

# Performance, Motivation, Engagement, and Interactions in MOOC-Based Learning

Min Wang, Zhejiang Yuexiu University, China

Zhonggen Yu, Beijing Language and Culture University, China\*

## ABSTRACT

With the rapid development of information technologies, the new decade has been witnessing an advancement of massive open online courses (MOOCs)-based learning. However, MOOCs are infamous for the lower engagement and completion rates and very few studies have systematically reviewed student performance, motivation, engagement, and interactions in MOOCs-based learning in order to provide constructive suggestions for researchers and practitioners. Through content analysis, this study firstly identified top 10 cited works and their major concerns and then discussed student performance, motivation, engagement, and interactions, as well as methods to improve the effectiveness of MOOCs-based learning. It also provides constructive suggestions for future design of MOOCs and complements for the missing link in literature. Future research could focus on the measurements of variables in MOOCs-based learning in order to improve the quality of MOOCs and help students achieve success in MOOCs.

## KEYWORDS

Engagement, Interactions, MOOCs, Motivation, Performance

## INTRODUCTION

With the fast development of information technologies, the recent decades have witnessed huge advancement of massive open online courses (MOOCs). MOOCs could transform and construct high-quality online courses based on information technologies (Wang & Zhu, 2019). Since their birth in 2008, MOOCs have become a significant innovation in online learning and teaching, which integrates contents into courses in university curricula (Castano, Maiz, & Garay, 2015).

MOOCs have obtained wide popularity among various kinds of universities. There are various reasons why students sign in MOOCs. They would like to learn new knowledge or extend their current knowledge. They may feel curious about MOOCs and want to improve their living standards by obtaining certificates or credentials. Most of them dropped out because of a lack of incentive, failure to perceive the contents, no assistance or other distractions. The reasons why teachers teach students via MOOCs include a sense of intrigue, personal rewards, or a sense of altruism. Teachers may also be faced with some challenges in MOOCs-based teaching such as difficulty in assessing student performance, no student feedback, limit of time and finance, and insufficient learning engagement (Hew & Cheung, 2014).

MOOCs could provide rich and flexible education experiences for students and practitioners in various fields (Mullen et al., 2017). MOOCs are actually online courses that can be accessed by a

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\*Corresponding Author

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large number of various kinds of students. Characterized by massiveness, rich online resources and datasets carried by MOOC platforms need sophisticated technologies and tools to make learning process go along smoothly, encouraging students to engage in MOOCs (Khalil & Ebner, 2017).

MOOCs were accessed by various levels of students, including those admitted to colleges with less preparation, prior to their entry into university or those having no ability to acquire knowledge (Jiang et al., 2014). Millions of students acquire knowledge via MOOCs designed by hundreds of institutes. By integrating videos, lectures, readings, quizzes with forum discussions, MOOCs attracted student attention and enhanced student engagement (Sunar et al., 2017).

MOOCs are an innovative learning form, combining formal with informal online learning (Walji et al., 2016). Hot debate has arisen about the transformation of higher education into openly accessible form via MOOCs. Concerns about the quality and completion rates of MOOCs have been attracting attention of professionals and researchers. High dropout rates have worried many students and teachers, which may be addressed by proper engagement strategies. Student engagement should, therefore, be seriously considered in MOOCs-based learning and teaching (de Freitas et al., 2015).

Although numerous studies have been committed to MOOCs in a number of aspects, few studies have systematically highlighted student performance, motivation, engagement and interactions in MOOCs-based learning. It is therefore necessary to explore these variables so as to provide solid foundation for future research. On basis of the top cited literature, we proposed five research questions that might be of global interest as follows:

- RQ1: What are top 10 cited works and their major concerns?
- RQ2: What influences student performance in MOOCs-based learning?
- RQ3: How to improve student motivation in MOOCs-based learning?
- RQ4: How to enhance student engagement in MOOCs-based learning?
- RQ5: What roles do interactions play in MOOCs-based learning?

Table 1. The STARLITE tool (Booth, 2006).

Element	Explanatory notes
<b>S:</b> Sampling strategy	<ul style="list-style-type: none"> <li>● Comprehensive: attempts to identify all relevant studies on the topic</li> <li>● Selective: attempts to identify all relevant studies but only within specified limits</li> <li>● Purposive: samples from specific disciplines, years, journals</li> </ul>
<b>T:</b> Type of studies	<ul style="list-style-type: none"> <li>● Fully reported: describes actual study types (e.g., grounded theory) or designs to be included</li> <li>● Partially reported: uses an ‘‘umbrella’’ category such as ‘‘qualitative studies’’ without defining what this means</li> </ul>
<b>A:</b> Approaches	<ul style="list-style-type: none"> <li>● Approaches other than electronic subject searches (see below)</li> <li>● Example: hand-searching</li> <li>● Citation snowballing</li> </ul>
<b>R:</b> Range of years (start date-end date)	<ul style="list-style-type: none"> <li>● Fully reported: includes start and end dates with justification for time period chosen</li> <li>● Partially reported: includes start and end dates but only determined available coverage of databases</li> </ul>
<b>L:</b> Limits	Functional limits that are applied for logistic reasons but do not alter the topic conceptually (e.g., human, English etc.)
<b>I:</b> Inclusion and exclusions	Conceptual limitations that mediate the scope of the topic area (e.g., geographical location, setting, or a specific focus of study)
<b>T:</b> Terms used	<ul style="list-style-type: none"> <li>● Fully present: example of a sample search strategy from one or more of the main databases</li> <li>● Partially present: reports terminology used but without evidence of search syntax and operators</li> </ul>
<b>E:</b> Electronic sources	Reports databases used and, optimally, search platforms and vendors to assist in replication

## METHODS

We obtained 964 results after searching Web of Science through “title: (MOOC\*) AND subject: (performance\* OR motivation\* OR engagement\* OR interaction\*)” in databases of SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, ESCI, CCR-EXPANDED, and IC, ranging from 1992 to 2020. We removed those that were unrelated or of lower quality based on the following methods.

## QUALITY ASSESSMENT OF THE OBTAINED LITERATURE

We adopted the method to assess the quality of literature, referred to as STARLITE (Table 1), an abbreviation for sampling strategy, type of study, approaches, range of years, limits, inclusion and exclusions, terms used, and electronic sources (Booth, 2006).

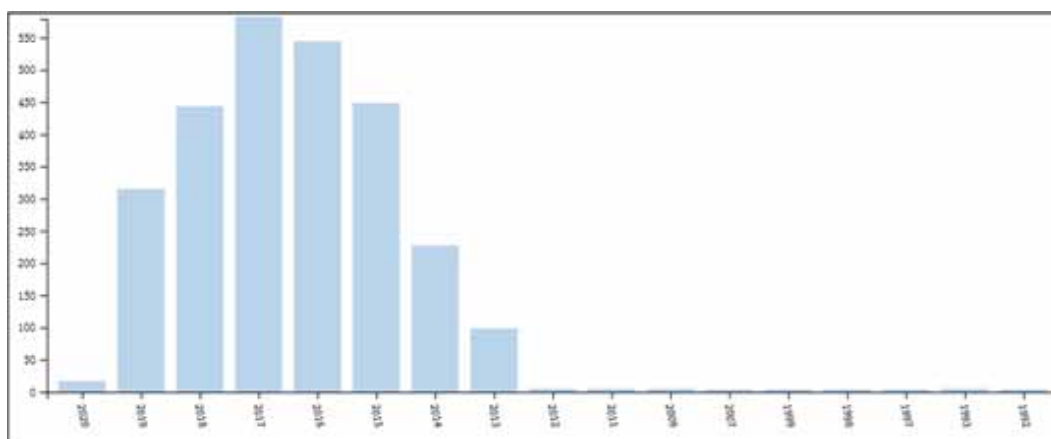
**Sampling Strategy.** We adopted purposive sampling within a vast number of studies on education field in order to obtain comprehensive research results. We then identified all relevant studies within specified limits by narrowing down the results to education-related MOOC studies.

**Type of Studies.** We selected both fully and partially reported studies, including those adopting qualitative, quantitative, or mixed methods.

**Approach.** A hand search was conducted within related journals after we obtained results from electronic relevant databases. Boolean searches on the term “MOOC\*” as the title led to a total of 2661 papers after removing unrelated and lower-quality publications. In order to reduce the redundant volume, we added individual terms via “advanced search” to enable a more precise output. We limited and specified the results using following methods.

**Range of Years.** The review was conducted on literature ranging from January of 1992 to February of 2020. The year 1992 witnessed the commencement of MOOC related studies, remaining a lower level until the year 2013 when MOOC related studies surged up, arriving at the peak in 2017. The number of MOOC related studies declined at the end of 2017 until present (Figure 1). The data was retrieved in February 2020, so the prospect of MOOC studies in 2020 is not revealed.

Figure 1. The number of publications on MOOC studies



**Limits.** This study is not limited to any country where the studies were conducted as long as it is ethically approved and the publications are written in English. The search was further refined to qualitative, quantitative or mixed research papers, excluding book chapters, reports or discussion works.

**Inclusions and Exclusions.** The refinement of the search included both inclusion and exclusion criteria. We selected works based on these criteria: (1) The study should be conducted between the

year 1992 and 2020; (2) The study should focus on student engagement, motivation, interaction, and performance in the context of MOOCs; (3) The study could explore student engagement, motivation, interaction, and performance in the context of MOOCs compared with other contexts; (4) The study could be qualitative, quantitative or mixed research papers.

The exclusion criteria included: (1) Prior to 1992 and after February 2020; (2) The study does not focus on student engagement, motivation, interaction, and performance in the context of MOOCs; (3) The study is book chapters, reports or discussion works; (4) The study does not compare MOOCs with other contexts.

**Terms Used.** In order to cover a comprehensive range of literature, the search terms included engagement, motivation, interaction, performance, and MOOCs.

**Electronic Sources.** Web of Science (Core Collection) was used as the platform to access and search relevant databases, e.g. Social Sciences Citation Index, Science Citation Index Expanded, Arts & Proceedings Citation Index- Social Science & Humanities, and Emerging Sources Citation Index. These databases are related to education, psychology, and other social sciences and humanities since the focus of the study is education and educational technology in terms of MOOCs.

Based on the advanced term search and the criteria proposed by The University of West England Framework (Appendix A), 13 results (Table 2) that fulfilled the criteria were selected.

**Table 2. A summary of highly evaluated studies**

Author	Objective of study	Methods	Sample	Findings	Critique
Deng et al. 2020	To explore student engagement in MOOCs	Mixed methods: interview, survey, review	Two experts in interview, 15 MOOC users for review, 590 cases	A MOOC engagement scale (MES) was designed to measure behavioral, cognitive, emotional, and social engagement.	Peer and faculty relationships, peer and student-staff engagement were not included in MES.
Luisa et al., 2019	To study behaviors and grouping strategies	Mixed methods: survey, analytics, communication	Two groups formed by homogeneous engagement	Students with more homogeneity could complete more task, interact better and were more satisfied and engaged than less.	Merely 3 variables were used. The homogeneous-engagement approach was tested only in a specified collaborative activity.
Barak et al., 2016	To study motivation and engagement	Mixed methods: questionnaire, forum, email	Participants (N=325) in English and Arabic MOOCs.	Motivation was positively related to forum posts and engagement.	The sample size is relatively small.
Milligan, & Littlejohn, 2016	To address regulation of health professionals in MOOC.	Qualitative: interviews	MOOC participants (N=35)	Great differences existed in goals set, and help seeking behavior, but slight differences were found in learning strategies and levels of self-efficacy.	Only a single MOOC; only active participants; no link between learning patterns, strategies and academic success; insufficient data of interview to analyze self-regulation
Wong et al., 2019	To study self-regulated learning (SRL) in MOOCs	Quantitative: Sequential Pattern Mining Algorithm Sequential Pattern Discovery	Students who viewed the SRL-prompt videos and those who did not	SRL-prompt viewers interacted with, completed, and followed course activities better than non SRL-prompt viewers.	Activity repetition and duration were excluded. SRL-prompt viewers were a self-selected group and could be self-regulated or conscientious students not other types. The analysis is based on only clickstream data without students' self-report.
Hone et al., 2016	To study MOOC design and factors that influence retention.	Quantitative: survey	Participants in MOOC (N=379)	No significant differences were found in completion rates by gender, educational level or MOOC platform. Course Content and Interaction with the Instructor predicted MOOC retention.	Exploratory in nature, meaning that the applicability of the constructs applied from previous e-learning literature was untested and the research model had to be revised during the analysis phase to accommodate measurement constructs
Tseng et al., 2019	To study drivers of teacher' adoption of MOOCs	Quantitative: survey	University teachers (N=161)	Performance expectancy, social influence, facilitating conditions, and price value facilitated teacher's behavioral intention. Facilitating conditions and behavioral intention determined teachers' adoption.	Findings may not be generalizable to other online systems; Teachers' adoption of MOOCs may be driven by extrinsic motivation rather than intrinsic motivation. Moderating effects were excluded from the study.

*Table 2 continued on next page*

Table 2 continued

Author	Objective of study	Methods	Sample	Findings	Critique
Rizvi et al., 2019	To study learning design and temporal engagement.	Quantitative: a taxonomy to study temporal progression or pathways	Three groups (N=2086) of students divided based on clicking behaviors.	The group of Markers remained far more active in MOOC than Partial and Non-Markers in terms of hourly activity.	Success in MOOCs is relative, still, without a deep knowledge of students' navigation through the system. It was hard to distinguish good or bad decisions.
Tseng et al., 2016	To study learning behaviors and outcomes of a MOOC platform	Mixed methods: statistical methods; descriptive analysis	Students in MOOC (N=1489)	The first 2 weeks was a critical point of time to retain students in MOOCs. Timely feedback by instructors on post forums could enhance students' engagement in MOOCs.	Whether the better outcomes resulted from personal positive attitude toward MOOC or specific pedagogical design needs to be further explored. Further work is required to verify factors that shape learning behaviors.
Leach, & Hadi, 2016	To study 3 MOOCs to support student goals.	Quantitative: three surveys during each MOOC.	Students (N=735) of 3 MOOCs	By awarding badges for achievements, students gained more recognition of their achievements than by a certificate.	The considered metrics are useful for making direct comparisons between MOOCs, without a detailed classification to decide motivations and backgrounds.
Eriksson et al., 2016	To study why students complete or drop	Qualitative: in-depth interviews	Students (N=34) with different degrees of course completion	Factors influencing dropout: perception of course contents and design; social situation and characteristics; time management	Merely a qualitative study with interviews could hardly include other influencing factors, e.g. lack of pressure, social influence, and long course start-up.
Henderikx et al., 2019	To study age, gender, educational level and experience in MOOCs.	Quantitative: survey	Participants were teachers and educational professionals joining 18 MOOCs.	More online learning experience positively affects student ability to cope with barriers. Students at a lower level may experience a lack of knowledge or difficulties with the course content.	Population is limited to Spanish speaking students. The study failed to study whether students experienced more or other barriers in MOOCs. The study did not explore whether the populations in various MOOCs are comparable.
Baker et al., 2016	To study effect of a self-directed scheduling nudge in MOOC	Quantitative: survey	Domestic and international students	Random assignment had no effects on near-term engagement and weakly significant negative effects on longer-term engagement, persistence, and performance.	Inability to study standard subgroups and external validity. External validity limitations arise because only a single course was on the platform.

## FINDINGS

This section will firstly determine the top cited works in order to establish the major themes in this study. We will then include and extend related contents of the critique (Table 2) centering on main research themes from the clustering. Readers could consult Table 2 for specific details of each study. The findings will be developed based on the sequence of the research questions proposed.

### RQ1: What are top 10 cited works and their major concerns?

We used co-citation as the type of analysis, cited works as unit of analysis, full counting as counting methods. The minimum number of citations of a cited reference was set at 20, which led to 191 citations meeting the threshold out of the 38043 cited works. For each of the 191 cited works, the total strength of the co-citation links with other cited works was calculated. The cited works with the greatest total link strength were selected and the network map was created (Figure 2).

Figure 2 presents total strength of the co-citation links with other cited works, which was then reduced to 10 highly cited works in order to determine the major research themes. As shown in Table 3, top 10 cited works source from “International Review of Research in Open and Distance Learning”, “Research & Practice in Assessment”, “Proceedings of the Third International Conference on Learning Analytics and Knowledge”, “Journal of Interactive Media in Education”, “Computers & Education”, “SSHRC Application, Knowledge Synthesis for the Digital Economy”, and “The New York Times”.

Figure 2. The cited works with total link strength

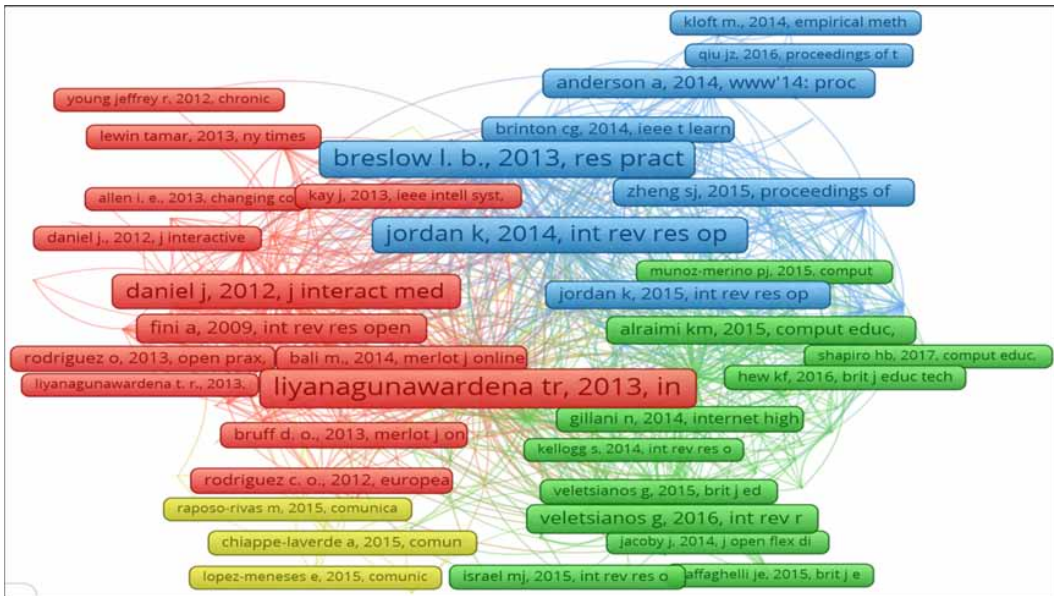


Table 3. Top 10 cited works and their major concerns

N	Cited works	Major concerns	Citations	Total link strength
1	Liyanagunawardena, T.R., Adams, A.A. and Williams, S.A. (2013). MOOCs: A Systematic Study of the Published Literature 2008-2012. <i>International Review of Research in Open and Distance Learning</i> , 14, 202-227. <a href="https://dx.doi.org/10.19173/irrodl.v14i3.1455">https://dx.doi.org/10.19173/irrodl.v14i3.1455</a> .	Motivation, engagement, theory, technology, participant, and provider	218	251
2	Breslow, L., Pritchard, D.E., DeBoer, J., Stump, G.S., Ho, A.D., & Seaton, D.T. (2013). Studying Learning in the Worldwide Classroom: Research into edX's First MOOC. <i>Research &amp; Practice in Assessment</i> , 8, 13-25.	Video lectures, interactions, and performance	192	252
3	Jordan, K. (2014). Initial Trends in Enrolment and Completion of Massive Open Online Courses. <i>International Review of Research in Open and Distance Learning</i> , 15, 133-159. <a href="https://dx.doi.org/10.19173/irrodl.v15i1.1651">https://dx.doi.org/10.19173/irrodl.v15i1.1651</a> .	Enrolment and Completion rates	166	221

Table 3 continued on next page

Table 3 continued

N	Cited works	Major concerns	Citations	Total link strength
4	Kizilcec, R.F., Piech, C., & Schneider, E. (2013). <i>Deconstructing disengagement: analyzing learner subpopulations in massive open online courses</i> . Proceedings of the Third International Conference on Learning Analytics and Knowledge, p.170-179. <a href="https://dx.doi.org/10.1145/2460296.2460330">https://dx.doi.org/10.1145/2460296.2460330</a> .	Engagement	160	192
5	Hew, K.F., & Cheung, W.S. (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. <i>Educational Research Review</i> , 12, 45-58. <a href="https://dx.doi.org/10.1016/j.edurev.2014.05.001">https://dx.doi.org/10.1016/j.edurev.2014.05.001</a> .	Motivation and challenge	143	197
6	Daniel, J. (2012). Making Sense of MOOCs: Musings in a Maze of Myth, Paradox and Possibility. <i>Journal of Interactive Media in Education</i> , 3, 18. <a href="https://dx.doi.org/10.5334/2012-18">https://dx.doi.org/10.5334/2012-18</a> .	Technology, quality and costs	141	152
7	Yuan, L., & Powell, S. (2013). MOOCs and Open Education: Implications for Higher Education. in <i>Learning Platforms, MOOCs, Open Educational Resources</i> . Cetus LLP. 2013:WP01.	Motivation, quality and completion rates	140	159
8	Margaryan, A., Manuel, B., & Allison, L. (2015). Instructional quality of Massive Open Online Courses (MOOCs). <i>Computers &amp; Education</i> , 80, 77-83. <a href="https://dx.doi.org/10.1016/j.compedu.2014.08.005">https://dx.doi.org/10.1016/j.compedu.2014.08.005</a> .	Quality	134	150
9	McAuley, A., Stewart, B., Cormier, D. & Siemens, G. (2010). <i>In the Open: The MOOC model for digital practice</i> . SSHRC Application, Knowledge Synthesis for the Digital Economy.	Effectiveness and engagement	119	132
10	Pappano, L. <i>The Year of the MOOC</i> . The New York Times. November 2, 2012.	engagement and interactions	93	98

As shown in Table 3, major concerns of top 10 cited works also include four dimensions, i.e. student performance, motivation, engagement and interactions in MOOCs-based learning, as major research directions. Although they separately discussed the four dimensions in order to improve quality of MOOCs, increase completion rates and improve learning outcomes, very few of them systematically reviewed the dimensions mentioned above. It is thus necessary and meaningful to systematically review the four dimensions in MOOCs-based learning.

RQ2: What influences student performance in MOOCs-based learning?

MOOCs have extended vast learning opportunities around the world to various fields. Success in MOOCs is, however, inconsistent and undecided (Rizvi et al., 2019). Student performance in MOOCs tends to be defined as either the completion of a given course or individual learning goals (Conijn et al., 2018). Student performance in MOOCs has been criticized despite of their success in education. It is thus important to review the performance in MOOCs-based learning.

**Quality of MOOCs.** Quality of MOOCs greatly influences student performance. MOOCs, whose number is rapidly increasing, have shortly become a hot topic of research, along with which the assessment of quality has also coupled. Quality assessment poses a challenge to MOOCs-based learning. Both formative and summative qualitative assessment is in need of innovative methods to evaluate the quality of MOOCs. Peer review is an effective method. It was evidenced that quality of peer review was positively correlated with the engagement in writing the review although different students held different opinions (Meek, Blakemore, & Marks, 2017). As for intermediate and advanced students, the ability of peer assessment of essays via MOOCs was positively correlated with essay performance. As for lower students, no significant correlation was, however, revealed (Huisman et al., 2018).

**Discussion forum.** Asynchronous online discussion forum could improve student performance. Students might have different learning behaviors due to their heterogeneous backgrounds. Reading various messages on the forum, other than posting or commenting, might cater for students with different backgrounds and learning behaviors, thus leading to improved performance (Chiu & Hew, 2018).

**Self-regulation, motivational strategies, cognitive strategies and satisfaction.** Self-regulation, motivational strategies, cognitive strategies and satisfaction play important roles in student performance in the context of MOOCs. Self-regulation-prompt viewers interacted with, completed, and followed course activities better than non self-regulation-prompt viewers (Wong et al., 2019). In a large-scale MOOC referred to as “Cloud-based Tools for Learning”, motivational strategies were ranked significantly higher than task value, intrinsic goal orientation, and self-efficacy for learning performance. Cognitive strategies were slightly lower than motivation in elaboration, organization, and meta-cognitive self-regulation. Motivation was closely related to cognitive strategies (Chan et al., 2015). The performance and motivation improved cooperation in MOOCs-based learning in tertiary education (Castano, Maiz, & Garay, 2015). Satisfaction with the design of MOOCs mediated the relationship between use of social networks, activities they conducted in Personal Learning Environments, and student performance.

**Other Influencing factors.** It is becoming increasingly important for students to identify factors that influence student performance in MOOCs-based learning. Various factors such as aggregated activity frequencies could predict student performance (Conijn et al., 2018). MOOCs integrated with flipped approach are effective (Wang & Zhu, 2019). Students in MOOC-aided Flipped pedagogical approach obtained significantly better performance than those in the traditional. The flipped pedagogical approach combined with MOOCs and gamification could fortify student motivation and performances. Students with higher self-confidence tended to perform significantly better than those with lower self-confidence (Hung et al., 2018).

Furthermore, close correlations were revealed among residence (country), sex, occupation, age, external motivation, amount of time spent, length of time in learning management system and performance in a MOOC (Namestovski et al., 2018). Students with different motivations, prior experiences and goals greatly influenced their performance and perception of the MOOCs-based learning (Littlejohn et al., 2016). Use of MOOCs may widen the gap of performance between students with different socioeconomic backgrounds (Jiang et al., 2014).

Posts and badges could predict student performance in MOOCs-based learning. Students' overall performance was positively correlated with the number of posts on social tools. Top students of MOOCs were those who learned assisted with social tools (Alario-Hoyos et al., 2016). By studying three surveys during learning based on three MOOCs, it was concluded that badges could obtain more acknowledgement of student performance compared with certificates (Leach & Hadi, 2016). Although the considered metrics were useful for making direct comparisons between MOOCs, the study failed to provide a detailed classification to decide motivations and backgrounds.

**Suggestions for future design.** Designers should develop MOOCs based on student behaviors. MOOCs could save detailed student behaviors, e.g. dropout and persistence, and provide an effective



and economical approach to identify any misdeeds of tests and to determine whether the student earned a certificate, completed learning, or watched a video (Xu & Yang, 2016).

Recent studies have concentrated on how to provide high-quality and large-scale MOOCs across the world other than performance measurement (Castano, Maiz, & Garay, 2015). Future studies could shift to measurement of performance in order to provide suggestions for designers to improve performance of students.

### RQ3: How to improve student motivation in MOOCs-based learning?

Motivation and goal-setting could also greatly shape behaviors of students who had various levels of self-regulation (Milligan & Littlejohn, 2016). Motivation levels could greatly improve self-regulation skills in the context of MOOCs, which could lead to satisfactory learning outcomes (de Barba et al., 2016). Motivation and participation in MOOCs-based learning greatly influenced learning outcomes, which differed in different patterns of MOOCs and different types of participants. Professional development motivation, rather than general interest, could improve success in learning via professional MOOCs (Brooker et al., 2018). However, no significant gender differences were revealed in learning outcomes and student behaviors (Alario-Hoyos et al., 2016).

**Problem.** Motivation is embedded in human brain, which is transient, perishable, and thus difficult to measure. Four types of motivation were revealed, i.e. interest in knowledge, curiosity and expansion, connection and recognition, and professional relevance. MOOCs have notorious completion rates due to lack of strong motivations. MOOCs have been confronted with the issues that students tend to drop out and fail to achieve success in learning due to lack of supervision and self-regulation in MOOCs (Xing, 2019). Lower motivation, barriers of work, time, personal commitments, and perceived outcomes could possibly weaken learning effect of MOOCs (Zielinski et al., 2019).

**Solution.** Based on task-technology fit (TTF) model, social motivation, and self-determination theory (SDT), it was revealed that TTF was positively related to behavioral intentions. Social recognition, perceived competence, and perceived relatedness also strongly and positively influenced behavioral intentions of MOOCs-based learning (Khan et al., 2018). Enhancement of TTF, social recognition, perceived competence and relatedness might improve the motivation in learning via MOOCs.

SDT, including autonomy, competence and relatedness needs, is a reputable theory to identify student motivation. SDT has, however, not received much attention of researchers. The context of MOOCs plays an essential role in and provides an important platform for relatedness need. Autonomy need is positively related to competence, of which relatedness, a distinct need, is independent (Durksen et al., 2016). Enhancement of autonomy, competence and relatedness could significantly improve intrinsic motivation, and facilitate psychological engagement, as well as behavioral engagement in MOOCs (Sun et al., 2019). Three needs could be enhanced in order to improve motivation in MOOCs.

Completion rate, self-efficacy, residence and gender also exert an important influence on the level of motivation. Students who could complete the whole learning process tended to be significantly more motivated than those who could not. The latter tended to drop out of the MOOC course once they lost interest (Barak et al., 2016). MOOC completers also showed stronger self-efficacy and self-confidence (Wang & Baker, 2015) than non completers. Furthermore, male students held more positive motivation towards MOOCs than female. Geography also exerts an important influence on motivation in MOOCs-based learning. Students from America more negatively evaluated MOOCs than those from Africa and Asia (Shapiro et al., 2017).

Properly used, information technologies could also improve student motivation of MOOCs-based learning. Innovative tools in MOOC could motivate students to engage in learning, and students' digital abilities and skills could greatly influence their performances in MOOC learning (Carrera & Ramirez-Hernandez, 2018). Assisted with information technologies, digital skills, prior knowledge,

and perceived satisfaction greatly influenced motivation and completion rate of MOOCs-based learning (Vazquez et al., 2018).

Student motivation could be enhanced by improving teachers' adoption of MOOCs, which was greatly influenced by performance expectancy, social influence, facilitating conditions, and price value, as well as other moderating factors. This findings was, however, not generalizable to other online systems. Teachers' adoption of MOOCs may be driven by extrinsic motivation rather than intrinsic motivation (Tseng et al., 2019).

**Suggestions for designers.** Designers could focus on different contexts of MOOCs in order to enhance motivations of different students and raise their satisfaction levels (Chen et al., 2019). Self-regulation could act as an effective strategy to fortify motivation and improve student engagement, persistence and performance. How to integrate self-regulation into MOOCs is thus important for designers to consider (Handoko et al., 2019). Designers should also provide enough online resources since MOOCs integrated with open educational resources could motivate students to feel confident to use learning strategies and engage in MOOCs-based learning (Alario-Hoyos et al., 2017).

RQ4: How to enhance student engagement in MOOCs-based learning?

**Problem.** Although MOOCs have been widely accepted by various students, little has been known about the student engagement in MOOCs (Shapiro et al., 2017). However, much more students dropped out of the courses as time went by. MOOCs allow students to engage in learning activities wherever and whenever they feel comfortable. Unfortunately, completion rate of MOOC remains at a low level. The large number of participants and low completion rates make it difficult for instructors to monitor their learning behavior and progress. Those who perform poorly are ready to drop out due to lack of encouragement and instruction.

There are many factors negatively influencing student engagement in MOOCs-based learning. Knowledge, work, convenience, and personal factors could not be ignored. Lack of time was the most frequent factors that discouraged student from engaging in MOOCs. Other discouraging factors included previous bad classroom experiences with the subject matter, inadequate background, and lack of money, outdated infrastructure, and poor internet connection (Shapiro et al., 2017). Self-directed scheduling nudge could insignificantly influence near or long-term engagement, persistence, and performance, which was limited in terms of external validity because merely a single course was explored (Baker et al., 2016).

Nevertheless, no significant differences were found in engagement and completion rates in terms of gender, educational level or MOOC platform, while course Content and Interaction with the Instructor predicted MOOC retention (Hone et al., 2016). Hone and co-researchers (2016) might have conducted an exploratory study in nature. The influencing constructs used in previous research were not explored and the research model could thus be rebuilt to accommodate measurement constructs (Hone et al., 2016).

Lower engagement in MOOCs is a serious problem, leading to a poor level of motivation of MOOCs participants. Lower social interactive engagement and short registered time exerted a negative influence on dropout ratio and student attitude toward MOOCs (Wang et al., 2019). Student engagement could be considered an important factor influencing academic achievement and student retention. Persistence, reflection, initiative and concentration could predict student engagement in MOOCs (Sun & Bin, 2018).

**Solution.** Student engagement in MOOCs, conceptualised as either a unidimensional or multidimensional construct (Deng et al., 2020), remains a difficult issue to be solved because it is hard to measure. Deng et al. (2020) attempted to measure it by developing and validating a MOOC engagement scale (MES), including four dimensions, i.e. behavioural engagement, cognitive engagement, emotional engagement and social engagement. However, Peer and faculty relationships,

peer and student-staff engagement were not included in MES. Studies on the measurement of engagement are scanty, to which much attention should be paid.

Enhancement of student engagement in and retention of MOOCs is of great interest to professionals of Vocational Education and Training (VET), who argued that student perceptions, engagement and retention were closely related and functional strategies could improve engagement in MOOCs (Paton et al., 2018). Frequent online instructions might address this dilemma. Completion rates could be raised by monitoring students' behaviors such as answering questions, watching videos, and discussing on forums (Chiu et al., 2018).

The first two weeks were the critical threshold for students. Those who passed this threshold tended to be retained in MOOCs, while those who failed would drop out. Thus, designers should make every effort to engage students for at least two weeks. Postings on online forums and punctual feedback were effective methods to attract students. However, it was not concluded whether students held positive attitudes towards MOOCs-based learning or pedagogical approach could improve engagement, leading to favorable learning outcomes (Tseng et al., 2016).

Student engagement could be enhanced by increasing social interactions and improving student competence. Social interactions could greatly influence student engagement in MOOCs. Immersive experience of MOOCs, psychological needs satisfaction including competence, relatedness, and autonomy needs could exert a great influence on the effect of interaction on student engagement in MOOCs. Competence was evidenced the strongest predictor, while autonomy the weakest one influencing the student engagement in MOOCs (Fang et al., 2019).

Student engagement could be enhanced by improving completion rates, performance, motivation, situational interest, and learning persistence. Social engagement was closely related to completion rates (Sunar et al., 2017). Engagement was the strongest indicator of performance in MOOCs, followed by motivation. Situational interest greatly and positively influences student engagement in MOOCs, and mediates the effect of intrinsic motivation and engagement on student performance (de Barba et al., 2016). Dropout rates tend to decline if students are engaged in repeated and frequent social interactions. If they follow others who interact with the same students as they do, their completion rates will rise (Sunar et al., 2017).

Teacher presence, social learning, and peer learning could improve student engagement in MOOCs. Student self-efficacy, teaching presence, and perceived usefulness were directly correlated with student engagement, and the student engagement was indirectly correlated with student self-efficacy, teaching presence, perceived usefulness, and learning persistence (Jung & Lee, 2018). Combination of both intrinsic and extrinsic factors could enhance engagement in MOOCs (Khalil & Ebner, 2017). With swift development of information technology, programming skills become increasingly important. Learning analytics applied to MOOCs could improve student engagement and learning outcomes (Lu et al., 2017). Rich digital resources, student learning scaffolding, student customization and lived experience could improve MOOCs effectiveness and enhance student engagement in MOOCs (Montgomery et al., 2015).

We could enhance engagements and reduce dropout ratios by improving perception of course contents, perception of course design, social situation and characteristics, and students' ability to manage time (Eriksson et al., 2016). However, this finding was concluded by merely a qualitative study with interviews, without any quantitative support. To improve the reliability, we could study other influencing factors, e.g. lack of pressure, social influence, and long course start-up.

Grouping strategies based on different degrees of homogeneity could improve effectiveness of MOOCs-based learning, increase engagement, task completion rates, peer interactions and levels of satisfaction (Luisa et al., 2019). Peer review, facilitated by high engagement, could improve formative feedback communication in MOOCs (Erkan et al., 2019), which would by turn improve engagement. The homogeneous-engagement approach should be tested in various collaborative activities (Luisa et al., 2019). Peer and faculty relationships, and peer and student-staff engagement should also be included to measure engagement levels (Deng et al., 2020).

Henderikx and co-researchers (2019) concluded that in order to enhance engagement in MOOCs, we could cultivate students' online learning experience, improve their knowledge of the related course content, and fortify their ability to deal with difficulties and overcome barriers. Nonetheless, the population was limited to Spanish speakers, which might have decrease the reliability. Worse, the study failed to compare different populations between various types of MOOCs (Henderikx et al., 2019).

**Design of MOOCs.** Designers of MOOCs should seriously consider three positively correlated behavioral, cognitive, and emotional engagement in MOOCs system development. Behavioral and cognitive engagement was also positively and strongly correlated with student performances (Liu et al., 2018). Understanding both the number and type of students could also help designers develop effective MOOC platforms to increase student engagement (Walji et al., 2016).

Designers should consider activity repetition and duration. Self-regulation learning-prompt could be included in MOOCs in order to engage self-regulated, conscientious or other types of students. Not only clickstream data but also students' self-report should be obtained to analyze the sequences of student activities in relation to self-regulated learning (Wong et al., 2019) in order to enhance engagement.

Designers should also pay enough attention to other influencing factors. Five factors could greatly influence student engagement in MOOCs, i.e. problem-centered learning with clear expositions, instructor accessibility and passion, active learning, peer interaction, and use of helpful course resources (Hew, 2016). High-quality MOOCs should be equipped with clear explanation and rich online resources. Instructors should also be ready to answer questions raised by students. Students should actively engage in peer interactions, which is supervised by the instructor.

RQ5: What roles do interactions play in MOOCs-based learning?

Active interactions, including student-to-student, student-to-instructor, and student-to-content interactions, could improve effectiveness of MOOCs-based learning. These interactions could be realized and activated by online forums.

**Online forum.** MOOCs, a globally popular learning medium, could provide both opportunities and challenges for students and teachers. However, MOOCs have been experiencing a high dropout rate due to the lack of face-to-face interactions. Forums in MOOCs could facilitate peer communication and increase engagement by improving interactions and learning outcomes. The online forum could complement for the absence of a teacher, motivate student continuance, encourage students to complete assignment and facilitate interactions between students, contents and teachers (Zhang, Chen, & Phang, 2018).

Social interactions in MOOCs tend to outnumber those in traditional courses, which makes it harder to analyze social learning. Students may interact with each other by typing messages in the online forum. Rich messages on MOOC forum can be a proper source to analyze student behaviors and learning outcomes. Social, Sentiments, Skills learning analytics and LATS, a learning analytics tool for edX/Open edX, could be used to analyze the messages (Moreno-Marcos et al., 2019).

Discussions on the MOOC forum, closely related to network structures, could facilitate understanding of learning contents. It is important to divide discussions into learning contents based and non-learning contents based in order to identify communicative purposes, conversation structures, and students' interaction techniques (Wise, & Cui, 2018). In this way, contents in the online forum could be effectively analyzed in order to improve various interactions, among which peer interactions are the most important predictor of the effectiveness of MOOCs-based learning.

**Peer interactions.** Peer interactions could improve MOOCs-based learning effect. Few studies have, however, focused on peer interactions in MOOCs-based learning. Despite the several studies have explored student perceptions of peer interactions, insufficient studies have been committed to the interaction contents and levels of interactions. Peer interactions, e.g. information sharing and

comparing, were at a lower level in a Chemistry MOOC from Coursera and were greatly initiated by a number of highly-engaged students (Tawfik et al., 2017).

MOOCs designers could shed light on interactions because student behaviors and interactions could predict the completion rate of MOOCs (Pursel et al., 2016). The instructor could also frequently post constructive discussions on the forum to initiate peer interactions. Assignments, especially those needing discussions, are also a useful tool to encourage peer interactions.

**Suggestions for future research.** Few researchers have paid enough attention to interactions of students beyond forums of MOOCs and out of teachers' reach regardless of their potential influence on student engagement and learning retention. However, interactions often occur outside MOOCs-based learning. Future research could focus on various extracurricular interactions such as collaborations, individual tasks, and learning assessments to increase engagement levels and reduce dropout rates (Cisel, 2018).

## DISCUSSION

This study, pivoting on the findings, discusses student performance, motivation, engagement, and interaction in MOOCs-based learning.

### Student Performance

Student performance is notoriously poor in MOOCs-based learning. However, improvements on motivation levels, and quality of MOOCs, as well as discussion forum, motivational strategies, cognitive strategies and satisfaction could improve performance of students in MOOCs-based learning. There are other factors influencing performance, e.g. aggregated activity frequencies, flipped approach, gamification, residence, sex, occupation, age, external motivation, amount of time spent, length of time, prior experiences, learning goals, and the number of posts on social tools. It is important for designers of MOOCs to transform these complicated factors into positive influence on MOOCs-based learning.

### Student Motivation

Students tend to present poor motivation in MOOCs-based learning in case they are not supervised and encouraged. Motivation could be enhanced by using Task-technology fit (TTF) model and innovative tools, improving social motivation, autonomy, competence and relatedness needs, prior knowledge, perceived satisfaction, self-efficacy and digital skills, and raising completion rates of MOOCs-based learning. Designers of MOOCs should also consider learners' residences and gender in order to enhance their motivation. Machine learning algorithms could be used to identify the level of motivation, providing teachers with suggestions for encouraging students to engage in MOOCs-based learning (Al-Shabandar et al., 2018).

### Student Engagement

Although MOOCs have been popularly accessed by millions of students, their engagement has been evidenced lower and poorer than face-to-face instruction. Enhancing learner perceptions and retention could improve engagement. In case learners could properly use functional strategies, social interactions and have lived or immersive experience of MOOCs, their engagement in MOOCs could also be improved. Increased psychological needs satisfaction, completion rates, situational interest, and learner self-efficacy could also improve learners' engagement in MOOCs, as well as perceived usefulness, social learning, and peer learning.

There are also other factors that may positively influence engagement, e.g. learning analytics, rich digital resources, student learning scaffolding, learner customization and grouping strategies based on different degrees of homogeneity. Decrease of dropout rates, and teacher presence could also improve engagement in MOOCs-based learning.

## Interactions

Interactions in MOOCs-based learning may improve student engagement, motivation, and performance, which can be realized and facilitated by online forums. Interactions include peer-to-peer, peer-to-content, peer-to-instructor interactions. In MOOCs-based learning, peer-to-peer interactions may be the most frequent form, which is in need of prompt attention of designers and instructors. Social interactions and peer discussions should also be promoted by designing convenient forums or other channels.

Considering the huge number of interactive data sourcing from students with various backgrounds, the analysis becomes difficult, which may be eased by using learning analytics techniques such as 3S and LATS. Through advanced learning analytics, instructors can keep trace of learning behaviors, based on which they can design appropriate learning contents and instructional framework. Designers should make every effort to develop innovative technologies to facilitate the transparency, convenience and efficiency of the analytical tools. In this way, can the engagement and completion rates be raised in MOOCs-based learning.

## CONCLUSION

### Major Findings

This study explored the literature to improve performance, motivation, engagement, and interactions in MOOCs-based learning, coupled with the approaches to improvements on the effectiveness of MOOCs-based learning. This study also provides constructive suggestions for future design of MOOCs, and complements for the missing link in literature that very few studies focus on a comprehensive review on performance, motivation, engagement, and interactions in MOOCs-based learning.

### Limitations

Although this study bridges a gap in literature, several limitations still exist. Firstly, the results cannot be generalized to all contexts. MOOCs in developed countries may have different features from those in the less developed because the former may provide better network infrastructure for learners than the latter. Secondly, learners with higher socioeconomic status may perform differently in MOOCs-based learning than those with lower since the former may possess more skills of information technologies than the latter. Lastly, the study is limited to several databases, which may not be able to include all the literature.

### Future Research Directions

Future research could focus on the measurements of performance, motivation, engagement, and interactions in MOOCs-based learning in order to improve the quality of MOOCs and help learners achieve success in learning. Influencing factors could also be extended to a large sample size (Barak et al., 2016), including different learners with different backgrounds. Future research could also study multiple MOOCs, include both active and passive participants, establish links learning patterns, strategies and academic success and provide sufficient data of interview to analyze self-regulation (Milligan & Littlejohn, 2016).

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## **APPENDIX A - UNIVERSITY OF WEST ENGLAND FRAMEWORK FOR CRITICALLY APPRAISING RESEARCH ARTICLES (MOULE ET AL., 2003)**

### **The Introduction**

Is there a clear statement about the topic being investigated?  
Is there a clear rationale for the research?

### **The Methods Section**

Is the research design clearly described?  
Are the research methods appropriate for the topic being investigated?  
Are any advantages or disadvantages of the design acknowledged by the researchers?  
Is there a clear statement about how the participants were selected?

### **Data Collection and Analysis**

Is there a clear description about how the data was collected?  
Was the data collected by appropriate people?  
Is the approach to data analysis appropriate to the type of data collected?

### **Quantitative**

Is there any explanation of sample size used?  
Are the type of statistical tests used appropriate for the sorts of data collected?

### **Qualitative**

Is the approach taken to data analysis clear?  
Is there a clear statement about how the researcher validated interpretations?

### **Ethics**

Is there a clear statement about ethical committee approval? Is there a clear description about gaining consent, maintaining anonymity and or confidentiality?

### **The Results/Findings**

Are the results related back to the literature review?  
Are the weaknesses in research design acknowledged?

### **Quantitative**

Is the presentation of results clear and unambiguous? Are all the results presented?  
Do the tables and charts used give a clear picture of the sample data and results?  
If percentages are recorded, are actual numbers also clearly shown?  
Are results of tests interpreted rightly?

### **Qualitative**

Does the research present evidence of the data collected?  
Does the data presented as part of a theme support the analysis suggested?  
Is there a clear audit trail?

### **The Conclusions**

Are the implications for further research acknowledged? Are areas for further research identified?  
Are further recommendations made for practice that come from the results/discussion?

*Min Wang (First author), associate professor in School of English Language, Zhejiang Yuexiu University, has authored a number of academic papers. Her research interest includes language learning and teaching, mobile learning, and blended learning. Email: angelawangacademic@163.com. ORCID: <https://orcid.org/0000-0002-0390-4553>.*

*Zhonggen Yu, Corresponding author, ORCID: 0000-0002-3873-980X, Scopus Author ID: 35975507500; Web of Science ResearcherID: AAJ-3063-2020), Professor (Distinguished) and Ph.D. Supervisor in Department of English Studies, Faculty of Foreign Studies, Beijing Language and Culture University, has already published over 100 academic papers in distinguished journals based on rich teaching and research experiences. His research interest includes educational technologies, language attrition, and language acquisition. He is Editor in Chief of International Journal of Technology-Enhanced Education and Academic Editor of Education Research International. Email: 401373742@qq.com; yuzhonggen@blcu.edu.cn.*