A learning model for improving in-service teachers' course completion in MOOCs[1]

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Abstract: The use of massive open online courses (MOOCs) for teacher professional development (TDP) has increased in the past decades. This study explored the key factors that influenced teachers' online course completion as a significant indicator of their success in a TPD MOOC. Participants' self-assessment of Technological Pedagogical Content Knowledge (TPACK), interaction with curriculum content and peers, satisfaction, and overall course score were identified as key influencing factors. Employing a learning model that was constructed as a hypothesis path model based on literature review, we analysed these influencing factors' effects on participants' online learning completion. Results showed that participants' TPACK self-assessment and overall course score had a strong direct effect on their course completion, while their interaction with course content and peers had a significant indirect effect on their course completion. The important role of social activities and formative feedback in the design of MOOC was emphasized in this study. Surprisingly, participants' TPACK self-assessment had a weak negative impact on teachers' online learning completion, which warrants further research. Implications for research and practice are discussed.

Keywords: teacher professional development; MOOCs; TPACK; online learning completion

Introduction

Teacher professional development (TPD) courses are recommended by international organisations such as UNESCO (2018) and OECD (Ainley & Carstens, 2018) as a

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viable means to meet teachers' professional learning needs. TPD is a complex process in which teachers need to actively interact with peer participants, learning materials, and instructors to attain professional learning outcomes (Avalos, 2011).

Recently, there has been a surge of TPD courses delivered in an online learning mode because of their greater flexibility and adaptability compared with face-to-face TPD courses (Duncan-Howell, 2010). In China, online learning mode has become an important part of the "National Training Plan" (Ministry of Education, 2010) which is dedicated to offering TPD courses for K-12 teachers nationwide. Over 16 million teachers have received training under the plan since its implementation in 2010 (Ministry of Education, 2020). Large-scale platforms where massive open online courses (MOOCs) are offered, such as Coursera, FutureLearn and EU Schoolnet, hold promises for widening teachers' access to TPD opportunities in order to enhance teachers' ICT competency and other professional skills (Laurillard, 2016). Some of these platforms are dedicated to TPD courses, such as the MOOC-ED (Massive Open Courses for Educators, https://place.fi.ncsu.edu/).

While TPD MOOCs are considered a viable approach to supporting teachers' professional learning (Kennedy & Laurillard, 2019), a number of challenges have been reported. These include low levels of instructor-participant and peer interaction, insufficient instructor guidance and feedback and, in some cases, low completion rates (Chiu et al., 2018). Understanding the influencing factors underlying such challenges, especially participants' course completion, is important for designing quality TPD MOOCs to support teachers' professional learning.

In the context of Chinese school education where a large number of teachers take part in TPD MOOCs promoted by the Ministry of Education, it is necessary to examine how the key factors of teachers' professional learning in such courses interact to affect teachers' course completion. In this study, a TPD MOOC was developed for in-service teachers on a large-scale online platform (LearningCell platform, http://etc.edu.cn) to support professional learning among teachers from different provinces and municipalities in China. Findings contribute to theory pertaining to how the development of TPD MOOCs affect teachers' professional learning and have implications for the design of future TPD MOOCs in China and similar contexts such as Greek (Koukis & Jimoyiannis, 2019a) and Spain (Castaño-Muñoz et al., 2018) where there is huge demand for TPD opportunities.

Literature review

Nature of teacher learning in TPD MOOCs

TPD consists of activities that support teachers' initial training and continuous professional development to improve professionals' practice and outcomes of teaching (Sancar et al., 2021). Benefits of such activities include enhanced instructional knowledge and skills, and changes of beliefs related to teachers' teaching practice in the classroom, and increased use of ICT in teaching (Fischer et al., 2018).

Teachers learn effectively in TPD courses when they are actively engaged in social interaction and collaborative learning with peer participants. TPD MOOCs support teachers' collaborative learning by enabling their exchange of ideas, co-construction of professional knowledge, and co-regulation of learning using a range of online learning tools, such as discussion forum, online collaborative documents, and peer-review of assignments (Elizondo-Garcia & Gallardo, 2020; Koukis & Jimoyiannis, 2019b). In turn, teachers' collaborative learning and sharing promote their teaching innovation (Laurillard, 2016).

Factors influencing the completion rates of TPD MOOCs

Despite potential benefits, a major concern over the delivery of MOOCs is low course completion among participants. In some cases, the number of registered participants reached more than one million, but only a small proportion (3%-6%) of them completed their MOOCs (Jordan, 2014). Existing studies investigated the reasons for the low completion rate and identified significant influencing factors, such as academic self-efficacy, teaching presence, and motivation (Chaw & Tang, 2019; Jung & Lee, 2018), perception of course content (Aldowah et al., 2020), performance in the course (Chen et al., 2020), and interaction with peer participants (Crane & Comley, 2021).

To explore how multiple factors influence MOOC completion rate, several conceptual models have been proposed. Jung and Lee (2018) introduced a model to account for the mechanism of multiple factors influencing learners' learning engagement and persistence in MOOCs. The following factors were reported: academic self-efficacy, teaching presence, perceived usefulness, and perceived ease of use.

Choi and Park (2018) proposed a path-analytic model of adults’ completion in online degree programs, identifying a number of factors including interaction with course content, basic scholastic aptitude, physical constraints, satisfaction, and GPA that influenced adult learners’ completion. However, the model excluded participants’ social interaction with instructors and peers. Considering the important role of interaction and self-efficacy in participants’ withdrawal or retention in MOOCs (Formanek et al., 2019; Sunar et al., 2020), it is necessary to construct a model that incorporates interaction and self-efficacy – along with other significant factors that are specific to teacher professional learning, such as self-assessed levels of TPACK – in examining MOOC completion rate.

Interaction with content and peers

Existing studies on MOOCs found that peer interaction reduced loneliness (Swinnerton et al., 2017), promoted the intention and behaviour of continuous learning (Hsu et al., 2018), increased engagement (Wu, 2021), supported co-construction of knowledge (Moreno-Marcos et al., 2019), and predicted satisfaction (Oyarzun et al., 2018). Interaction with peers also positively impacted MOOC completion rate (Formanek et al., 2019) and learning outcomes (Ma et al., 2020).

Dai and co-authors (2020) did not find significant relationship between social interaction and satisfaction, while knowledge transmission quality was significantly related to satisfaction, which in turn affected completion rate. Their findings might be explained by participants' perceived low need for peer interaction, low expectations for the role of social interaction in learning through MOOCs (Rieber, 2017), and teacher-centred conception of learning. The effect of interaction with content on retention in MOOCs was also reported by Zhu (2017).

To sum up, interaction with content and peers should both be considered as influencing factors of MOOC completion rate. The inconclusive findings from existing studies on these two factors warrant further exploration.

Self-efficacy

Self-efficacy refers to one's self-assessment of the ability to complete a task; and it directly affects a person's behaviour and motivation. Several researchers reported a direct positive relationship between learners' self-efficacy and completion in MOOCs (Handoko et al., 2019; Wang & Baker, 2015). Rabin and co-authors (2020) found that self-efficacy negatively predicted perceived barriers to knowledge acquisition and technology use and that self-efficacy positively impacted satisfaction which positively influenced learning persistence.

TPACK self-assessment

When it comes to TPD MOOCs that focus on teachers' development of expertise in ICT-enhanced teaching, teachers' self-assessment of Technological Pedagogical Content Knowledge (TPACK) was found to positively impact perceived ease of use (Yang et al., 2019), which was an influencing factor of completion rate reported in Jung and Lee's (2018) study. TPACK self-assessment also influenced teachers' attitudes towards technology influenced their intention to continue with learning in MOOCs (Wu & Chen, 2017), which was another influencing factor of completion rate (Tømte et al., 2015). Since TPACK captures teachers' integrated knowledge in the domains of teaching, ICT, and subject content, it was not surprising that TPACK played a significant role in teachers' completion of MOOCs. Thus, teachers' self-assessed TPACK should be included when further investigating the relationships between influencing factors of teachers' completion of TPD MOOCs.

Satisfaction and performance

Participants' satisfaction with the course was reported to have a direct positive impact on the completion rate and success of MOOCs (Pozón-López et al., 2020). The indirect positive impact of satisfaction on learning persistence was also reported. For example, Dai et al. (2020) found that satisfaction positively affected intention to persist learning through the mediating effect of attitude; they also reported that participants' performance positively affected participants' intention for learning persistence through the mediating of satisfaction. Other studies revealed a direct positive relationship between participants' performance and persistence in learning (Choi & Park, 2018; Dupin-Bryant, 2004). Therefore, both satisfaction and performance are important factors affecting the completion rate of MOOCs. Based on our analysis of existing empirical evidence, it is necessary to develop an explanation of completion in TPD

MOOCs by tracking potential influencing factors. The following key factors were examined in this study: TPACK self-assessment, self-efficacy, interaction, satisfaction, and performance.

Research design

To reveal the critical factors affecting completion of teachers' online learning, we developed a large-scale course to help teachers acquire innovative teaching strategies using ICT. Drawing on data from teachers, we empirically tested a path-analytic model based on Choi and Park’s (2018) model to explain the relationships between the critical factors that affected teachers’ online learning completion.

A conceptual model

Unlike Choi and Park’s (2018) study, the online learning participants in our study were teachers. Thus, we took teachers as the starting point by including teacher-related variables, such as TPACK self-assessment and self-efficacy. The MOOC platform supported participants’ interaction with learning content and peers. Thus, our hypothesis path model included these additional variables. In Table 1, we specify the variables in relation to those in Choi and Park’s (2018) model.

Table 1. The equivalence between variables in the Choi & Park model and those in the model of this study

Variables in the Choi & Park model	Variables in the present study
Scholastic aptitude: Scholastic aptitude is based on student scores on the test they took upon admission.	(1) Teachers’ TPACK self-assessment (2) Participant' self-efficacy (SE)

Interaction with the course content: Each individual participant's average number of login hours per week in one course.	Interactions with course content (ICC) (1) reading and watching curriculum content (2) annotating content Interaction with peers (IP): (1) No. of posts in discussion: making comments with peers in discussion (2) No. of reviews done: doing peer review (3) No. of reviews received: receiving peer review
Satisfaction: The mean score of course evaluations for all the courses a learner took.	**Satisfaction:** score in a satisfaction questionnaire about the course
GPA: The score of mid-term and final online examinations.	**Overall Course Score (OCS)**: the average score of all units that the participant got. The score of each unit was calculated automatically by the system based on the activities that the participants attended, as shown in Fig. 4.
Completion: Drop-out or Persistence	**Completion of Unit (CU)**: Presence in the unit activities and the learning score of the unit >0. **Completion of the Course (CC)**: Presence in all the units of the course and OCS>0.

Based on the above analysis, we constructed a modified learning model in MOOCs, which is discussed next.

Study model and hypotheses

In order to reveal the key factors affecting the MOOCs completion rate of large-scale TPD and the potential relationships between these factors, we adopted Choi & Park's (2018) path-analytic model on adult learners' drop-out rates but with a breakdown of the variables with some of nodes in the model, to develop a learning model (see Figure 1). The model was named LMC-MOOCs (Learning Model for Completion in MOOCs), which presented information on influencing factors on the levels of completion in online learning.

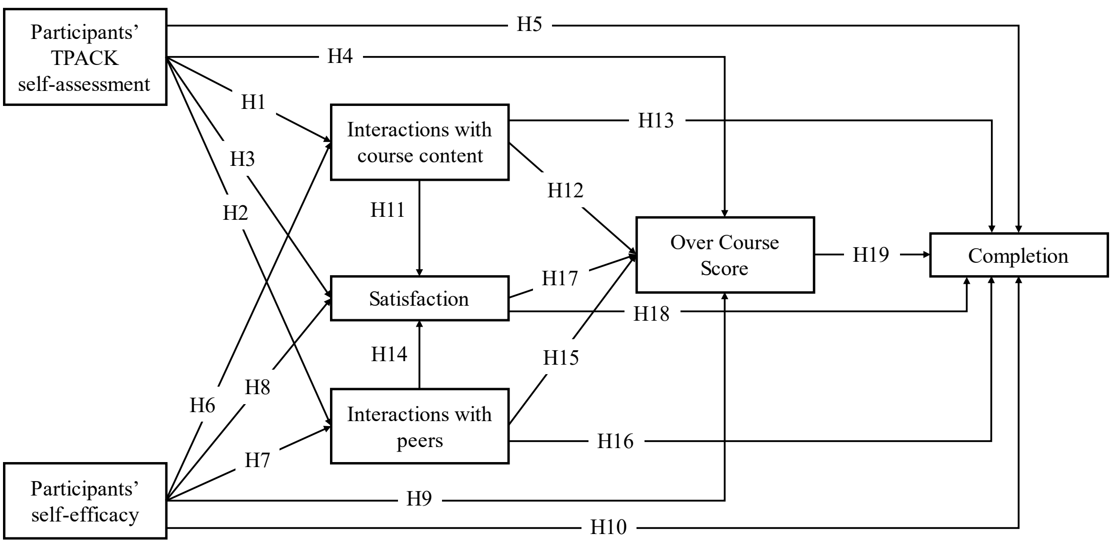


Fig 1. The hypothesized learning model for completion in MOOCs

Based on the LMC-MOOCs model, we formulated the hypotheses as follows:

Hypotheses 1 to 5: Participants' TPACK self-assessment will directly and positively predict their interaction with course content (H1), interaction with the peers (H2), satisfaction (H3), overall course score (H4), and completion of online learning (H5).

Hypotheses 6 to 10: Participants' self-efficacy will directly and positively predict their interaction with course content (H6), interaction with the peers (H7), satisfaction (H8), overall course score (H9), and completion of online learning (H10).

Hypotheses 11 to 13: Participants' interactions with course content will directly and positively predict their satisfaction (H11), overall course score (H12), and completion of online learning (H13).

Hypotheses 14 to 16: Participants' interactions with the peers will directly and positively predict their satisfaction (H14), overall course score (H15), and completion of online learning (H16).

Hypotheses 17 to 18: Participants' satisfaction will directly and positively predict their overall course score (H17), and completion of online learning (H18).

Hypotheses 19: Participants' overall course score will directly and positively predict their completion of online learning (H19).

Course design

The structures of the course

In this study, a MOOC course entitled Project Based Learning in Blended Learning (PBL in BL) was offered on the Learning Cell Platform (http://www.etc.edu.cn/), with the purpose to help teachers develop knowledge and skills about PBL. The course was informed by the Conversational Framework, which identifies six types of learning, all of which should form part of the pedagogical sequence in order to optimise participants' learning experience. The course was divided into 5 weeks (90 teaching minutes in each week), and delivered in consecutive weeks (see Table 2). The weekly lessons focused on a given theme and was divided into two or three units (14 units in total) to facilitate participants' self-paced learning. Each unit contained 4-6 online learning activities offering learning experience of six basic types, including: acquisition (reading and video watching), inquiry (exercises), discussion (forum activities), practice (design activities), collaboration (peer review activities) and production (a learning design).

Table 2. The structure of the "PBL in BL" Course

Week	Course Theme
Week 1	The Role of Digital Technology in PBL
Week 2	PBL & the Selection of a PBL Topic
Week 3	The Design of Learning Outcomes and Study Plan
Week 4	Information Search & Activity Developing
Week 5	Project Design & Assessment

Learning activities in the course

Based on the functions of the learning platform, connections were established between participants, learning resources and learning communities through a series of activities in each unit.

Individual activities included interaction with learning resources, such as videos and reading materials. To facilitate participants' interaction with content, the function of annotation was set up for participants to give comments on the design of learning activities.

Discussion forums related to the learning themes were set for participants' communication and collaboration, which promoted the construction of a learning community among participants. Figure 2 provides an example of such discussions that were set according to broad subject areas among participants.

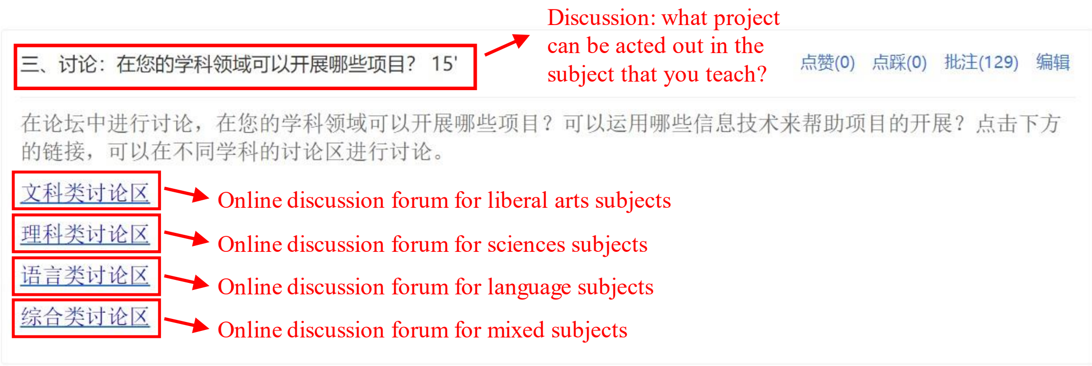


Fig 2. The discussion area in the course

A peer review function was developed to facilitate participants' mutual support of learning in the course. The participants were divided randomly into different groups, each consisting of 20 teachers. In the group, each participant could submit one instructional design about the PBL in his/her subject area. Others could review the instructional designs and give comments. Fig. 3 shows the interface of peer review.

Fig 3. The interface for peer review in Learning Cell platform

Participants were provided with formative feedback on their performance in each unit to assist in their self-reflection and improvement. The assessment framework of each unit varied according to the learning activities involved in the unit. There were 4-6 learning activities in each unit, which might include watching videos, discussions, peer reviews, submitting instructional designs, making online annotations, and downloading resources.

To give an example, Figure 4 presents formative feedback on learning activities in Unit 3.2. The pie chart shows the proportion of the score for each activity in this unit. Six learning activities were assessed based on the completion or time spent on the activities: making comments, downloading resource, making online annotations, submitting instructional designs, learning time, and peer review. The total score was 100 points. Learning time accounted for 25% of the total score, which could be obtained when a participants' cumulative learning time was or exceeded 30 minutes. 20% of the total score could be obtained by participating in peer review. 20% of the total score was obtained by submitting an instructional design. 5% score could be obtained by making annotations to this learning unit; 20% score could be obtained by downloading the resources embedded into the platform; 10% score could be obtained by making comments to the course.

As participants moved through the units, the Learning Cell platform collected the learning information of each participant and calculated their scores for each unit automatically. The overall course score (OCS) of the participant was subsequently calculated according to their average scores across all units.

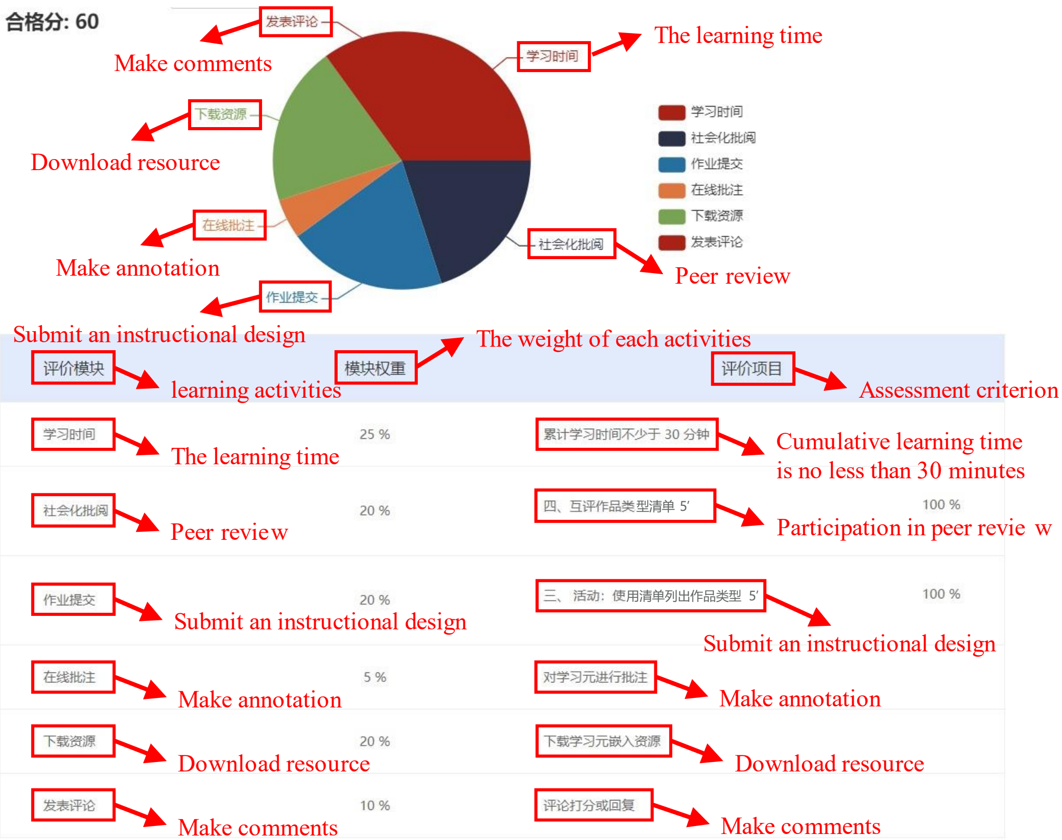


Fig 4. The example OCS of unit 3.2

Methodology

Participants and research context

Learning platform

The course investigated in this study was opened on the LearningCell Platform (http://www.etc.edu.cn/), which is an interactive platform to support ubiquitous learning developed by the research team of Beijing Normal University, and has been widely used and highly recognized by education experts. The platform collected all the data that the study needed, such as the participants' online learning time of each unit, qualitative data of the teachers' participation in the discussion area, and then calculated the scores they obtained in each unit.

Participants

2,650 teachers from China attended this course. A total of 826 learners were selected as the research objects through data filtering with the data integrity of the questionnaire as the index. Most of the participants were teachers from K-12schools, and principals. Among them, 698 were K-12 teachers, accounting for 84.5% of all participants. The participants had an average of 18.5 years of teaching experience and were from a range of subject areas (e.g., Chinese, math, physics and chemistry). Before the course started, participants received technical training to use the LearningCell platform and its functions.

Method and Instruments of data collection

A pre-course survey was conducted via the platform to collect participants' demographic information (including teaching subjects, teaching time, identity and online learning experience), their self-assessments of TPACK, and self-efficacy. Then a post-course survey was conducted to obtained information on participants' satisfaction and assessment of the course.

As explained in the preceding section, the independent variables in the hypothesized learning model for completion in MOOCs comprised the following: self-assessment of TPACK, self-efficacy score, amount of interaction with peers and course content, course satisfaction score, overall course score, and course completion. The pre- and post-course surveys measured these key variables except the last two variables.

For the pre-course questionnaire, Chai and co-authors' (2012) 32-item scale of TPACK was adopted, which include seven dimensions: Technological Knowledge (TK), Pedagogical Knowledge (PK), Content Knowledge (CK), Technological Pedagogical Knowledge (TPK), Technological Content Knowledge (TCK), Pedagogical Content Knowledge (PCK), and Technological Pedagogical Content Knowledge

(TPACK). The Cronbach alpha of the overall survey was 0.98, which indicated good internal consistency of the items. Schwarzer et al.'s (1999) general self-efficacy scale was used to measure participants' confidence in their ability to complete the online course successfully. The Cronbach's alpha of the scale 0.86. The questionnaire included 10 four-point scaled items ranging from "not at all true" to "very true".

For the post-course questionnaire, we measured participants' interaction with curriculum contents including reading and video watching by calculating each learner's total number of login time per unit in the course. Each individual participant's total number of comments in the peer discussions, assignments submitted for review, completed peer reviews were used to measure his interaction with the peers. The satisfaction scale consisted of 17 items on a 5-point Likert-type scale (1=strongly disagree; 5=strongly agree) (e.g., *The quality of the course met my expectations; The forum discussions were useful for my learning*). The Cronbach's alpha of the scale was 0.95.

The overall course score for the assessment of participants was defined as the average score of all units that the participant achieved. Finally, Completion of the Course (CC) refers to the participant's presence in all the units' activities of the course and OCS>0.

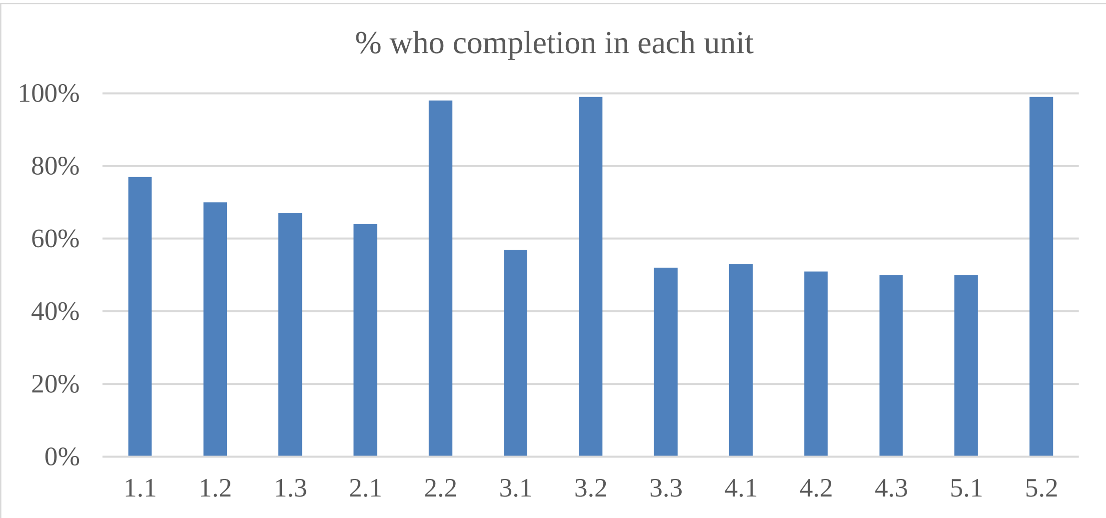
Data analysis

To test the hypotheses, we analysed the data using the structural equation model (SEM) method (Niels, 2013). This enabled us to determine the interactions between the various factors and to test the proposed path model on participants' completion of MOOC learning. SEM is a method to establish, estimate and test a causal relationship model. The model contains both observable variables and potential variables that cannot be directly observed. In addition, SEM can replace a series of methods, such as multiple regression, path analysis, factor analysis, covariance analysis, to clearly analyse the role of individual indicators and the relationship between individual indicators.

We first used SPSS22.0 to describe the data and observed the skewness and kurtosis of the data to ensure its normality. On the basis of ensuring the normal distribution of data, we then used the AMOS tool to conduct a confirmatory factors analysis (Niels, 2013) to examine the relationships between the variables. Finally, the learning model presented in Figure6 were obtained.

Results

The participant data collected in all the stages of the project showed that the attendance and completion level of teachers' online learning in this MOOC reached a very high level, as shown in Fig. 5. For example, the completion rate of the unit1.1 is close to 80%. There were 2,650 participants began the course. More than 2,500 participants were present in all units. Moreover, 1,160 participants completed all the steps of the course.



1.1 Introduce the development of technology and its effect on education.

1.2 New requirements to the students and teachers in new time.

1.3 Introduction of BL & PBL

2.1 The definition and learning process of project-based learning

2.2 Project selection and goal setting

3.1 Situation setting and problem decomposition

3.2 Determination of the form of project works

3.3 Making a study plan

4.1 Efficient resource retrieval and collection

4.2 Field exploration activities were carried out

4.3 Handling of project materials

5.1 Production of project works

5.2 Evaluation of learning results

5.3 Complete and evaluate the course

Fig 5. Attendance and Completion data for each unit of the course

The completion rate of this MOOC was drastically different from the typical low completion rates of MOOCs in the literature, which were less than 10% (Garrett, 2018). In three unites (Units 2.2, 3.2 and 5.2), the completion rate of the unit learning exceeded 90%. It was interesting to find reasons for such exceptionally high completion rates at unit and course levels.

Because some participants were constantly entering the study halfway, they did not follow the process of our course to answer the questionnaire about their TPACK self-assessment and self-efficacy, which resulted in incomplete sample data. Therefore, we only included 826 participants who participated in the surveys in our analysis of the reasons for high completion rate in this MOOC.

To verify the normalization of the collected data, a descriptive statistical analysis of the data was performed, with the skewness ranged from .31 to .4.02, and kurtosis ranged from .46 to 20.66. Kline (2011) proposed that the criteria of normality were skewness <3 and kurtosis <10. Our data satisfied such normality assumptions.

The fit of the structural model was analysed by using maximum likelihood estimation (MLE). The results indicated that the measurement model agreed well with the data, according to the accepted criteria (Browne & Cudeck, 1993; Kim, 2016). Where CFI = .96, i.e.>.09, SRMR = .04, i.e. <.08, RMSEA = .07, i.e. <.08. This result indicated that our model was valid.

Descriptive statistics of the variables by completion/dropout group

Table 3 displays the means and standard deviations of the scores of participants in different groups, those who completed (i.e., being present in all the units) and those who dropped out (i.e., being absent in certain units). The eight indicators of comparison between completion group and drop-out group were interaction with course content, OCS, interaction with peers (including numbers of posts in the discussion, numbers of reviews done, and numbers of reviews received), satisfaction, TPACK self-assessment, and self-efficacy.

The dropout group had significantly lower mean scores than the completion group regarding participants' interactions with course content, interactions with peers, and OCS. A similar but not significant trend was observed of the differences between the two groups' mean scores in terms of the number of reviews received, satisfaction, TPACK self-assessment, and self-efficacy. The participants who completed the course made up 73% of all participants, and those who dropped out from the course accounted for 27% of all participants.

Table 3. Descriptive statistics of the variables by completion group (n = 601), and drop-out group (n = 225)

Variables	Completion group		Drop-out group	
	Mean	S.D.	Mean	S.D.
Interaction Content	116.87	134.79	49.08	78.07
Overall Course Score	89.36	13.97	29.43	22.95
Numbers of Posts in the Discussion	6.18	3.75	3.93	2.40
Numbers of Reviews Done	12.60	20.21	2.79	9.76
Numbers of Reviews Received	11.48	6.13	10.60	2.43
Satisfaction	4.03	.52	4.02	.14
TPACK	3.93	.54	3.75	.59
Self-Efficacy	4.22	.52	4.23	.14

The main differences between the two groups, therefore, lied in the participants' levels of engagement with the course, leading naturally to a higher OCS for the completion group. On the other hand, the two groups had similar prior characteristics of TPACK and self-efficacy, and similar levels of satisfaction with the course.

Hypothesis testing in terms of correlations among variables

Table 4 presents a correlation matrix of the variables. Participants' interaction with course content has a significant correlation with OCS. The number of posts in the discussion, the number of reviews done and Completion ($p<0.001$). The number of posts in the discussion and the number of peer reviews conducted also had a significant correlation with OCS ($p<0.05$, $p<0.001$). OCS, the number of posts in the discussion, the number of reviews done and the number of reviews received had a statistically remarkable correlation with Completion ($p<0.001$).

Table 4. Correlations among variables

Variables							
Interaction Content							
Overall Course Score	257**						
No. of posts in the discussion	201**	242**					
No. of reviews done	153**	216**	267**				
No. of reviews received	032	064	058	320**			
Satisfaction	052	016	086*	.036	.030		
TPACK	032	087*	017	.012	.004	021	

Self-Efficacy	033	.001	.042	.032	007	277**	006	
Completion	240**	845**	280**	236**	072*	.013	050	.044

Note. n=826, * p <.05, **p<.001.

Table 5 presents the results of the direct impacts between each pair of variables. Six of the hypotheses were shown to be valid:

H12 Interaction with Content and OCS significant (β=0.223, at p<.001)

H15 Interaction with peers and OCS significant (β = 0.335, at p<.001)

H17 Satisfaction with OCS significant (β = 0. 195, at p < .001)

H16 Interaction with peers with completion significant (β = 0.135, at p < .001)

H5 TPACK self-assessment with completion significant (β = -0.175, at p <.001)

H19 OCS with completion significant (β = 0.823, at p< .001)

These are shown in the Table 5 in bold.

Table 5. Path coefficients of the measurement model

Hypothesis				Estimate(B)	Standardized Estimate(β)	S.E.	t
H1	ICC	---	TPACK	6.362	0.037	.866	1.085
H2	IP	---	TPACK	-0.811	-0.039	.86	-0.942
H6	ICC	---	SE	7.109	0.029	.459	0.84

H7	IP	---	SE	-0.328	-0.011	.24	-0.264
H3	Satisfaction	---	TPACK	0.027	0.045	.021	1.293
H11	Satisfaction	---	ICC	0	0.058		1.624
H14	Satisfaction	---	IP	-0.001	-0.042	.001	-0.988
H8	Satisfaction	---	SE	0.016	0.019	.031	0.538
H12	OCS	---	ICC	0.070***	0.223	.014	5.097
H4	OCS	---	TPACK	0.002	0	.419	0.001
H15	OCS	---	IP	0.969***	0.335	.216	4.481
H9	OCS	---	SE	0.752	0.011	.331	0.323
H17	OCS	---	Satisfaction	15.017***	0.195	.751	5.459
H16	Completion	---	IP	0.006***	0.135	.002	3.146
H13	Completion	---	ICC	0	0.019		0.999

H10	Completion	---	SE	-0.018	-0.02	(.016	-1.086
H5	Completion	---	TPACK	-0.120***	-0.175	.018	-6.678
H18	Completion	---	Satisfaction	-0.023	-0.023	(.018	-1.232
H19	Completion	---	OCS	0.012 ***	0.823	(	40.979

Note. n=826, *** p <0.001.

Indirect, direct and total effects of the research model

To examine OCS's mediating effect, we tried to verify the statistical significance of indirect effects by a significant level of 0.001. Figure 6 shows the valid path after hypothesis verification, indicating the indirect and direct effects of the variables on completion.

Participants' interaction with course content had significant indirect (β=0.184, $p<.001$) effects only on completion. Their interaction with peers had both direct (β = 0.135, $p < .001$) and indirect (β = 0.279, $p<.001$) effect on completion. Therefore, the total effect of the interaction with the peers on completion was β =0.414 ($p < .001$).

Participants' satisfaction had significant indirect effects (β = 0.16, $p < .001$) on completion. Participants' TPACK self-assessment had significant direct effects (β = -0.175, $p < .001$) on completion, and the OCS also had significant direct effects (β = 0.823, $p < .001$) on completion. Counter-intuitively, participants' TPACK self-assessment had a negative impact on completion.

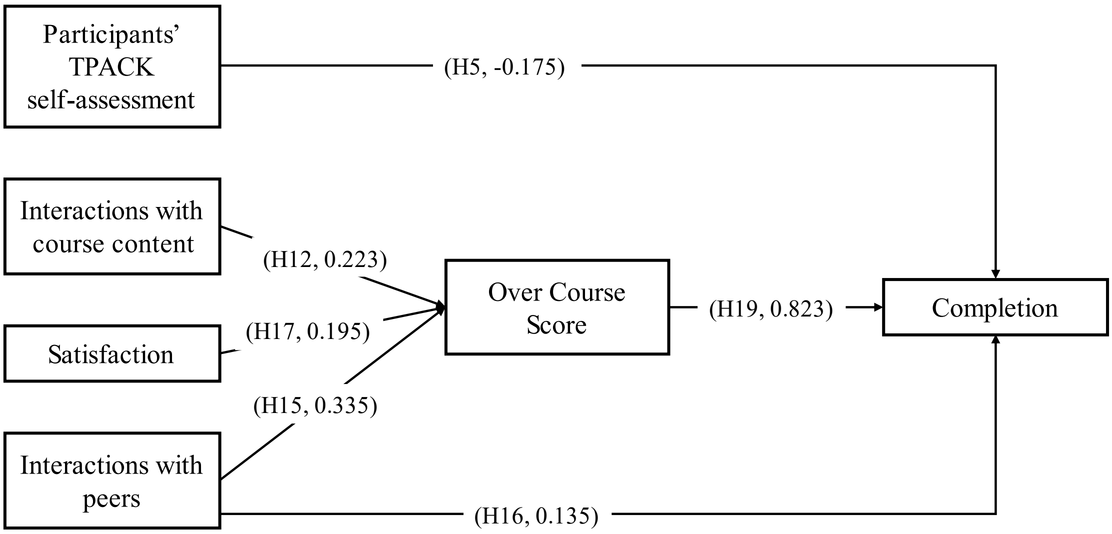


Fig 6. Modified model with standardized path coefficients

Discussion

This study aimed to analyse the data about teachers' online learning to determine the key factors that affected the completion of teachers' online learning and to clarify the direct and indirect influence of these factors. In our review of existing research, we examined the factors affecting teachers' online learning, and built a preliminary model of how the factors affected teachers' online learning completion. The research findings and implications of the modified path model hypotheses are summarized below.

We investigated the measures that focused on participants' interaction with their peers and their interaction with the learning content. The results of this study showed that both of these interactions had a direct impact on participants' OCS (H15 and H12). The results confirmed that these two types of interaction had positive impact on online learning performance. It was possible that the diverse learning materials, such as teaching videos, reading materials and cases of PBL helped participants to understand the content of the course, which promoted participants' interaction with content and peers. Previous studies also showed positive correlation between the interaction with course content and the academic performance of the learner (Choi & Park, 2018; Zimmerman, 2012).

Meanwhile, peer interaction assisted learners to generate additional cognitive mechanisms, such as knowledge creation and sharing (Hew & Cheung, 2014). Ma et al. (2021) suggested that effective peer interaction can improve the level of knowledge construction through “sharing, conflict, in -depth information mining, consultation and agreement, knowledge application”. Our findings show that affording effective peer interaction is important for online learning participation. The discussion areas that were built in this course enabled participants to express their opinions without being limited by time and promoted a high level of participation in the course. Peer review as an activity also played an important role in promoting participation by engaging participants in meaningful evaluation and self-reflection. In turn, the participants’ high level of participation in the course promoted their high OCS.

Participants’ satisfaction was also a key factor influencing the completion of teachers’ online learning. The results of the path coefficient in Figure 6 show that the path coefficient of satisfaction pointing to OCS was 0.195 (H17), but the path between satisfaction and both types of interaction was not established. These findings were unexpected. Previous studies indicated that students’ satisfaction in online courses was significantly impacted by perceived interaction in the online environment (Khalil & Ebner, 2014; Lawson, 2020). However, in this study, the amount of participants' interaction in online courses did not have a significant impact on satisfaction. This might be related to the participants’ quality of interaction, which warrants further research. Besides, as one of the sub-dimensions of motivation, satisfaction had an important influence on the persistence or dropout decision of distance learners, which echoed previous research (Choi & Park, 2018). It was the motivation that enabled learners to continue online learning, complete the corresponding curriculum links, and achieve higher scores.

In addition, this study has revealed the direct impact of OCS and TPACK on participants' online learning completion (H5 and H19). This finding corresponded to the existing research evidence that GPA was a direct factor affecting whether participants withdrew from class (Choi & Park, 2018; Dupin-Bryant, 2004). In our path model, OCS as an intermediate variable affecting participants' online learning completion played an important role.

Based on the above discussion, instructional designers should pay attention the key factors (such as interaction, self-efficacy, satisfaction, etc.) to ensure that teachers can actively participate in the course. Besides, the results in Figure 6 showed that participants' TPACK self-assessment had a weak negative effect on the completion, which was different from the previous literature that teachers' information literacy may affect their acceptance of online learning. It was possible that teachers who perceived themselves to possess a high level of TPACK had a low level of expectation to gain new knowledge from the course, which negatively affected their participation and intention to complete the course.

The completion rate of teachers' participation in this TPD MOOC was very high. We set out to explain this in terms of the key factors that might contribute to this. The online learning completion rate was related primarily to participants' interaction with peers and with course content, both leading to a high OCS, which in turn correlated with the high completion rate.

The course design incorporated several features to improve participants' engagement with the course. Specifically, a range of learning activities and regular scored assignments were provided in the course. It also linked the assignments to a social learning environment in the form of focused discussion activities and peer review to promote more in-depth interaction between participants. Participants’ high engagement with these activities helped to sustain them throughout the five weeks, so that most participants did complete most of the course. These design features could be adopted by instructors of future TPD MOOCs to boost success of professional learning among teachers.

Conclusion

The preceding discussion shows that social activities, such as online discussion and peer review, played a crucial role in the completion of teachers’ online learning in the context of this study. The social activities enhanced participants’ interaction in the online course, and improved participants’ engagement in the course, which promoted participants' completion in the course. The findings suggest that it is important to use a ‘social learning model’ when designing online courses for TPD. In addition, as one of the important factors affecting the completion degree, the overall course scores may play the role of formative feedback that promotes participants' continuous learning in the course. These characteristics of online course design provide a reference for other educators in achieving higher online completion rates among their participants.

There are several limitations in the present study. The findings of this study are limited in that they were derived from one MOOC. Despite the large sample size, the applicability of the model requires further verification. In addition, we only considered participants' interaction with curriculum content and their peers, did not obtain data on other types of interactions, which precluded us from analysing differences in dropout or achievement using such variables.

Further research should consider more diverse dropout factors, such as participants' interactions with instructors, and seek to detail the relationships between them. Moreover, the level of knowledge construction in the social learning environment of teachers' online learning might be an important issue that requires attention in future research.

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