swan 2001), affective *learning* (Baker 2010), perceived *learning* quality (Picciano 2002), and persistence (Jung and Lee 2018).

Unlike cognitive and teaching presence, social presence or interaction has been found to be associated with *learning* differently in different studies. Some studies have suggested that higher social presence is associated with higher affective *learning*, cognitive *learning*, and satisfaction with online courses (Ke and Kwak 2013; Richardson and Swan 2003; Swan and Shih 2005). Other studies have determined that increased social presence had no association with *learning* performance or satisfaction (Cho and Tobias 2016; Mackey and Freyberg 2010). One study (He 2013) on live video teaching found that student-student interaction related to emotional communication was not associated with *learning* performance and in one course was even negatively related to *learning* performance.

Some of these researchers have indicated that the associations between *learning* and social interaction or presence were affected by system and course aspects, such as system design and course content. For example, most current MOOC platforms enable social interaction through discussion forums. Interactions via forums convey fewer social context cues, which make it more difficult to develop social presence (Rovai 2002a). Learners have to make more effort to interact with others and develop adequate social presence, and the amount of effort can affect *learning* outcomes such as satisfaction and retentions.

Besides system and course aspects, learners' characteristics, especially motivation, can affect these associations between social presence and *learning* outcomes but have rarely been studied. An empirical study found that social interaction with instructors and other learners affected *learning* engagement in MOOCs, and this effect was mediated by the extent of how learners' needs were satisfied (Fang et al. 2019). This need satisfaction was determined by both system/course and learners. It indicated that besides the system/course aspects, learners' motivations could affect these associations between social presence and *learning* outcomes.

Learners with different types of motivation expect to obtain different things from social interactions. They have different behavioural patterns (Kizilcec and Schneider 2015) that further affect the associations between social presence and *learning* outcomes. Highly task-oriented learners feel unsatisfied with social interaction if they cannot find enough value from it (Rosé et al. 2015). Non-signature students (those who registered for a course for free) benefited from increased social interaction in the forum, whereas signature-track students (those who registered for a course with a fee) did not (Zhang, Allon, and Mieghem 2017). These two groups of students were very likely to have different motivations for enrolling in MOOCs. These studies indicate that motivation affects the association of social presence with *learning* outcome. However, little previous research has studied this effect of learners' motivations. Thus, the third research question concerns the effect of motivation on the association between presence and *learning* outcomes:

> RQ3. How do learners with different motivations differ in the associations between presence and *learning* outcomes?

3. Methods

3.1. Participants

We conducted an online survey study. We posted links to the questionnaire in the forums of XuetangX and WeChat Moments from December 2016 to April 2017. If a learner enrolled in a course and quickly dropped out, he or she would rarely have experienced most types of interaction or developed adequate presence. Therefore, we screened the responses and only used those from participants who had completed at least half of the schedule of any course on any MOOC platform in the previous six months.

In total, 646 valid questionnaires were collected (see Table 2 for details). The age of the participants ranged from 15 to 50 years (mean [M] = 21.53 years, standard deviation [SD] = 5.06 years). Most participants were less than 30 years old (N = 605, 94%), indicating that our sample was younger than the average population of MOOC learners. Previous reports have found that less than 80% of Chinese MOOC learners were younger

Table 2. Demographic information of participants

Age	Count (Percentage)	Occupation	Count (Percentage)
15–19	286 (44.27%)	Campus student	552 (85.45%)
20–24	259 (40.09%)	Working	80 (12.38%)
25–29	60 (9.29%)	Unemployed	14 (2.17%)
30–50	41 (6.35%)	Retired	0 (0.00%)
Education			
Campus students enrolled in	Count (Percentage)	(Others) academic degree	Count (Percentage)
Junior high school or lower	2 (0.31%)	Junior high school or lower	3 (0.46%)
High school	12 (1.86%)	High school	2 (0.31%)
College	484 (74.92%)	Vocational degree	8 (1.23%)
Graduate school (Master)	44 (6.81%)	Bachelor	61 (9.41%)
Graduate school (Ph.D.)	9 (1.39%)	Master	18 (2.78%)
		Ph.D.	2 (0.31%)

than 30 years old (Zheng, Chen, and Burgos 2018). Regarding gender, 433 (67%) of the respondents were men, and 213 (33%) were women. Most participants ($N = 627$, 97%) took higher *education*. Probably due to the young age and high educational background, 552 participants (85%) were campus students. This proportion of students was also higher than that in the general population of MOOC learners (less than 60% in Zheng, Chen, and Burgos 2018).

The participants were asked to complete the questionnaire based on a course they had taken in the previous six months. More than 80% of the selected courses were from XuetangX ($N = 513$, 79.41%), since we posted the questionnaire in the forums of XuetangX. Other platforms included icourse163.org ($N = 70$, 10.84%), Coursera ($N = 31$, 4.80%), and other platforms ($N = 32$, 4.95%). Among the selected courses, 204 were on STEM subjects (science, technology, engineering, and mathematics), with the remainder being on subjects such as arts, history, language, and sociology.

3.2. Questionnaire design

The first section of the questionnaire asked for information about the course, including (1) its name, (2) the platform providing the course, and (3) the percentage of the course schedule that the participant had finished.

The second section was about *motivation*. As shown in section 2, we obtained motivation items from 11 studies that investigated MOOC motivation by bottom-up methods (Hew and Cheung 2014; Huang and Hew 2017; Kizilcec and Schneider 2015; Loizzo et al. 2017; Milligan and Littlejohn 2017; Salmon et al. 2017; Shapiro et al. 2017; Watted and Barak 2018; Xu and Yang 2016; Yousef et al., 2015b; Zheng et al. 2015). First, we summarised motives into four themes, then similar motives were combined into one item. Too generalised statements were removed. Finally, we identified 16 potential motivation items (Table 4). The participants rated their agreement or disagreement with each item using a five-point Likert scale.

The third section was about *interactions*. We asked the participants (1) whether they would watch a lecture video once or for several times and (2) to describe their behaviours when taking notes by a single question (options were 'using the note function on the platform', 'using a note application', 'on paper', and 'never took notes'). Regarding interactions in forums, the *frequency of reading* threads in the forum was measured by a single item with five levels scored from 0 to 4 (i.e. 'never or very rarely', 'once or twice per month', 'once or twice per week', 'more than twice per week but not every day', and 'every day'). The *frequency of posting* or replying to threads in the forum was measured using a single item with four levels scored from 0 to 3 (i.e. 'never or very rarely', 'once or twice per month', 'once or twice per week', and 'more than twice per week'). Moreover, the participants were asked whether they had made friends on the forum. Outside MOOC platforms, the participants were asked whether they had joined discussion groups (if any) organised by teaching assistants (TAs) or the instructor in an instant messaging application (e.g. QQ or WeChat). Next, the participants were asked whether they had direct contact with the TAs or the instructor (e.g. email, instant message, or face-to-face). Based on these questions, we measured interaction level by *variety of behavior*, defined as how many of the following common activities the participant had performed: (1) taking notes, (2) reading the forum, (3) posting in the forum, (4) making friends in the forum, (5) joining the discussion group, and (6) directly contacting the TAs or instructor.

The fourth section concerned *cognitive, teaching, and social presence*. These were measured using nine items on a five-point Likert scale (Table 3) adapted and simplified from the CoI Questionnaire (Akyol and Garrison 2008; Arbaugh et al. 2008). The original scale of each presence involved several dimensions, and each dimension consisted of several items. In the simplified scale, items of a dimension were combined into one item to reduce the workload of filling the questionnaire (see Table 3). The level in each presence was calculated using the

Table 3. Questionnaire items for measuring presence, perceived *learning*, satisfaction, and self-regulated *learning*.

variables	Items
Cognitive presence (Cronbach's $\alpha = 0.826$)	Taking the course increased my interest in the related field.
	I gathered information related to the course in various ways, thought about related problems, and learned from the perspectives of others in the forum discussion.
	I integrated new information, thought about concepts, and solved problems.
	I was able to apply the knowledge from the course to my life, my study in school, or my work.
Teaching presence (Cronbach's $\alpha = 0.799$)	I think the instructor of the course provided clear goals, topics, requirements, and guidance.
	I think the instructor was helpful in guiding learners.
	I think the instructor could directly guide me and provide feedback in time.
Social presence (Cronbach's $\alpha = 0.855$)	I could communicate with other learners in the same course and have a sense of belonging.
	I could communicate with other learners comfortably.
Perceived cognitive learning (Cronbach's $\alpha = 0.831$)	I could summarise the logic structure of the course.
	I could provide guidance for people who were going to take the course.
	I could critically think about the content in the course.
	Taking the course promoted my self-directed *learning*.
	I could do more complex thinking after taking the course.
Perceived affective learning (Cronbach's $\alpha = 0.786$)	I think the course was valuable.
	I would like to take other courses in the same way.
Satisfaction (Cronbach's $\alpha = 0.851$)	The course met my needs for the related knowledge.
	I felt satisfied about the course generally.
	I felt satisfied about the MOOC platform.
	I will take part in more MOOCs.
Self-regulated learning (Cronbach's $\alpha = 0.877$)	Goal setting: I set goals when taking the course.
	Environment structuring: I chose a quiet location and time to take the course in order to avoid distraction.
	Task strategies: I prepared a lot to complete different *learning* tasks.
	Time management: I managed my time and scheduled the *learning*.
	Help seeking: I tried to find others for help or discussion when I encountered problems during *learning*.
	Self-evaluation: I regularly evaluated myself during the course.

mean of the scores of the items of that type of presence. The Cronbach's α coefficients of cognitive, teaching, and social presence were 0.826, 0.799, and 0.855 respectively.

The fifth section concerned learning *outcomes*, including perceived *learning* and satisfaction. Two aspects of perceived *learning* were considered: cognitive and affective *learning*. *Cognitive* learning is a learner's memory or recognition of knowledge and the development of intellectual abilities (Bloom 1956). It was measured using a five-point Likert scale with five items, including three cognitive items and two affective items from the CAP Perceived *Learning* Scale (Rovai et al. 2009) (Table 3). Some statements in the two items on affective *learning* also reflected cognitive aspects of *learning*, and they were therefore modified to measure cognitive *learning* in this study (see the last two items of cognitive *learning* in Table 3). The Cronbach's α of the five items was 0.831. *Affective* learning is increasing internalisation of positive attitudes toward the *learning* content, subject, or instructor (Russo and Benson 2005). It was measured using a five-point Likert scale with two items adapted from Gorham (1988) (Table 3). The original questionnaire asked about learners' attitudes toward both the content and the instructor and whether learners would like to learn in the same way in the future. This scale simply combined the content and the instructor into the term 'course'. The Cronbach's α of affective *learning* was 0.786. Objective measures of performance, such as grades, were not employed for two reasons. First, our participants took different courses, and thus it was difficult to compare objective scores across courses. Second, MOOC learners have diverse educational backgrounds and previous knowledge, rendering it unfair to compare objective performance.

Satisfaction was measured using four items with a five-point Likert scale (Table 3), including satisfaction with the course and satisfaction with the platform. The level of each variable was calculated as the mean of the scores of the items corresponding with the variable. The Cronbach's α was 0.851.

The sixth section concerned *self-regulated* learning and helped to explain how motivation affected the *learning* outcomes. It was measured using six items with a five-point Likert scale adapted from the Online Self-Regulated *Learning* Questionnaire (Barnard et al. 2009) (Table 3). The six dimensions in the original questionnaire were converted into six items respectively. The participants rated how often they experienced each item using the scale, and their extent of self-regulated *learning* was calculated as the mean of the scores for these items. The Cronbach's α was 0.877.

Finally, the questionnaire asked for the participants' background information, such as age, gender, educational background, and occupation.

Because we simplified the scales for presence, affective *learning*, and self-regulated *learning*, we conducted a pilot test for the adapted scales to initially validate the simplification. Besides the internal reliability, we also conducted correlation analyses of the original and adapted scales. We conducted a survey involving 32 valid responses. Participants were asked to fill out two questionnaires in two consecutive days based on a course they had taken in the previous six months. The first questionnaire included the original scales for cognitive, teaching, and social presence and the adapted scales for self-regulated *learning* and affective *learning*. The second questionnaire included the original scales for self-regulated *learning* and affective *learning* and the adapted scales for cognitive, teaching, and social presence. The score of a scale was calculated by the mean values of all the items in the scale.

All the participants had completed at least half of the schedule of any course on any MOOC platform in the previous six months. The age of the participants ranged from 19 to 29 years (mean [M] = 22.88 years, standard deviation [SD] = 2.81 years). Regarding gender, 19 (59%) were men and 13 (41%) were women. All participants participated in higher *education*. Most ($N = 31$) were students.

The results suggested that all the values of the adapted scales were correlated with the values of the original scales (Pearson's r values > 0.70). The Pearson's r values for cognitive presence, teaching presence, social presence, self-regulated *learning*, and affective *learning* were 0.81, 0.75, 0.90, 0.86, and 0.84.

3.3. Data analysis

To answer RQ1 on identifying the types of motivation to enrol in MOOCs, we conducted principal component factor analysis with varimax rotation on the 16 motivation items. To answer RQ2, we first clustered learners based on motivation types from factor analysis. The clustering method was k-means with the algorithm of Hartigan and Wong (1979). Then we compared different learner clusters in terms of motivation, interaction, presence, and *learning* outcomes. The frequencies of reading the threads and of posting in the forum violated the assumption of normality. Therefore, Kruskal–Wallis rank sum tests were conducted, and the post hoc analyses were Wilcoxon rank sum tests with the Bonferroni correction. For other variables, analysis of variance (ANOVA) was applied, and the post hoc analyses were pairwise t-tests with the Bonferroni correction. To answer RQ3 on how motivation affected the relationship between presence and outcomes, we conducted Pearson correlation analysis for the relationships between presence and outcomes in different learner clusters.

4. Results

4.1. Motivation to enrol in MOOCs

To answer RQ1 on identifying types of motivation to enrol in MOOCs, we conducted exploratory factor analysis for motivation items. The results suggested a four-factor structure with no cross-loading higher than 0.45 (see Table 4). The ratings of each item are illustrated in Figure 1. Altogether, 68% of the total variance was explained by the four factors, indicating acceptable fit of the model. The Cronbach's α coefficients of the factors were all above the threshold of 0.60 suggested for exploratory research (Hair 2009).

Factor 1, named *interest in knowledge*, consists of five items and explains 19% of the total variance. It represents the intrinsic motivation to learn new things and broaden knowledge. It contains four items with positive loadings and one item with negative loading (the requirement from teachers). It was relatively intrinsic, and some items with high ratings were 'I want to

Table 4. Factor loadings (principal components, varimax rotation) of types of motivation for course enrolment

Item	Description	Mean (SD)	Loading
F1	*Interest in knowledge (M = 3.80, SD = 0.87, Cronbach's α = 0.772)*		
1	I am interested in this course.	4.12 (0.96)	0.78
2	The teacher at my school asked us to take this course.	3.32 (1.72)	−0.77
3	I want to broaden my knowledge through this course.	4.21 (0.90)	0.76
4	I take this course to learn about topics that are new for me.	3.88 (1.06)	0.67
5	I take MOOCs because I enjoy lifelong *learning*.	3.47 (1.21)	0.52
F2	*Curiosity and expansion (M = 3.45, SD = 0.83, Cronbach's α = 0.764)*		
6	I am attracted by the resources from famous universities.	3.78 (1.13)	0.75
7	I am attracted by famous teachers.	3.47 (1.15)	0.75
8	I learn about different majors through MOOCs.	3.29 (1.20)	0.59
9	I challenge myself by taking MOOCs.	3.32 (1.18)	0.58
10	I am curious about the form of MOOCs.	3.40 (1.16)	0.54
F3	*Connection and recognition (M = 2.55, SD = 0.98, Cronbach's α = 0.751)*		
11	I keep in touch with acquaintances by taking the same course with them.	2.56 (1.18)	0.86
12	I want to make friends who share the same interests through this course.	2.71 (1.20)	0.84
13	I want to collect as many certifications as possible.	2.38 (1.22)	0.64
F4	*Professional relevance (M = 3.56, SD = 1.01, Cronbach's α = 0.707)*		
14	I learn knowledge and skills that my major requires me to have through this course.	3.30 (1.38)	0.85
15	I take this course to support my *learning*, for example, in school.	3.54 (1.29)	0.82
16	I want to improve my skills and abilities and promote my career through this course.	3.84 (1.13)	0.52

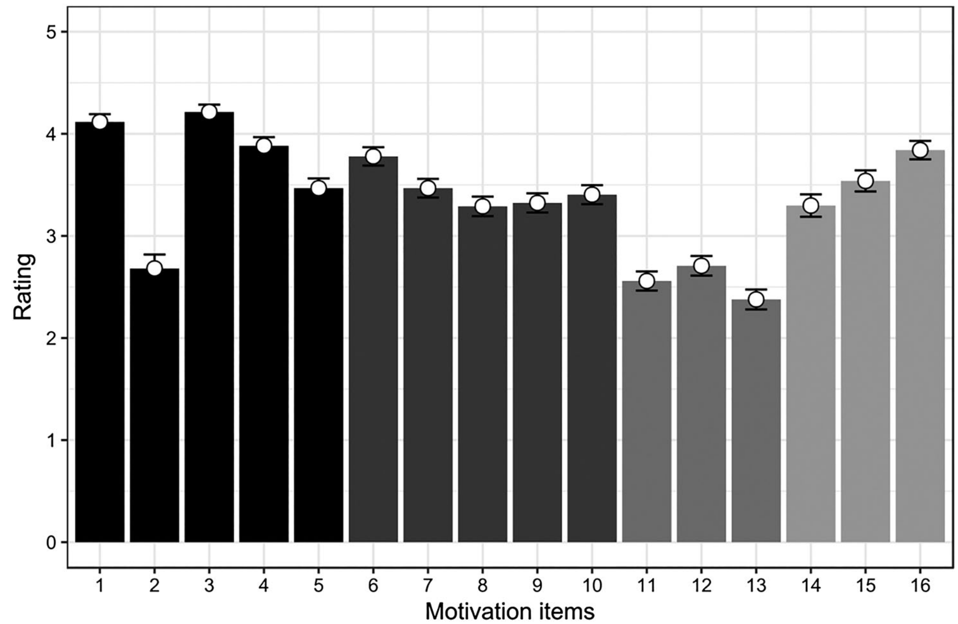

Figure 1. Rating of 16 motivation items with the 95% confidence interval (ordered as in Table 4).

broaden my knowledge through this course' and 'I am interested in this course'.

Factor 2, named *curiosity and expansion*, comprises five items and explains 16% of the total variance. It covers (1) the need to satisfy curiosity about MOOCs and different majors and (2) the need for high-quality educational resources and self-challenge. Items with the highest ratings were mainly about resources from famous universities and professors.

Factor 3, named *connection and recognition*, consists of three items and explains 15% of the total variance. It represents the need to connect with and be recognised by others. Participants rated relatively low scores in these three items, especially the item about collecting certifications.

Finally, factor 4, named *professional relevance*, consists of three items and explains 13% of the total variance. It represents the motivation to support the learner's current offline *learning* or working. The highest rated item was about improving skills and abilities to promote career goals.

The score for each factor (except interest in knowledge) was the mean value of the scores for all items in that factor. Interest in knowledge contained an item with negative loading; therefore, its score was calculated as the mean value of the scores for the four items with positive loadings and 6 minus the score for the item with negative loading. Generally, participants reported the highest scores in interest in knowledge ($M = 3.80$, $SD = 0.87$), followed by curiosity and expansion ($M = 3.45$, $SD = 0.83$) and professional relevance ($M = 3.56$, $SD = 1.01$, p values of t tests with Bonferroni correction < 0.001). They reported the lowest scores in connection and recognition ($M = 2.55$, $SD = 0.98$, p values < 0.001).

4.2. Descriptive statistics of overall interaction, presence, and learning outcomes

We compared interaction, presence, and *learning* outcomes of learners with different motivations. First, we summarised the overall statistics of all the participants. Regarding interaction, Table 5 presents a summary of whether participants performed six behaviours. Participants performed 2.44 of the six behaviours on average ($SD = 1.45$). The mean frequency of reading threads in the forum was between the levels of 'once or twice per month' and 'once or twice per week'. Nearly half of the participants ($N = 260$) read threads in the forum once or twice per week. The mean frequency of posting in the forum was between the level 'never or very rarely'

Table 5. Frequency of performance of behaviours

Items in the variety of behaviours	Yes		No	
1. Did you take notes when watching the lecture video?	319	49.38%	327	50.62%
2. Did you read any posts in the forum?	496	76.78%	150	23.22%
3. Did you post any threads or reply in the forum?	361	55.88%	285	44.12%
4. Did you make friends in the forum?	57	8.82%	589	91.18%
5. Did you join in any group of the course managed by TAs or the teacher? (e.g. QQ or WeChat group)	210	32.51%	436	67.49%
6. Did you contact the teacher or TAs directly? (e.g. by email or instant message)	131	20.28%	515	79.72%

and ‘once or twice per month’. Nearly half of the participants ($N = 285$) had never posted in the forum.

The participants perceived different levels of the three types of presence ($F_{2,1935} = 251.3$, $p < .001$, partial $\eta^2 = .206$). Social presence ($M = 2.93$, SD = 1.08) was significantly lower than cognitive presence ($M = 3.83$, SD = 0.78, $p < .001$) and teaching presence ($M = 3.93$, SD = 0.75, $p < .001$). Generally, participants reported good *learning* outcomes in terms of cognitive *learning* ($M = 3.63$, SD = 0.71), affective *learning* ($M = 4.05$, SD = 0.85), self-regulated *learning* ($M = 3.69$, SD = 0.74), and satisfaction ($M = 4.11$, SD = 0.70).

4.3. Learner groups based on types of motivation

To answer RQ2, learners were clustered and compared. Three groups emerged (Table 6): (1) high-motivation learners (learners who had relatively high scores in all four motivation factors), (2) asocial learners (learners who had high scores in all motivation factors except connection and recognition); and (3) low-motivation learners (learners who had relatively low scores in all four motivation factors). Their demographic information is shown in Table 6.

4.3.1. Comparing motivation

The three groups of learners differed in all four motivation factors (see Table 7). High-motivation learners and asocial learners did not differ in interest in knowledge ($M = 4.18$, SD = 0.60 for high-motivation learners and $M = 4.07$, SD = 0.62 for asocial learners) and professional relevance ($M = 3.97$, SD = 0.79 for high-motivation learners and $M = 4.09$, SD = 0.68 for asocial learners; p values of t tests with the Bonferroni correction were 0.28 and 0.26). Compared with these two groups, low-motivation learners gave the lowest scores for interest in knowledge ($M = 3.05$, SD = 0.90) and professional relevance ($M = 2.53$, SD = 0.69, p values < 0.001). High-motivation learners rated higher for curiosity and expansion ($M = 4.05$, SD = 0.57) than asocial learners ($M = 3.33$, SD = 0.68), followed by low-motivation learners ($M = 2.80$, SD = 0.69, p values < 0.001). High-motivation learners rated higher for connection and recognition ($M = 3.44$, SD = 0.65) than low-motivation learners ($M = 2.13$, SD = 0.71), followed by asocial learners ($M = 1.76$, SD = 0.53, p values < 0.001).

Within each group, we also compared their ratings of the four factors. For high-motivation learners, the highest ratings were for interest in knowledge and curiosity and expansion. Professional relevance was slightly lower than interest in knowledge ($p = 0.002$). Connection and recognition was the lowest motivation factor (p values < 0.001).

For asocial learners, the highest ratings were for interest in knowledge and professional relevance. These two factors were higher than curiosity and expansion and connection and recognition (p values < 0.001). Connection and recognition was the lowest motivation factor (p values < 0.001).

Low-motivation learners gave significantly different scores among the four motivation factors. Factors from the highest to the lowest were interest in knowledge, curiosity and expansion, professional relevance, and connection and recognition (p values < 0.01).

4.3.2. Comparing interaction and presence

The participants in different motivation groups reported significantly different interactions and presence (Table 7). Kruskal–Wallis rank sum tests and ANOVA revealed that the difference in the frequency of posting in the forum was marginally significant ($p = 0.057$) and the

Table 6. Demographic information of learner groups

Group *Motivations*	1 High-motivation learners ($N = 258$) M (SD)	2 Asocial learners ($N = 187$) M (SD)	3 Low-motivation learners ($N = 201$) M (SD)
Interest in knowledge	4.18 (0.60)	4.07 (0.62)	3.05 (0.90)
Curiosity & expansion	4.05 (0.57)	3.33 (0.68)	2.80 (0.69)
Connection & recognition	3.44 (0.65)	1.76 (0.53)	2.13 (0.71)
Professional relevance	3.97 (0.79)	4.09 (0.68)	2.53 (0.69)
Age	22.1 (5.4)	22.3 (5.7)	20.0 (3.3)
Gender	Count (Percentage)	Count (Percentage)	Count (Percentage)
Male	182 (70.5%)	119 (63.6%)	132 (65.7%)
Female	76 (29.5%)	68 (36.4%)	69 (34.3%)
Employment status			
Student	212 (82.2%)	151 (80.7%)	189 (94.0%)
	39 (15.1%)	31 (16.6%)	10 (5.0%)
Unemployed	7 (2.7%)	5 (2.7%)	2 (1.0%)
Educational level (in progress)			
High school	10 (3.9%)	5 (2.7%)	4 (2.0%)
Bachelor or junior college	219 (84.9%)	149 (79.7%)	186 (92.5%)
Master	26 (10.1%)	27 (14.4%)	9 (4.5%)
PhD	3 (1.2%)	6 (3.2%)	2 (1.0%)

Table 7. Statistics for variety of behaviours, frequency of reading and posting in the forum, presence, perceived *learning*, satisfaction, and self-regulated *learning* of learners in different groups

Items	High-motivation learner M (SD)	Asocial learners M (SD)	Low-motivation learners M (SD)	Statistics[a]	p value	η^{2b}
Interest in knowledge	4.18 (0.60)	4.07 (0.62)	3.05 (0.90)	161.6	<.001	.334
Curiosity & expansion	4.05 (0.57)	3.33 (0.68)	2.80 (0.69)	218.4	<.001	.405
Connection & recognition	3.44 (0.65)	1.76 (0.53)	2.13 (0.71)	436.6	<.001	.576
Professional relevance	3.97 (0.79)	4.09 (0.68)	2.53 (0.69)	290.9	<.001	.475
Variety of behaviours	2.71 (1.49)	2.30 (1.41)	2.22 (1.37)	7.746	<.001	.024
Frequency of reading threads in the forum	1.69 (1.06)	1.37 (1.10)	1.36 (0.94)	13.89	<.001	
Frequency of posting in the forum	0.87 (0.90)	0.75 (0.87)	0.97 (0.94)	5.731	.057	
Cognitive presence	4.17 (0.54)	3.97 (0.69)	3.27 (0.80)	106.1	<.001	.248
Teaching presence	4.17 (0.62)	4.05 (0.67)	3.50 (0.79)	57.34	<.001	.151
Social presence	3.30 (1.04)	2.55 (1.08)	2.80 (0.98)	33.13	<.001	.088
Cognitive *learning*	3.93 (0.56)	3.74 (0.58)	3.15 (0.73)	93.23	<.001	.225
Affective *learning*	4.38 (0.61)	4.29 (0.66)	3.40 (0.90)	119.4	<.001	.271
Satisfaction	4.35 (0.51)	4.27 (0.61)	3.64 (0.75)	82.00	<.001	.203
Self-regulated *learning*	4.02 (0.61)	3.81 (0.59)	3.17 (0.75)	101.7	<.001	.240

[a]For frequency of reading threads in the forum and frequency of posting in the forum, the Kruskal-Wallis rank sum test was applied, and the statistic was χ^2_2. For other variables, ANOVA was applied, and the statistic was $F_{2,643}$.
[b]η^2 = .01, small; .06, medium; .14, large.

difference in all the other variables was significant (p values < 0.001).

The variety of behaviours of the high-motivation learners ($M = 2.71$, SD = 1.49) was significantly greater than that of the asocial learners ($M = 2.30$, SD = 1.41, $p = 0.0097$) and low-motivation learners ($M = 2.22$, SD = 1.37, $p < 0.001$). The frequency of reading the forum of the high-motivation learners ($M = 1.69$, SD = 1.06) was significantly higher than that of the asocial learners ($M = 1.31$, SD = 1.10, $p = 0.007$) and low-motivation learners ($M = 1.36$, SD = 0.94, $p = 0.004$).

The cognitive presence of the high-motivation learners ($M = 4.17$, SD = 0.54) was higher than that of the asocial learners ($M = 3.97$, SD = 0.69, $p = 0.007$), followed by the low-motivation learners ($M = 3.27$, SD = 0.80, $p < 0.001$). The teaching presence of the low-motivation learners ($M = 3.50$, SD = 0.79) was significantly lower than that of the high-motivation learners ($M = 4.17$, SD = 0.62, $p < 0.001$) and asocial learners ($M = 4.05$, SD = 0.67, $p < 0.001$). The social presence of the high-motivation learners ($M = 3.30$, SD = 1.04) was significantly higher than that of the asocial learners ($M = 2.55$, SD = 1.08, $p < 0.001$) and low-motivation learners ($M = 2.80$, SD = 0.98, $p < 0.001$).

4.3.3. Comparing learning *outcomes*

The participants from different groups also reported significantly different perceived *learning*, satisfaction, and self-regulated *learning* (p values < 0.001 as shown in Table 7). The cognitive *learning* of the high-motivation learners ($M = 3.93$, SD = 0.56) was higher than that of the asocial learners ($M = 3.74$, SD = 0.58, $p = 0.006$), followed by the low-motivation learners ($M = 3.15$, SD = 0.73, $p < 0.001$). The affective *learning* of the low-motivation learners ($M = 3.40$, SD = 0.90) was significantly lower than that of the high-motivation learners ($M = 4.38$, SD = 0.61, $p < 0.001$) and asocial learners ($M = 4.29$, SD = 0.66, $p < 0.001$).

Regarding satisfaction, the low-motivation learners ($M = 3.64$, SD = 0.75) were significantly less satisfied than the high-motivation learners ($M = 4.35$, SD = 0.51, $p < .001$) and asocial learners ($M = 4.27$, SD = 0.61, $p < 0.001$). The self-regulated *learning* of the high-motivation learners ($M = 4.02$, SD = 0.61) was higher than that of the asocial learners ($M = 3.81$, SD = 0.59, $p = .003$) followed by the low-motivation learners ($M = 3.17$, SD = 0.75, $p < 0.001$).

4.4. Comparing the associations of presence with outcomes

To answer RQ3, we conducted Pearson correlation analysis for the relationships between the three types of presence and *learning* outcomes (Table 8).

When we analysed all the participants together, higher cognitive presence and teaching presence were significantly correlated with higher perceived *learning* and satisfaction. Furthermore, higher social presence was significantly correlated with higher cognitive *learning*, and no significant correlation was discovered between social presence and affective *learning* or satisfaction.

However, across different learner groups, the correlations between social presence and *learning* outcomes were slightly different. For the high-motivation learners, higher social presence was correlated with higher cognitive *learning*; for the asocial learners, higher social presence was correlated with higher cognitive *learning* but lower satisfaction; and for the low-motivation learners, higher social presence was correlated with higher cognitive *learning* and satisfaction (marginally significant).

Table 8. Pearson product-moment correlations of cognitive, teaching, and social presence with measures of *learning* outcomes for different learner groups

	Cognitive presence	Teaching presence	Social presence
All participants			
Perceived cognitive *learning*	.646 ($p < .001$)	.486 ($p < .001$)	.220 ($p < .001$)
Perceived affective *learning*	.664 ($p < .001$)	.569 ($p < .001$)	.076 ($p = .053$)
Satisfaction	.644 ($p < .001$)	.600 ($p < .001$)	.062 ($p = .117$)
High-motivation learners			
Perceived cognitive *learning*	.533 ($p < .001$)	.465 ($p < .001$)	.137 ($p = .028$)
Perceived affective *learning*	.547 ($p < .001$)	.509 ($p < .001$)	.046 ($p = .464$)
Satisfaction	.552 ($p < .001$)	.572 ($p < .001$)	.047 ($p = .452$)
Asocial learners			
Perceived cognitive *learning*	.426 ($p < .001$)	.339 ($p < .001$)	.169 ($p = .021$)
Perceived affective *learning*	.530 ($p < .001$)	.390 ($p < .001$)	−.070 ($p = .342$)
Satisfaction	.517 ($p < .001$)	.495 ($p < .001$)	−.171 ($p = .019$)
Low-motivation learners			
Perceived cognitive *learning*	.615 ($p < .001$)	.322 ($p < .001$)	.240 ($p < .001$)
Perceived affective *learning*	.565 ($p < .001$)	.485 ($p < .001$)	.082 ($p = .250$)
Satisfaction	.557 ($p < .001$)	.494 ($p < .001$)	.137 ($p = .053$)

5. Discussion

5.1. Motivations to enrol in MOOCs

Because MOOC learners had much more diverse motivation and backgrounds than learners in traditional schools, the overall motivations or general categorizations were insufficient to show the effects of motivation on *learning* (e.g. Barba, Kennedy, and Ainley 2016). This study provides a detailed and initially verified motivation model for MOOC enrolment (RQ1). It has two distinguishing features. First, the detailed items were gathered from 11 previous bottom-up studies. They covered various courses and learners and suggested the comprehensiveness of the item set. Second, the structure was initially evaluated by exploratory factor analysis and could explain 68% of the total variance. It can be further validated by confirmatory factor analysis and used to develop a questionnaire for measurement of motivations to enrol in MOOCs.

In detail, the model includes four motivation types or factors: interest in knowledge, curiosity and expansion, connection and recognition, and professional relevance. Our data suggest that the most important reason or motivation is interest in knowledge, supporting the previous studies that found the greatest motivation to take MOOCs is general interest in the course content (Kizilcec and Schneider 2015; Watted and Barak 2018). Our data also reveal that the least significant reason is connection and recognition. Fewer learners enrol in MOOCs with the aims of connecting with others or earning a certificate. This is probably one of the reasons for the low participation in social interactions and low completion rate in MOOCs.

5.2. Grouping and comparing learners by motivation

This study also clustered learners based on motivation factors and compared learner clusters in a number of variables (RQ2). Three groups of learners emerged: 258 high-motivation learners, 187 asocial learners, and 201 low-motivation learners. Each group had significantly different motivations, interactions, presence, and *learning* outcomes.

High-motivation learners rated the highest scores in all four motivation factors. In this group, the highest ratings were for interest in knowledge and curiosity and expansion. In other words, high-motivation learners expect to obtain related knowledge and to fulfil their interests and curiosity in knowledge, the resources they can gain from university and professors, and how MOOC *learning* works. They participate in more types of *learning* activities and read the forum more frequently. They perceived the highest cognitive, teaching, and social presence. Moreover, they reported the highest cognitive *learning*, affective *learning*, satisfaction, and self-regulated *learning*.

Low-motivation learners rated the lowest scores in all four motivation factors. As with high-motivation learners, low-motivation learners also value interest in knowledge most among the four motivation factors. Since they have a low level of overall motivation, they reported the lowest levels of interaction, presence, and *learning* outcomes.

In addition to high- and low-motivation learners, this study identified a special group of learners that we termed asocial learners. They reported interest in knowledge and professional relevance as important as high-motivation learners did. However, they rated the lowest score in connection and recognition, even lower than low-motivation learners. In this group, the highest ratings were for interest in knowledge and professional relevance. In other words, asocial learners most expect to obtain related knowledge and to improve skills and abilities to promote professional careers. Compared with high-motivation learners, asocial learners are more pragmatic, focus on the knowledge and skills, and avoid inefficient social interactions. They reported interacting as little as the low-motivation learners did and perceived social presence as low as the low-motivation learners did. Regardless of the low levels of interaction and social presence, they still perceived teaching presence, affective *learning*, and satisfaction as high as the high-motivation learners perceived. Their cognitive presence, cognitive *learning*, and self-regulated *learning* were slightly lower than those of high-motivation learners.

These asocial learners were similar to the 'performers' (4% of the participants) identified in a relevant study from HarvardX–MITx (Arora et al. 2017). The performers also valued efficiency and performed better with less effort and interaction. However, the proportion of asocial learners in this study is much higher than performers in Arora et al.'s study. In addition, previous research indicated that superior *learning* outcomes were associated with higher overall motivation (e.g. Barba, Kennedy, and Ainley 2016; Niu 2019). Our results also supplement this previous research: the positive associations were contributed mainly by the motivation factors of interest in knowledge and professional relevance, whereas connection and recognitive contributed little to it.

5.3. Association of presence and learning *outcomes*

To investigate the effects of motivation on the associations of presence and *learning* outcomes (RQ3), correlation analyses were conducted in different learner groups. Regardless of motivation groups, cognitive presence and teaching presence were positively associated with perceived affective *learning*, cognitive *learning*, and satisfaction. Social presence was also positively associated with cognitive *learning* in all three groups, consistent with previous studies (Akyol and Garrison 2011; Ke and Kwak 2013; Picciano 2002; Richardson and Swan 2003; Swan 2001).

However, different from previous studies, we found motivation affected the association of social presence and satisfaction. In the high-motivation group, social presence was not associated with satisfaction; in the low-motivation group, higher social presence was correlated with higher satisfaction (marginally significant); but in the asocial group, higher social presence was associated with lower satisfaction. We explain this negative association as follows. Asocial learners have strong motivation to acquire knowledge and improve abilities efficiently. They want to concentrate on interactions with content and instructors. They are unwilling to connect with other learners and do not care about recognitions. However, to develop social presence, learners are required to have a number of social interactions, such as participating in forums or discussion groups. Our data also found significantly positive associations of social presence with the frequency of reading forum discussions (Pearson's $r = 0.235$, $p < 0.001$) and with the frequency of posting messages in the forum (Pearson's $r = 0.271$, $p < 0.001$). The participants who joined discussion groups perceived higher social presence ($M = 3.44$, SD = 0.93) than did those who did not join any group ($M = 2.68$, SD = 1.06, p value of t test < 0.001). More social interactions engendered higher perceived social presence but lowered satisfaction for the asocial learners.

6. Conclusion

6.1. Implications

This study developed and initially evaluated a four-factor model to describe the diverse motivations to enrol in MOOCs, including interest in knowledge, curiosity and expansion, connection and recognition, and professional relevance. The 16 detailed items covered various courses and learners, and the model was initially evaluated by a survey with 646 responses. On the one hand, this model provides an alternative way to study the experience of MOOC *learning* systematically from different dimensions of motivation instead of the overall motivation level or general motivation categories. On the other hand, it can be further validated by confirmatory factor analysis and used to develop a questionnaire for measurement of motivation to enrol in MOOCs.

This study also applied the motivation model and clustered learners into high-motivation, low-motivation, and asocial learners. Each group had significantly different motivations, interactions, presence, and *learning* outcomes. In particular, asocial learners (29% of the sample) rated interest in knowledge and professional relevance as high as high-motivation learners, but they rated connection and recognition even lower than low-motivation learners. These asocial learners omit social interactions and pragmatically focus on *learning* content. Despite the low social presence, they still have high teaching presence, affective *learning*, and satisfaction, whereas cognitive presence, cognitive *learning*, and self-regulated *learning* were slightly impeded compared with high-motivation learners. Moreover, these asocial learners also differ from other learners in the association of social presence and satisfaction. For all groups, social presence promotes cognitive *learning*. But for asocial learners, social presence is negatively associated with satisfaction.

These results of asocial learners suggested the following implications. First, a great number of learners treat *learning* as a solitary activity. They want to concentrate on interactions with content and instructors, ignoring the value and potential opportunities of academic social interaction and collaborative online *learning*. They tend to use Internet-based communication tools for daily social activities but not for academic purposes (Winter et al. 2010). A relevant empirical study from Germany found that most learners preferred to complete MOOCs alone (Staubitz et al. 2014), and in Japan, learners preferred solitary completion of online distance courses for university degrees (Bray, Aoki, and Dlugosh 2008).

Therefore, it is necessary to show MOOC learners high-quality discussions to help them become aware of the benefits from social presence and the value of collaborative *learning*. For example, one approach is to expose learners to more high-quality and meaningful discussions. Researchers identified useful information related to the course (Wise, Cui, and Vytasek 2016) and summarised knowledge or status of other learners from discussions (Chen et al. 2018). This information can benefit asocial learners, and therefore they are likely to have a more positive attitude toward meaningful social interactions during *learning*.

Second, current ways to interact, such as forums, in MOOC platforms do not support efficient interactions well. Perceived convenience affects attitude and intention to learn (Hsu, Chen, and Ting 2018). Learners will not join in forum discussions if they cannot get valuable information efficiently (Rosé et al. 2015). Consistent with previous research, this study also revealed low participation in forum discussion. Our participants had finished at least half of a MOOC and were thus presumed to be active learners. However, two-thirds of the participants were in the low-motivation and asocial groups. We found that 23.22% of the participants had never read the forum for their MOOC, 44.12% had never posted anything in the forum, and only 8.82% had made friends in the forum.

Therefore, rather than a forum, a MOOC platform or course should provide more supports that require little effort from learners to interact and should find ways to enhance learners' presence so that learners can be more attracted to continuous *learning*. One approach is to involve learners in more discussions passively, such as by making it easier to access discussions. Passive participation in discussions (i.e. reading) was found to strongly predict *learning* performance and completion rate of MOOCs (Brooker et al. 2018; Chiu and Hew 2018; Cisel 2014; Wise and Cui 2018). To promote passive participation, some studies have increased the visibility of high-quality discussions by integrating discussions with videos (e.g. Chen et al. 2019; Chen, Gao, and Yuan 2017; Yao, Bort, and Huang 2017; Yousef et al. 2015a). For low-motivation learners, another approach is to support attractive and collaborative ways to interact. For example, some studies have designed tools for use in online *learning* to increase learners' motivation and engagement (Chen and Chen 2018; De-Marcos et al. 2014; DomíNguez et al. 2013; Jagušt, Botički, and So 2018; Simões, Redondo, and Vilas 2013). This study highlighted the necessity of these studies of new ways to interact in MOOCs.

Third, cultural differences exist in motivations to take MOOCs. Similar to our identification of asocial learners in this study, the previous study in HarvardX-MITx (Arora et al. 2017) identified 'performers' who made less effort and had fewer interactions but performed well. The proportion of performers was only 4%, which was much lower than the proportion of asocial learners in the present study. Previous research has also indicated that although teachers in China encouraged students to participate in discussions, many Chinese students were unwilling to express their feelings or opinions publicly (Tu 2001). In the context of MOOCs, Chinese learners were found to post far fewer messages than did German learners (Che et al. 2016). Future research is needed to study how to satisfy MOOC learners from different cultures.

6.2. Limitations

This study has some limitations. First, most participants were campus students (85%), whereas less than 60% of learners were campus students in another report about MOOC learners in China (Zheng, Chen, and Burgos 2018). The occupation may affect motivations. Our data found that student participants reported interest in knowledge and curiosity and expansion as motivating factors far less than other participants did (p values of t-tests < 0.001). The proportion of student participants in the low-motivation group was also higher than in the other two groups (p values of Chi-squared tests $<$ 0.001). Previous research also revealed different motivations of university-affiliated students and general participants (Watted and Barak 2018). Future research on a broader sample is required.

Second, we initially found that interactions, presence, and *learning* outcomes differed in different group of learners with different motivations. However, we did not develop an integrated model including these variables and types of motivation by structural equation modelling, probably due to (1) a limited sample size but many relationships between constructs and (2) simplified scales without strict validation. Future research is required to verify these results more strictly.

Third, interactions were self-reported. Self-reports may be biased and easily influenced by individual characteristics, such as reading and comprehension ability. Future research is required to measure interactions using actual behaviour data. In addition, this study did not distinguish between social interactions that were related to the course and those that were unrelated. One study (Lambić 2016) discovered a positive association between *learning* performance and frequency of using social networking sites to share and discuss content related to a course but no association between *learning* performance and the frequency of general social networking site use (including interactions both related and unrelated to the course). Therefore, future research needs to consider the different effects of social interactions related or unrelated to a course.

Finally, we did not investigate the objective *learning* performance or retention rate, which many stakeholders are interested in. The reason was that our participants took different courses. This makes it difficult to evaluate their *learning* using objective scores or retention rates. Future research is required to collect data from one specific course so that objective performance and retention rate can then be studied.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by National Natural Science Foundation of China: [grant number 71671102].

References

Akyol, Z., and D. R. Garrison. 2008. "The Development of a Community of Inquiry Over Time in an Online Course: Understanding the Progression and Integration of Social, Cognitive and Teaching Presence." *Journal of Asynchronous* Learning *Networks* 12: 3–22.

Akyol, Z., and D. R. Garrison. 2011. "Understanding Cognitive Presence in an Online and Blended Community of Inquiry: Assessing Outcomes and Processes for Deep Approaches to *Learning*." *British Journal of Educational Technology* 42 (2): 233–250. doi:10.1111/j.1467-8535.2009.01029.x.

Alraimi, K. M., H. Zo, and A. P. Ciganek. 2015. "Understanding the MOOCs Continuance: The Role of Openness and Reputation." *Computers &* Education 80: 28–38.

Angelaina, S., and A. Jimoyiannis. 2012. "Analysing Students' Engagement and *Learning* Presence in an Educational Blog Community." *Educational Media International* 49 (3): 183–200. doi:10.1080/09523987.2012.738012.

Arbaugh, J. B., M. Cleveland-Innes, S. R. Diaz, D. R. Garrison, P. Ice, J. C. Richardson, and K. P. Swan. 2008. "Developing a Community of Inquiry Instrument: Testing a Measure of the Community of Inquiry Framework Using a Multi-Institutional Sample." *The Internet and Higher* Education 11 (3): 133–136.

Arora, S., M. Goel, A. S. Sabitha, and D. Mehrotra. 2017. "Learner Groups in Massive Open Online Courses." *American Journal of Distance* Education 31 (2): 80–97.

Baker, C. 2010. "The Impact of Instructor Immediacy and Presence for Online Student Affective *Learning*." *Cognition, and Motivation. Journal of Educators Online* 7 (1). https://eric.ed.gov/?id=EJ904072.

Barak, M., A. Watted, and H. Haick. 2016. "Motivation to Learn in Massive Open Online Courses: Examining Aspects of Language and Social Engagement." *Computers &* Education 94: 49–60.

Barba, P. de, G. E. Kennedy, and M. D. Ainley. 2016. "The Role of Students' Motivation and Participation in Predicting Performance in a MOOC." *Journal of Computer Assisted* Learning 32 (3): 218–231.

Barnard, L., W. Y. Lan, Y. M. To, V. O. Paton, and S.-L. Lai. 2009. "Measuring Self-Regulation in Online and Blended *Learning* Environments." *The Internet and Higher* Education 12 (1): 1–6. doi:10.1016/j.iheduc.2008.10.005.

Bernacki, M. L., A. C. Aguilar, and J. P. Byrnes. 2011. "Self-regulated *Learning* and Technology Enhanced *Learning* Environments: An Opportunity-Propensity Analysis." *Fostering Self-Regulated* Learning *Through ICT*. Hershey, PA: Information Science Reference. 1-26.

Bloom, B. S. 1956. *Taxonomy of Educational Objectives*. Vol. 1: Cognitive Domain. New York: McKay, 20–24.

Bray, E., K. Aoki, and L. Dlugosh. 2008. "Predictors of *Learning* Satisfaction in Japanese Online Distance Learners." *The International Review of Research in Open and Distributed* Learning 9 (3). http://www.irrodl.org/index.php/irrodl/article/view/525.

Brooker, A., L. Corrin, P. De Barba, J. Lodge, and G. Kennedy. 2018. "A Tale of Two MOOCs: How Student Motivation and Participation Predict Learning Outcomes in Different MOOCs." *Australasian Journal of Educational Technology* 34 (1): 73–87.

Castaño, C., I. Maiz, and U. Garay. 2015. "Design, Motivation and Performance in a Cooperative MOOC Course." *Online Submission* 22 (44): 19–26.

Che, X., S. Luo, C. Wang, and C. Meinel. 2016. "An Attempt at MOOC Localization for Chinese-Speaking Users." *International Journal of Information and* Education *Technology* 6 (2): 90.

Chen, B., Y.-H. Chang, F. Ouyang, and W. Zhou. 2018. "Fostering Student Engagement in Online Discussion Through Social *Learning* Analytics." *The Internet and Higher* Education 37: 21–30.

Chen, C.-C., and C.-Y. Chen. 2018. "Exploring the Effect of *Learning* Styles on *Learning* Achievement in a u-Museum." *Interactive* Learning *Environments* 26 (5): 664–681.

Chen, Y., Q. Gao, and Q. Yuan. 2017. "DanMOOC: Enhancing Content and Social Interaction in MOOCs with Synchronized Commenting." In *Cross-Cultural Design*, 509–520. Cham: Springer. doi:10.1007/978-3-319-57931-3_40.

Chen, Y., Q. Gao, Q. Yuan, and Y. Tang. 2019. "Facilitating Students' Interaction in MOOCs Through Timeline-Anchored Discussion." *International Journal of*

Human–Computer Interaction, 1–19. doi:10.1080/10447318.2019.1574056.

Chen, K.-C., and S.-J. Jang. 2010. "Motivation in Online *Learning*: Testing a Model of Self-Determination Theory." *Computers in Human Behavior* 26 (4): 741–752.

Chiu, K. F. T., and K. F. T. Hew. 2018. "Factors Influencing Peer *Learning* and Performance in MOOC Asynchronous Online Discussion Forum." *Australasian Journal of Educational Technology* 34 (4): 16–28.

Cho, M.-H., and S. Tobias. 2016. "Should Instructors Require Discussion in Online Courses? Effects of Online Discussion on Community of Inquiry, Learner Time." *Satisfaction, and Achievement. The International Review of Research in Open and Distributed* Learning 17 (2). http://www.irrodl.org/index.php/irrodl/article/view/2342.

Cisel, M. 2014. "Analyzing Completion Rates in the First French xMOOC." In *Proceedings of the European MOOC Stakeholder Summit*, 26. Lausanne, Switzerland.

De-Marcos, L., A. Domínguez, J. Saenz-de-Navarrete, and C. Pagés. 2014. "An Empirical Study Comparing Gamification and Social Networking on e-*Learning*." *Computers &* Education 75: 82–91.

Deci, E. L., and R. M. Ryan. 1985. *Intrinsic Motivation and Self-Determination in Human Behavior*. Boston, MA: Springer US. http://link.springer.com/10.1007/978-1-4899-2271-7.

Deci, E. L., and R. M. Ryan. 1991. "A Motivational Approach to Self: Integration in Personality." *Perspectives on Motivation* 38: 237.

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

Denker, K. J., J. Manning, K. B. Heuett, and M. E. Summers. 2018. "Twitter in the Classroom: Modeling Online Communication Attitudes and Student Motivations to Connect." *Computers in Human Behavior* 79: 1–8.

DomíNguez, A., J. Saenz-De-Navarrete, L. De-Marcos, L. FernáNdez-Sanz, C. PagéS, and J.-J. MartíNez-HerráIz. 2013. "Gamifying *Learning* Experiences: Practical Implications and Outcomes." *Computers &* Education 63: 380–392.

Ellison, N., R. Heino, and J. Gibbs. 2006. "Managing Impressions Online: Self-Presentation Processes in the Online Dating Environment." *Journal of Computer-Mediated Communication* 11 (2): 415–441.

Everaert, P., E. Opdecam, and S. Maussen. 2017. "The Relationship Between Motivation, *Learning* Approaches, Academic Performance and Time Spent." *Accounting* Education 26 (1): 78–107. doi:10.1080/09639284.2016.1274911.

Fang, J., L. Tang, J. Yang, and M. Peng. 2019. "Social Interaction in MOOCs: The Mediating Effects of Immersive Experience and Psychological Needs Satisfaction." *Telematics and Informatics* 39: 75–91. doi:10.1016/j.tele.2019.01.006.

Garrison, D. R., T. Anderson, and W. Archer. 1999. "Critical Inquiry in a Text-Based Environment: Computer Conferencing in Higher *Education*." *The Internet and Higher* Education 2 (2): 87–105.

Garrison, D. R., and J. B. Arbaugh. 2007. "Researching the Community of Inquiry Framework: Review, Issues, and Future Directions." *The Internet and Higher* Education 10 (3): 157–172.

Giesbers, B., B. Rienties, D. Tempelaar, and W. Gijselaers. 2013. "Investigating the Relations Between Motivation, Tool Use, Participation, and Performance in an E-*Learning* Course Using Web-Videoconferencing." *Computers in Human Behavior* 29 (1): 285–292. doi:10.1016/j.chb.2012.09.005.

Gillani, N., and R. Eynon. 2014. "Communication Patterns in Massively Open Online Courses." *The Internet and Higher* Education 23: 18–26.

Goh, W., E. Ayub, S. Y. Wong, and C. L. Lim. 2017. "The Importance of Teacher's Presence and Engagement in MOOC *Learning* Environment: A Case Study." In 2017 *IEEE Conference on e-*Learning, *e-Management and e-Services (IC3e)*, 127–132, IEEE.

Gorham, J. 1988. "The Relationship Between Verbal Teacher Immediacy Behaviors and Student *Learning*." *Communication* Education 37 (1): 40–53.

Hair, J. F. 2009. *Multivariate Data Analysis*. https://works.bepress.com/joe_hair/2/.

Hartigan, J. A., and M. A. Wong. 1979. "Algorithm AS 136: A k-Means Clustering Algorithm." *Journal of the Royal Statistical Society. Series C (Applied Statistics)* 28 (1): 100–108.

He, W. 2013. "Examining Students' Online Interaction in a Live Video Streaming Environment Using Data Mining and Text Mining." *Computers in Human Behavior* 29 (1): 90–102. doi:10.1016/j.chb.2012.07.020.

Hew, K. F., and W. S. Cheung. 2014. "Students' and Instructors' use of Massive Open Online Courses (MOOCs): Motivations and Challenges." *Educational Research Review* 12: 45–58.

Hsu, J.-Y., C.-C. Chen, and P.-F. Ting. 2018. "Understanding MOOC Continuance: An Empirical Examination of Social Support Theory." *Interactive* Learning *Environments* 26 (8): 1100–1118.

Huang, B., and K. F. Hew. 2017. "Factors Influencing *Learning* and Factors Influencing Persistence: A Mixed-method Study of MOOC Learners' Motivation." In *Proceedings of the 2017 International Conference on Information System and Data Mining*, 103–110, ACM.

IBL News. 2019. "XuetangX, China's Open edX Platform, Reaches 16M Learners." *IBL News*, January 3. Accessed April 21, 2019. https://iblnews.org/2019/01/03/xuetangx-open-edx-chinas-platform-reaches-16m-learners-2/.

Jagušt, T., I. Botički, and H.-J. So. 2018. "Examining Competitive, Collaborative and Adaptive Gamification in Young Learners' Math *Learning*." *Computers &* Education 125: 444–457.

Jung, Y., and J. Lee. 2018. "*Learning* Engagement and Persistence in Massive Open Online Courses (MOOCS)." *Computers &* Education 122: 9–22. doi:10.1016/j.compedu.2018.02.013.

Ke, F., and D. Kwak. 2013. "Online *Learning* Across Ethnicity and Age: A Study on *Learning* Interaction Participation, Perception, and *Learning* Satisfaction." *Computers &* Education 61: 43–51.

Keller, J. M. 2010. *Motivational Design for* Learning *and Performance*. Boston, MA: Springer US. http://link.springer.com/10.1007/978-1-4419-1250-3.

Khalil, M., C. Kastl, and M. Ebner. 2016. "Portraying MOOCs Learners: A Clustering Experience Using *Learning* Analytics." In *Proceedings of the European Stakeholder Summit on Experiences and Best Practices in and around MOOCs (EMOOCS 2016)*, 265–278.

Khan, I. U., Z. Hameed, Y. Yu, T. Islam, Z. Sheikh, and S. U. Khan. 2018. "Predicting the Acceptance of MOOCs in a Developing Country: Application of Task-Technology Fit Model, Social Motivation, and Self-Determination Theory." *Telematics and Informatics* 35 (4): 964–978. doi:10.1016/j.tele.2017.09.009.

Kilis, S., and Z. Yıldırım. 2018. "Investigation of Community of Inquiry Framework in Regard to Self-Regulation, Metacognition and Motivation." *Computers & Education* 126: 53–64.

Kim, W. 2015. Learning *Flow, Motivation, and Community of Inquiry in an Online Graduate Degree Program* (PhD Thesis). Purdue University.

Kim, J., P. J. Guo, C. J. Cai, S.-W. Li (Daniel), K. Z. Gajos, and R. C. Miller. 2014. "Data-driven Interaction Techniques for Improving Navigation of Educational Videos." In *Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology*, 563–572.

Kizilcec, R. F., M. Pérez-Sanagustín, and J. J. Maldonado. 2017. "Self-regulated *Learning* Strategies Predict Learner Behavior and Goal Attainment in Massive Open Online Courses." *Computers &* Education 104: 18–33.

Kizilcec, R. F., C. Piech, and E. Schneider. 2013. "Deconstructing Disengagement: Analyzing Learner Subpopulations in Massive Open Online Courses." In In *Proceedings of the Third International Conference on* Learning *Analytics and Knowledge*, 170–179, ACM.

Kizilcec, R. F., and E. Schneider. 2015. "Motivation as a Lens to Understand Online Learners: Toward Data-Driven Design with the OLEI Scale." *ACM Transactions on Computer-Human Interaction* 22 (2): 6:1–6:24.

Lambić, D. 2016. "Correlation Between Facebook Use for Educational Purposes and Academic Performance of Students." *Computers in Human Behavior* 61: 313–320.

Littlejohn, A., N. Hood, C. Milligan, and P. Mustain. 2016. "*Learning* in MOOCs: Motivations and Self-Regulated *Learning* in MOOCs." *The Internet and Higher* Education 29: 40–48.

Loizzo, J., P. A. Ertmer, W. R. Watson, and S. L. Watson. 2017. "Adult MOOC Learners as Self-Directed: Perceptions of Motivation, Success, and Completion." *Online* Learning 21 (2): 1–24.

Mackey, K. R., and D. L. Freyberg. 2010. "The Effect of Social Presence on Affective and Cognitive *Learning* in an International Engineering Course Taught Via Distance *Learning*." *Journal of Engineering* Education 99 (1): 23–34.

Milligan, C., and A. Littlejohn. 2017. "Why Study on a MOOC? The Motives of Students and Professionals." *The International Review of Research in Open and Distributed* Learning 18 (2): 92–102.

Moore, M. G. 1989. "Editorial: Three Types of Interaction." *American Journal of Distance* Education 3 (2): 1–7. doi:10.1080/08923648909526659.

Mukhtar, F., K. Muis, and M. Elizov. 2018. "Relations Between Psychological Needs Satisfaction, Motivation, and Self-Regulated *Learning* Strategies in Medical Residents: A Cross-Sectional Study." *MedEdPublish* 7. https://doi.org/mep.2018.0000087.1.

Ngoyi, L., S. Mpanga, A. Ngoyi, V. V. Sudhir, A. S. N. Murthy, D. E. Rani, and P. Vikram. 2014. "The Relationship Between Student Engagement and Social Presence in Online *Learning*." *International Journal of Advances in Computer Science and Technology* 3 (4): 242–247.

Niu, L.-G. 2019. "Decision-making Determinants of Students Participating in MOOCs: Merging the Theory of Planned Behavior and Self-Regulated *Learning* Model." *Computers &* Education 134: 50–62.

Pardo, A., F. Han, and R. A. Ellis. 2017. "Combining University Student Self-Regulated *Learning* Indicators and Engagement with Online *Learning* Events to Predict Academic Performance." *IEEE Transactions on* Learning *Technologies* 10 (1): 82–92.

Picciano, A. G. 2002. "Beyond Student Perceptions: Issues of Interaction, Presence, and Performance in an Online Course." *Journal of Asynchronous* Learning *Networks* 6 (1): 21–40.

Poquet, O., V. Kovanović, P. de Vries, T. Hennis, S. Joksimović, D. Gašević, and S. Dawson. 2018. "Social Presence in Massive Open Online Courses." *The International Review of Research in Open and Distributed* Learning 19: 3.

Preston, C. C., and A. M. Colman. 2000. "Optimal Number of Response Categories in Rating Scales: Reliability, Validity, Discriminating Power, and Respondent Preferences." *Acta Psychologica* 104 (1): 1–15.

Qu, H., and Q. Chen. 2015. "*Visual* Analytics for MOOC Data." *IEEE Computer Graphics and Applications* 35 (6): 69–75.

Richardson, J., and K. Swan. 2003. "Examing Social Presence in Online Courses in Relation to Students' Perceived *Learning* and Satisfaction." *Journal of Asynchronous* Learning *Networks* 7 (1): 68–88.

Rosé, C. P., P. Goldman, J. Zoltners Sherer, and L. Resnick. 2015. "Supportive Technologies for Group Discussion in MOOCs." *Current Issues in Emerging ELearning* 2 (1): 5.

Rovai, A. P. 2002a. "Building Sense of Community at a Distance." *The International Review of Research in Open and Distributed* Learning 3 (1). doi:10.19173/irrodl.v3i1.79.

Rovai, A. P. 2002b. "Sense of Community, Perceived Cognitive *Learning*, and Persistence in Asynchronous *Learning* Networks." *The Internet and Higher* Education 5 (4): 319–332.

Rovai, A. P., M. J. Wighting, J. D. Baker, and L. D. Grooms. 2009. "Development of an Instrument to Measure Perceived Cognitive, Affective, and Psychomotor *Learning* in Traditional and Virtual Classroom Higher *Education* Settings." *The Internet and Higher* Education 12 (1): 7–13.

Russo, T., and S. Benson. 2005. "*Learning* with Invisible Others: Perceptions of Online Presence and Their Relationship to Cognitive and Affective *Learning*." *Journal of Educational Technology & Society* 8 (1): 54–62.

Salmon, G., E. Pechenkina, A.-M. Chase, and B. Ross. 2017. "Designing Massive Open Online Courses to Take Account of Participant Motivations and Expectations." *British Journal of Educational Technology* 48 (6): 1284–1294. doi:10.1111/bjet.12497.

Shapiro, H. B., C. H. Lee, N. E. W. Roth, K. Li, M. Çetinkaya-Rundel, and D. A. Canelas. 2017. "Understanding the Massive Open Online Course (MOOC) Student Experience: An Examination of Attitudes, Motivations, and Barriers." *Computers & Education* 110: 35–50.

Simões, J., R. D. Redondo, and A. F. Vilas. 2013. "A Social Gamification Framework for a K-6 *Learning* Platform." *Computers in Human Behavior* 29 (2): 345–353.

So, H.-J., and T. A. Brush. 2008. "Student Perceptions of Collaborative *Learning*, Social Presence and Satisfaction in a Blended *Learning* Environment: Relationships and Critical Factors." *Computers &* Education 51 (1): 318–336.

Staubitz, T., J. Renz, C. Willems, and C. Meinel. 2014. "Supporting Social Interaction and Collaboration on an Xmooc Platform." *EDULEARN14 Proceedings*, 6667–6677.

Sujatha, R., and D. Kavitha. 2018. "Learner Retention in MOOC Environment: Analyzing the Role of Motivation, Self-Efficacy and Perceived Effectiveness." *International Journal of* Education *and Development Using ICT* 14 (2): 62–74.

Swan, K. 2001. "Virtual Interaction: Design Factors Affecting Student Satisfaction and Perceived *Learning* in Asynchronous Online Courses." *Distance* Education 22 (2): 306–331.

Swan, K., and L. F. Shih. 2005. "On the Nature and Development of Social Presence in Online Course Discussions." *Journal of Asynchronous* Learning *Networks* 9 (3): 115–136.

Tao, Y. 2009. *The Relationship Between Motivation and Online Social Presence in an Online Class*. University of Central Florida. http://search.proquest.com/openview/f64e7dc5aa99e3ea09beb6a81885e9f7/1?pq-origsite=gscholar&cbl=18750&diss=y.

Tu, C.-H. 2001. "How Chinese Perceive Social Presence: An Examination of Interaction in Online *Learning* Environment." *Educational Media International* 38 (1): 45–60.

Watted, A., and M. Barak. 2018. "Motivating Factors of MOOC Completers: Comparing Between University-Affiliated Students and General Participants." *The Internet and Higher* Education 37: 11–20.

Winter, J., D. Cotton, J. Gavin, and J. D. Yorke. 2010. "Effective e-*Learning*? Multi-Tasking, Distractions and Boundary Management by Graduate Students in an Online Environment." *ALT-J* 18 (1): 71–83.

Wise, A. F., and Y. Cui. 2018. "*Learning* Communities in the Crowd: Characteristics of Content Related Interactions and Social Relationships in MOOC Discussion Forums." *Computers &* Education 122: 221–242. doi:10.1016/j.compedu.2018.03.021.

Wise, A. F., Y. Cui, and J. Vytasek. 2016. "Bringing Order to Chaos in MOOC Discussion Forums with Content-related Thread Identification." In *Proceedings of the Sixth International Conference on* Learning *Analytics & Knowledge*, 188–197, New York, NY: ACM. doi:10.1145/2883851.2883916

Wu, W., and Q. Bai. 2018. "Why Do the MOOC Learners Drop Out of the School? – Based on the Investigation of MOOC Learners on Some Chinese MOOC Platforms." *2018 1st International Cognitive Cities Conference (IC3)*, 299–304. doi:10.1109/IC3.2018.00039.

Wu, B., and X. Chen. 2017. "Continuance Intention to Use MOOCs: Integrating the Technology Acceptance Model (TAM) and Task Technology Fit (TTF) Model." *Computers in Human Behavior* 67: 221–232.

Xiong, Y., H. Li, M. L. Kornhaber, H. K. Suen, B. Pursel, and D. D. Goins. 2015. "Examining the Relations Among Student Motivation, Engagement, and Retention in a MOOC: A Structural Equation Modeling Approach." *Global* Education *Review* 2 (3). http://ger.mercy.edu/index.php/ger/article/view/124.

Xu, B., and D. Yang. 2016. "Motivation Classification and Grade Prediction for MOOCs Learners." *Computational Intelligence and Neuroscience* 2016: 4.

Yang, Q. 2014. "Students Motivation in Asynchronous Online Discussions with MOOC Mode." *American Journal of Educational Research* 2 (5): 325–330.

Yang, J. C., B. Quadir, N.-S. Chen, and Q. Miao. 2016. "Effects of Online Presence on *Learning* Performance in a Blog-Based Online Course." *The Internet and Higher* Education 30: 11–20.

Yao, Y., J. Bort, and Y. Huang. 2017. "Understanding Danmaku's Potential in Online Video *Learning*." In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems* m3034–3040, New York, NY, USA: ACM. doi:10.1145/3027063.3053258.

Yousef, A. M. F., M. A. Chatti, U. Schroeder, and M. Wosnitza. 2015a. "A Usability Evaluation of a Blended MOOC Environment: An Experimental Case Study." *The International Review of Research in Open and Distributed* Learning 16 (2). http://www.irrodl.org/index.php/irrodl/article/view/2032.

Yousef, A. M. F., M. A. Chatti, M. Wosnitza, and U. Schroeder. 2015b. "A Cluster Analysis of MOOC Stakeholder Perspectives." *Revista de Universidad y Sociedad Del Conocimiento* 12 (1): 74–90.

Zhang, D. J., G. Allon, and J. A. V. Mieghem. 2017. "Does Social Interaction Improve *Learning* Outcomes? Evidence From Field Experiments on Massive Open Online Courses." *Manufacturing and Service Operations Management* 19 (3): 347–367. doi:10.1287/msom.2016.0615.

Zheng, Q., L. Chen, and D. Burgos. 2018. *The Development of MOOCs in China*. Singapore: Springer.

Zheng, S., M. B. Rosson, P. C. Shih, and J. M. Carroll. 2015. "Understanding Student Motivation, Behaviors and Perceptions in MOOCs." In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 1882–1895, ACM. http://dl.acm.org/citation.cfm?id=2675217

Zhou, M. 2016. "Chinese University Students' Acceptance of MOOCs: A Self-Determination Perspective." *Computers &* Education 92–93: 194–203. doi:10.1016/j.compedu.2015.10.012.

Zimmerman, B. J. 2000. "Chapter 2 - Attaining Self-Regulation: A Social Cognitive Perspective." In *Handbook of Self-Regulation*, edited by M. Boekaerts, P. R. Pintrich, and M. Zeidner, 13–39. San Diego: Academic Press. doi:10.1016/B978-012109890-2/50031-7.