



Understanding the impact of quality elements on MOOCs continuance intention

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Abstract

Online learning has captured much attention, while given for high dropout rate, continuance of MOOCs is now a most concerned critical topic in both research and practical field. From teaching-based quality and platform-based quality perspectives, this study aims to investigate the impact of quality elements on continuance intention based on Expectation Confirmation Model, Task Technology Fit, flow theory and trust. We conducted our research through online questionnaire from July to September in 2020 and collected 555 valid responses which were mainly from university students who had already participated in MOOCs. A Partial Least Square Structural Equation Model approach is employed to test the research model. The results show that teaching-based quality will increase both students' task technology fit and confirmation, and platform-based quality can improve the confirmation and perceived value about learning in MOOCs. Task technology fit, confirmation and perceived value will further facilitate the using experience and enhance trust and satisfaction. This research comprehensively illustrates the importance of quality relevant to teaching and platforms on continuance intention of MOOCs.

Keywords Teaching-based quality · Platform-based quality · Expectation confirmation model · Task technology fit · Flow theory · Continuance intention

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1 Introduction

Online learning platforms can provide many benefits compared to face-to-face learning. With the eruption of COVID-19, online education market has experienced a huge expansion. For example, in China, the market size of online education reached 450 billion yuan by 2020 (IIMediaConsulting, 2020). With the flourishing of online learning, many universities and institutions provide online courses. How to attract students to keep studying in online platform is now the focus of many scholars and managers. While quality always plays an important role in shaping individuals' satisfaction and their continuance intention (Prasetya et al., 2021). Therefore, it's significant to study the role of quality in online learning.

Many researchers invest lots of efforts in trying to evaluate online education quality. A multidisciplinary criterion was created to assess the quality of online learning (Vasconcelos et al., 2020). The dimensions of service quality (SERVQUAL) were adapted to e-learning context and found that ergonomics, assurance and empathy were the most important factors (Ivanaj et al., 2019). Some literatures examine how perceived quality affect individuals' continuance intention in online learning. Daghan and Akkoyunlu (2016) validated that information, system and service quality could enable users' continuous participation in online learning. Xing (2019) verified the effect course design on students' performance and persistence.

Although literature has highlighted the significant role of quality in online learning, less work has been accomplished on how the nuanced quality elements affect continuance intention. Quality is a general concept including many dimensions. The comprehensive role of these quality elements on continuance intention is not clear. And different key elements maybe manifested under different contexts. Furthermore, the comprehensive effect mechanism and process of quality on continuance intention is still need to be unveiled. As such, the research questions for this study include:

- (1) Under the online learning setting, what specified elements are those key quality elements?
- (2) How these key quality elements affect continuance intention?

Therefore, in this paper, we will make a detailed and deep study on the effects of these quality elements from two quality dimensions which are teaching-based quality and platform-based quality. The present study identifies 4 teaching-based and 3 platform-based quality elements, and tries to disclose the effect mechanism through the integration of Expectation Confirmation Model (ECM), Task Technology Fit (TTF) and flow. This study will be profoundly helpful to understand the inner effect mechanism of quality on continuance intention.

2 Theoretical background and literature review

2.1 Theoretical background

2.1.1 Expectation confirmation model (ECM) and flow theory

ECM, first proposed by Bhattacharjee (2001) to evaluate the connection between the intention to use information system and post-adoption belief, is always applied to understand continuance intention. Developed from Expectation Confirmation Theory (ECT) and Technology Acceptance Model (TAM), ECM encompasses four constructs which are confirmation, perceived usefulness, satisfaction, and continuance intention. Confirmation is an individual's perception of the

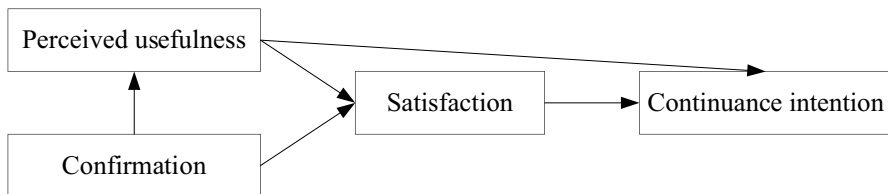


Fig. 1 ECM model (Bhattacharjee, 2001)

extent of consistency between expected and actual using experience of the system. Perceived usefulness is the individual's perception of the extent of improved performance brought by the system. Satisfaction is the individual's affected state after using the system. Continuance intention is the propensity to keep using the system. As shown in Fig. 1, confirmation significantly affects perceived usefulness and satisfaction, perceived usefulness significantly affects satisfaction and continuance intention, and satisfaction significantly affects continuance intention (Bhattacharjee, 2001).

Flow theory, originated from and Csikszentmihalyi (1975), can describe the state that individuals completely lost in certain activities with unconsciousness of time or location. Csikszentmihalyi explains that flow is a state that occurs when an individual is indulged in an activity which is satisfying that the individual wants to keep continuing. In flow state, people are so immersed in the activity that they experience complete concentration, feelings of control, loss of self-consciousness, and a distorted sense of time (Csikszentmihalyi, 1975). Flow means total involvement and the focus of the attention is narrowed to the activity itself (Csikszentmihalyi, 1990). Accordingly, flow experience can be regarded as an intrinsic motivator and is always considered as an important factor that affect human's behavior (Guo et al., 2016).

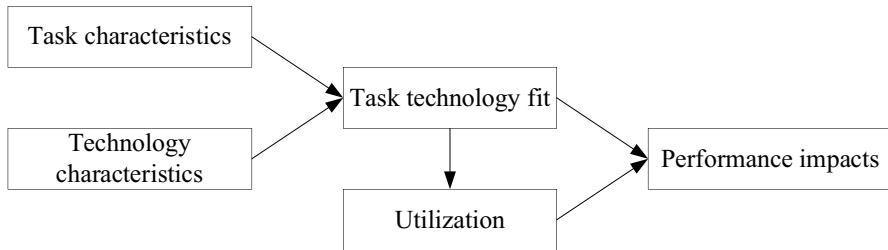


Fig. 2 TTF model (Goodhue & Thompson, 1995)

2.1.2 Task technology fit model (TTF)

TTF, proposed by Goodhue and Thompson (1995), describes the relationship between task, technology features and users' performance (Wu & Chen, 2017), implying the matching extent of the capabilities provided by technology and the demands of the task (Dishaw & Strong, 1999). There are five constructs in TTF model, which are technological characteristics, task characteristics, task technology fit, utilization, and performance. In TTF, technological characteristics and task characteristics significantly affect task technology fit, task technology fit significantly affects utilization and performance, and utilization significantly affects performance, as shown in Fig. 2.

2.2 Continuance intention in online learning

Continuance learning is dominantly beneficial for both learners to keep acquiring knowledge and learning platform to hold users, a large body of literature in the online learning research field focuses on the continuance topic. Abundant theoretical frameworks are adopted by researchers to delve the influencing factors and to disclose the effect mechanism. The most popular theoretical frameworks are ECM (Cheng, 2021) and TAM (X. Wang et al., 2022). Task-Technology Fit (TTF) (Kim & Song, 2021), flow theory (Goh & Yang, 2021) and value theory (Qi et al., 2021) are also widely adopted. Other most employed frameworks involve uses and gratifications theory (U&G) (Zhang et al., 2022), Diffusion of Innovation Theory (DOI), Unified Theory of Acceptance and Use of Technology (UTAUT) (Taghizadeh et al., 2021), and Theory of Planned Behavior (TPB) (Dalvi-Esfahani et al., 2020). Stimulus-Organism-Response (SOR) model (Shao & Chen, 2021), Technology-User-Environment (TUE) framework (Gupta & Maurya, 2021), and Information Success System (ISS) (San-Martin et al., 2020) framework are also leveraged.

Some scholars further explore the influencing factors by extending the framework via combining two or more frameworks like Wang et al. (2021a), Taghizadeh et al. (2021). Some added more antecedents when integrating frameworks, for example Wang et al. (2022), Wang and Lin (2021), Kim and Song (2021), Goh and Yang (2021), Zhao et al. (2020), Wu and Chen (2017).

Some scrutinized and delved more detailed antecedents, making a deeper understanding. Zhang et al. (2022) focused on gratification and classified it into extrinsic and intrinsic gratification to analyze more factors. Based on value theory, Qi et al. (2021) partitioned value into platform resource, teacher resource, and learner resource value and analyzed their influence. Anchored on instructor related, course related, and system related factors, Liu and Pu (2021) further validated the effects of the factors under these three dimensions. While Gupta and Maurya (2021) were from the aspects of technological context, user context, environment context factors. And Reparaz et al. (2020) were based on human and context factors.

Some focused on one specific aspect and further explored the effects of the elements. Shao and Chen (2021) emphasized on interactivity and investigated the effects of three interactivity elements. Quality is also an import aspect that many researchers specially mentioned. Cheng (2021) investigated the effects of two elements under course quality. San-Martin et al. (2020) examined two elements of teachers' self-efficacy and the four elements of system quality. Pham et al. (2019) highlighted three elements of quality. Larmuseau et al. (2019) focused on instructor quality. Yang et al. (2017) explored the importance of three elements of quality which were information quality, system quality, service quality.

It can be found that although researchers have recognized the importance of quality on continuance, the nuanced effects of elements under quality have not yet comprehensively explored. The extant research mainly generally accentuated the prominent role of quality, the effects of fine-grained quality elements and their effect mechanism still need to be further investigated. The present study will complement the extant research and make a deeper understanding on the nuanced quality elements and their effect mechanism.

3 Research model and hypothesis

Quality can affect satisfaction and has a positive and significant influence on people's continuance intention (Cheng, 2021). The interaction quality and environment quality can directly strengthen users' satisfaction and continuance intention, and information quality has a positive influence on satisfaction (Sun et al., 2021). External factors that affect students are mainly from teaching and platform, and quality elements belong to external factors (Qi et al., 2021).

Based on this, we will analyze the influence of quality on continuance intention in MOOCs from two dimensions which are teaching-based quality and platform-based quality. The most popular and widely adopted service quality model is SERVQUAL developed by Parasuraman (Pham et al., 2019), which comprises of reliability, assurance, tangibles, empathy, and responsiveness. In online learning, the most famous quality framework is Quality Matters rubrics (QM), which is focused on course design, composed of learning objectives, assessment and measurement, instructional materials, learning activities and learner interaction, and course technology (Sadaf et al., 2019). Under the online learning setting, students essentially acquire teaching service from the platform. Therefore, referring to teaching-based quality factors, we considered

factors from both SERVQUAL and QM. Malanga et al. (2022) highlighted reliable online course material. QM also recommends ample course resource (Alizadeh et al., 2019). Utilizing appropriate teaching method and technology can help students better understand course content (Wang et al., 2021a, b). Appropriate work load is an important teaching guideline and a vital standard of course quality (Elaasri & Bouziane, 2019). Empathy is a crucial component of SERVQUAL (Pham et al., 2019). In virtual environment, empathy is also a non-negligible element (Pelau et al., 2021). Compared with face-to-face teaching, a major disadvantage of online learning is that teachers can't share and

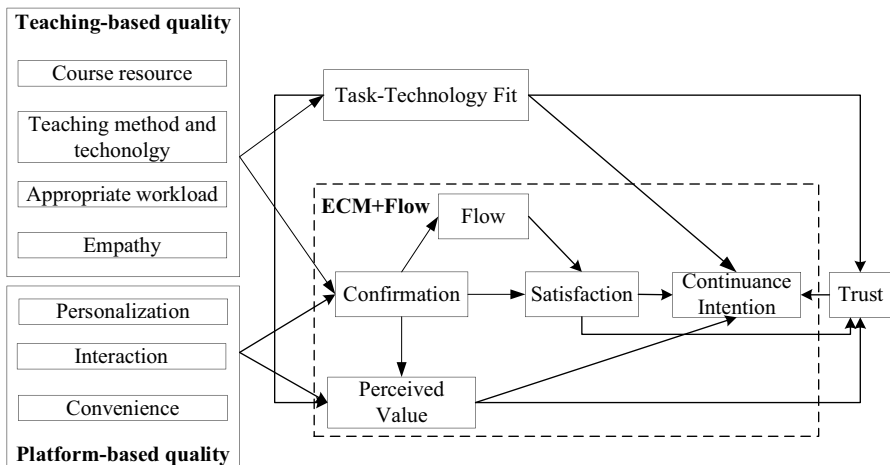


Fig. 3 Research model

impart their passion and affection to students. Thus, more and more scholars stress the vital role of empathy in online learning (Cartee, 2021). Referring to platform-based quality factors, MOOCs platform is also an information system. Recently, lots of scholars emphasize that a prominent feature that an information system should own is personalization (Anwar, 2021). The well supported interaction (Shao & Chen, 2021) and the convenience of the platform (Faisal et al., 2020) have been highlighted by many researchers as well. Accordingly, from the teaching-based and platform-based angle, we encompass four teaching-based quality elements which are course resource, teaching method and technology, appropriate workload and empathy, and platform-based quality elements which are interaction personalization, and convenience. Our research model is shown in Fig. 3.

3.1 Teaching-based quality, TTF and confirmation

Given that elements of teaching-based quality are not corresponding to a certain course and it's hard to evaluate the value, we do not consider these effects on perceived value. Therefore, we only consider their effects on confirmation and TTF.

3.1.1 Course resource

Choi and Jeong (2019) adopted ANP to examine relative weights of factors which influence quality of e-learning systems. They found that information quality cluster is the most important, including course content, subjects and items. This implies that substantial course resource in online learning is required to develop online courses and lead students to have higher confirmation. According to TTF model, the characteristics of technology and task can both affect the task-technology fit (Wu & Chen, 2017). The course resource can be considered as task features in courses. Course resource is an important part of course content quality, and course content quality significantly affect confirmation in MOOC learning (Cheng, 2021). Thus, we posit that:

H1a: Course resource has a positive influence on users' TTF.

H1b: Course resource has a positive influence on users' confirmation

3.1.2 Teaching method and technology

Muhammad et al. (2020) identified relevant course quality factors through previous literatures and proved the importance of diversified presentation in courses to users' perceived quality. Mejia-Madrid et al. (2020) explored how to evaluate quality in online environment and emphasized the significance of teaching method and technology. Thus, we conclude that teaching method and technology can be used to reflect the quality of online courses. Many researches have shown that quality will strengthen the confirmation. Also, it can be the feature of the technology which will influence TTF (Wu & Chen, 2017). Teaching method and technology is an important part of course design quality, and course design quality significantly affect confirmation in MOOC learning (Cheng, 2021). Based on this, we posit that:

H2a: Teaching method and technology has a positive influence on users' TTF.

H2b: Teaching method and technology influence on users' confirmation

3.1.3 Appropriate workload

Both appropriate workload and assignment type are quite important in online courses (Xiao et al., 2019). MOOCs are open to the public and there are less students with similar capability. Therefore, it should be with fitted workload or standard. Waheed et al. (2016) has divided course quality into five dimensions, one of which demonstrated that appropriate amount of data was indispensable. Similarly, it is also the feature of the technology which will influence TTF (Wu & Chen, 2017). QM also suggests that one important standard is appropriate workload (Lowenthal

& Hodges, 2015). Quality affects confirmation in e-learning (Prasetya et al., 2021). Therefore, appropriate workload can influence TTF and confirmation. Thus, we posit that:

H3a: Appropriate workload has a positive influence on users' TTF.

H3b: Appropriate workload has a positive influence on users' confirmation

3.1.4 Empathy

Empathy refers to the individuals' tendency to imagine and experience others' feelings or experiences. It is found that students engaging online courses with higher empathy would have better performance (Fuller, 2012). Thus, similar with Udo et al. (2011), we adopt empathy to evaluate the quality of teaching in MOOCs. Instructors' empathy has been argued as having positive impact on users' perceived quality of e-learning (Aldrup et al., 2022). Empathy is also an important requirement for students (Ivanaj et al., 2019). TTF measures how well the technology provided meet the requirements (Kim & Song, 2021). Thus, we propose that empathy can influence TTF and confirmation as well:

H4a: Empathy has a positive influence on users' TTF.

H4b: Empathy has a positive influence on users' confirmation

3.2 Platform-based quality, confirmation and perceived value

As TTF refers to the match between task and technology, our three elements of platform-based quality only describe the characteristics of the system and there is no corresponding task. Therefore, we will not consider their influence on users' task technology fit. Instead, we will explore their impact on learners' confirmation and perceived value of MOOCs.

3.2.1 Personalization

Personalized learning environment through information technology has been regarded to be especially promising (Schmid & Petko, 2019). Personalized e-learning system, emerged as a critical issue of MOOCs (Paquette et al., 2015), is described as offering individual system layout and personalized learning material, contents and assistance (Panjaburee et al., 2022). Personalization in MOOCs is to provide identified students with targeted support, which owns the potential to impact students' learning experience (Gardner & Brooks, 2018). It has been well-recognized that personalization is of huge importance for effective MOOCs learning given to the massive volume of a course (Yu et al., 2017). Komalawardhana et al. (2021) reported that the personalized conceptual learning is helpful to promote students' learning achievement. System quality in the e-learning system is positively associated with the confirmation of system (Lin & Wang, 2012). Personalization is

a dimension of system quality (Stracke, 2017). Thus, we assume personalization can influence users' confirmation in MOOCs learning.

Perceived value can mediate the relationship between information system quality and continuance intention in online learning environment (Qi et al., 2021). Perceived quality positively affects students' perceived value (de Moura et al., 2021). Personalization in MOOCs can realize the system adaptation to individuals' personal learning needs and is an important part of MOOCs platform quality (Stracke, 2017). Therefore, we put forward that:

H5a: Personalization has a significant influence on users' confirmation.

H5b: Personalization has a significant influence on users' perceived value of MOOCs.

3.2.2 Interaction

Interaction is acted as an antecedent of the online learning adoption (Panigrahi et al., 2018). It affects users' confirmation about MOOCs. Zhao et al. (2020) examined how technological environment impacted users' virtual experience, and they found that interactivity positively strengthened users' telepresence in online learning. Chen et al. (2019) highlighted the prominent role of the interaction in enhancing learning experience. Interaction is helpful to gain learners' confirmation so that to sustain their engagement (Sunar et al., 2016). Qi et al. (2021) found that the platform interaction had a positive influence on users' perceived value in MOOCs learning. Based on this, we posit that:

H6a: Interaction has a significant influence on users' confirmation.

H6b: Interaction has a significant influence on users' perceived value of MOOCs.

3.2.3 Convenience

Convenience refers to the extent of how easy to use the service (Pereira & Tam, 2021). MOOCs convenience is the extent of easiness regards with place, time, and execution when using MOOCs, and MOOCs convenience will promote learners' perceived usefulness (Al-Adwan, 2020). Perceived value includes utilitarian value (Wattjatrakul, 2016), accordingly, convenience can enhance learners' perceived value. The convenience can also significantly strengthen the confirmation in online learning (Daghan & Akkoyunlu, 2016). Thus, we propose that:

H7a: Convenience has a significant influence on users' confirmation.

H7b: Convenience has a significant influence on users' perceived value of MOOCs.

3.3 TTF, Confirmation and perceived value

Task technology fit (TTF) can largely increase individual's perceived ease of use and perceived usefulness in online learning (Wu & Chen, 2017). Also, task technology fit will positively influence the utilization of new technologies (Howard & Rose, 2019). Thus, we infer that this fit will also increase users' perceived value and lead to higher continuance intention in MOOCs.

Alraimi et al. (2015) explored factors that influenced students' MOOCs continuance intention and they found that the confirmation increased perceived usefulness. Utilitarian value reflects an aspect of perceived value (Watjatrakul, 2016). Also, confirmation can augment users' perceived benefit and then increase perceived value in online learning (Panigrahi et al., 2018). Ashrafi et al. (2021) also proposed that confirmation would have positive influence on perceived value. Therefore, we propose that:

H8a: TTF has a significant influence on users' perceived value.

H8b: Confirmation has a significant influence on users' perceived value of MOOCs.

3.4 Confirmation, satisfaction and flow

In conformation with ECM, this research supports that users' confirmation can influence their satisfaction of the system (Bhattacharjee, 2001). Many researches have shown that confirmation has a positive impact on satisfaction (Daghan & Akkoyunlu, 2016). Confirmation can influence user experience of flow, and satisfaction is found to be the outcomes of flow experience (Mulik et al., 2019). Cheng (2021) adopted ECM and flow theory in MOOCs context and they found confirmation influenced flow and flow improved students' satisfaction about MOOCs. Therefore, we propose that:

H9a: Confirmation has a positive effect on users' satisfaction in MOOCs.

H9b: Confirmation has a positive effect on flow in MOOCs.

H9c: Flow has a positive effect on satisfaction in MOOCs.

3.5 TTF, satisfaction, perceived value and trust

Khan et al. (2018) examined how task technology fit (TTF), social motivation and self-determination influenced behavioral intention and usage of MOOCs. They found that TTF positively increased the intention to use MOOCs. TTF can also promote more adoptions of online learning (Wu & Chen, 2017). Thus, in MOOCs, we consider TTF also arises users' trust and lead to higher intention to continuance usage.

Satisfaction can predict students trust which is useful to develop sound user relationships (Latif et al., 2021). MOOC participants do not trust the validity and reliability of peer assessment results due to the low perceived satisfaction (Yousef et al., 2015). When students are satisfied with MOOCs, they will show higher level

of trust. Students' satisfaction is helpful to build their trust (Wang, 2014). Therefore, in online learning, we infer that users' satisfaction can largely increase trust in MOOCs.

Jin (2020) observed strong and positive relationship between students' perceived value and perceived trust in MOOCs learning. Higher perceived value can strengthen students' trust and then enable their intention of participation in online learning (Thoms, Garrett, Herrera, & Ryan, 2008). Positive perceptions of the social value can frame trust in MOOCs (Yoon et al., 2020). Thus, we assume this kind of relationship in MOOCs as well and propose that:

H10a: TTF is positively related to trust on MOOCs.

H10b: Satisfaction is positively related to trust on MOOCs.

H10c: Perceived value is positively related to trust on MOOCs.

3.6 Continuance intention

3.6.1 Perceived value and continuance intention

Daghan and Akkoyunlu (2016) studied the antecedents of continuance usage intention in online learning environments, and found that perceived value had significant influence on continuance. Guo et al. (2016) also pointed out that improving learners' perceived value could be helpful to enhance learners' continuance intention. Thus, we posit that:

H11: Perceived value can positively influence users' continuance intention in MOOCs.

3.6.2 Trust and continuance intention

Trust is of great importance in online learning environment (Wang, 2014). Trust is an antecedent of the continuance intention to use online learning systems (Panigrahi et al., 2018). Students are willing to continuously use online learning only when they lay trust on the platform (Anwar, 2021). Shao et al. (2017) also observed that trust can enhance MOOCs learners' continuous participation. Therefore, we propose that:

H12: Trust positively influences users' continuance intention in MOOCs.

3.6.3 Satisfaction and continuance intention

Many researches show that satisfaction enables continuance intention to use services. In online learning, satisfaction also significantly influences students' intention to continuance usage as well (Dai et al., 2020a, b). And the positive relationship between satisfaction and continuance intention in e-learning has been widely approved (Cheng, 2021; Joo et al., 2018; Kim et al., 2021). Thus, we posit that:

H13: Satisfaction is positively related to MOOC continuance intention.

4 Method

4.1 Participants and research context

In this paper, we empirically tested our research model through an online survey. Our research purpose is to examine the effects of quality elements on students' MOOC continuance intention through ECM, TTF, and flow. Therefore, we invite students who have used Chinese University MOOC (iCourse) at least once to participate in the survey. Chinese University MOOC was launched in 2014, well known as an official online learning platform supported by the Chinese Education Ministry and widely accepted by students and universities, owning the largest number of active users in China (Wu & Chen, 2022). All participation in the survey was anonymous and voluntary. To encourage participation, we provided a monetary compensation for each participant. To ensure quality, we manifested that only those who carefully answer the questions would get the compensation.

The collection last for three months from July to September in 2020. In total, we get 604 answers and 49 of them never used MOOCs. Thus, we get 555 valid replies actually. 61.6% of the respondents are female and 38.4% are male. Most are aged between 18 and 25 years (69.9%), 15.9% are aged between 26 and 30, 4.3% are less than 18, and 9.9% are older than 30. The majority of the participants are undergraduate (56.8%) and postgraduate students (31%). Most of the participants are students (64.7%). 20.5% have used MOOCs for less than six months, 43.2% have used for six months to one year, 27% have used for 1–3 years and 9.2% have used for more than three years. As for using frequency, 26.1% use MOOCs less than twice a month, 45.9% use MOOCs between 2–5 times, and 27.9% use more than 5 times a month. We also ask about the number of courses the participants have finished within 6 months, 56.4% have finished 1–2 courses, 26.1% have finished 3–4 courses, 7.6% have finished more than 5 courses, and only 9.9% of the respondents haven't finished any course during the last six months.

4.2 Instruments

We developed the questionnaire by adapting the measurement items from existing, validated, and well-tested scales in the relevant literature. All the measurements employ seven-point Likert scale, ranging from “strongly disagree” to “strongly agree.” There are 14 constructs in our research and all of them are measured by using multiple perceptual items and are slightly modified to suit for MOOCs context. The detailed measurements are shown in Table 1.

Table 1 Constructs and Measurements

Construct	Items	Source
Course resource	I think there are abundant learning materials in MOOCs	Sadaf et al. (2019)
	I think there are sufficient exercises in MOOCs	
	I think there are comprehensive teaching materials in MOOCs	
Teaching method and technology	I think MOOCs adopt diversified teaching method	Alizadeh et al. (2019)
	I think MOOCs have used a variety of teaching methods	
	I think MOOCs have used a variety of technologies	
Appropriate workload	I think that MOOCs have a moderate amount of homework	Kyndt et al. (2011)
	I think that MOOCs have a moderate amount of teaching content, and I can understand all the information	
	I think MOOCs are moderately difficult	
Personalization	MOOCs can provide courses or services that meet my personal needs	Schmid and Petko (2019)
	MOOCs can provide courses or services that meet my personal preferences	
	MOOCs can provide courses or services that meet my personal preferences	
Interaction	The tools provided by the MOOC system allow me to modify the content that exists in the system	Zhao et al. (2020)
	The tools provided by the MOOC system allow me to create any content I wish	
	The MOOC system allows me to change or influence the appearance of the environment	
Convenience	Using MOOCs would make it easier to access course services than traditional offline learning	Al-Adwan (2020)
	Using MOOCs would be more convenient than traditional offline learning	
	In MOOCs platform, the operation is very simple	
Empathy	The instructor is genuinely concerned about the students	Udo et al. (2011)
	The instructor understands the individual needs of students	
	The instructor encourages and motivates students to do their best	
Task-technology fit	MOOCs are fit for the requirements of my learning	Wu and Chen (2017)
	Using MOOCs fits with my educational practice	
	MOOCs are suitable for helping me complete online courses	

Table 1 (continued)

Construct	Items	Source
Perceived Value	Compared to the effort I need to put in, the use of online learning environment is beneficial to me	Daghan and Akkoyunlu (2016)
	Compared to the time I need to spend, the use of online learning environment is worthwhile to me	
Trust	Overall, the use of online learning environment delivers me good value	Thoms et al. (2008)
	Generally speaking, I trust MOOCs very much	
	I trust the content and information sent to me by MOOCs	
	I think the content and information provided by MOOCs are real and reliable	
Confirmation	My experience using MOOCs was better than I expected	Dai et al., (2020a, 2020b)
	The service level provided by MOOCs was better than what I expected	
	Overall, most of my expectations of MOOCs were confirmed	
	When I used MOOCs, I was not distracted by the disturbances in the environment surrounding me	
Flow	When I used MOOCs, I did not feel frustrated or give up	Goh and Yang (2021)
	When I used MOOCs, I concentrated on the MOOCs and ignored what was happening around me	
	I am satisfied with MOOCs	
Satisfaction	I enjoyed the learning experience through MOOCs	Cheng (2021)
	Overall my experience with MOOCs has been positive	
Continuance intention	I intend to continue to use MOOCs in the future	Gu et al. (2021)
	I plan to use MOOCs in the future	
	I will continue using MOOCs	

4.3 Data analysis

Partial Least Square Structural Equation Model (PLS-SEM) was leveraged to testify hypotheses in the present study mainly for three reasons: (1) PLS-SEM is widely utilized and accepted to confirm hypothesis, in accordance with this study (Hair et al., 2021); (2) Latent variable scores can easily be gained through PLS-SEM without extra specification modifications (Hair et al., 2019); (3) PLS-SEM is suitable for mediation test, which is also needed in our research (Henseler et al., 2015).

SmartPLS 3.0 which is a widely applied software to do PLS-SEM analysis in many researches (Durcikova et al., 2018) is employed to validate the hypotheses. Common method bias, measurement model, structure model and hypothesis test will be assessed in the following sections.

5 Results

5.1 Common method bias

To eliminate concerns about common method bias (CMB), we carefully designed the survey and do the CMB statistical test. First, all the questions in the survey are selected from exiting literature, and to assure the clarity and non-confusion in the questions, comprehensive pre-test and pilot test were also implemented (Podsakoff et al., 2003). Further, all respondents answered questions anonymously and confidentially. For CMB statistical test, Harman Single Factor test ($\leq 40\%$) (C. M. Fuller et al., 2016), Highest value in inter-construct correlation matrix (≤ 0.9) (Bagozzi et al., 1991), pathological VIF values (≤ 3.3) (Kock, 2015), were employed. Our results are 26.135%, 0.812, and 1.697 to 2.939 individually, and we can see that there is no CMB in our survey.

5.2 Measurement assessment

The reliability and validity are testified to verify the proposed model. Cronbach's alpha and composite reliability (CR) are applied to assess the reliability. As displayed in Table 2, the Cronbach's alpha value of all constructs ranged from 0.829 to 0.918. The CR values are all higher than 0.8 which all exceed 0.7, representing a high construct reliability (Fornell & Larcker, 1981).

We adopt average variance extracted (AVE) to measure convergent validity. The AVE is between 0.747 and 0.859, higher than the recommended threshold value of 0.5 (Fornell & Larcker, 1981). The factor loadings range from 0.849 to 0.936 and are all significant ($p=0.05$). Therefore, the model has a high convergent validity.

Fornell-Larcker criterion was applied to evaluate the construct-level discriminant validity: the square root of the AVE of each latent construct should exceed its correlation with other latent constructs (Fornell & Larcker, 1981). All of the values of the square roots of the AVE values are larger than the other values of the inter-construct

Table 2 Measurement statistics

	Indicators	Factor loadings*	Cronbach's Alpha	CR	AVE
CRR	CR-1	0.871	0.871	0.921	0.795
	CR-2	0.898			
	CR-3	0.905			
TMT	TMT-1	0.916	0.886	0.930	0.815
	TMT-2	0.901			
	TMT-3	0.891			
AW	AW-1	0.856	0.829	0.898	0.746
	AW-2	0.850			
	AW-3	0.884			
EMP	EMP-1	0.934	0.915	0.947	0.855
	EMP-2	0.921			
	EMP-3	0.920			
INT	INT-1	0.885	0.831	0.899	0.747
	INT-2	0.856			
	INT-3	0.852			
PER	PER-1	0.913	0.889	0.931	0.818
	PER-2	0.880			
	PER-3	0.921			
CONV	CONV-1	0.878	0.835	0.901	0.753
	CONV-2	0.849			
	CONV-3	0.876			
TTF	TTF-1	0.898	0.882	0.927	0.810
	TTF-2	0.895			
	TTF-3	0.906			
CONF	CONF-1	0.922	0.891	0.932	0.821
	CONF-2	0.895			
	CONF-3	0.900			
FLOW	FLOW-1	0.903	0.855	0.912	0.775
	FLOW-2	0.865			
	FLOW-3	0.873			
SAT	SAT-1	0.922	0.895	0.935	0.827
	SAT-2	0.886			
	SAT-3	0.920			
PV	PV-1	0.918	0.888	0.930	0.817
	PV-2	0.875			
	PV-3	0.918			
TRUST	TRUST-1	0.897	0.887	0.930	0.816
	TRUST-2	0.891			
	TRUST-3	0.921			
CI	CI-1	0.925	0.918	0.948	0.859
	CI-2	0.918			
	CI-3	0.936			

CRR: course resource, TMT: teaching method and technology, AW: appropriate workload, EMP: empathy, INT: interaction, PER: personalization, CONV: convenience, TTF: task-technology fit, CONF: confirmation, FLOW: flow, SAT: satisfaction, PV: perceived value, TURST: trust, CI: continuance intention.

Table 3 Construct correlations and discriminant validity

	CR	TMT	AW	EMP	INT	PER	CONV	TTF	CONF	FLOW	SAT	PV	TRUST	CI
CR	0.892													
TMT	0.816	0.903												
AW	0.811	0.799	0.863											
EMP	0.731	0.723	0.732	0.925										
INT	0.734	0.737	0.777	0.706	0.864									
PER	0.772	0.776	0.825	0.704	0.742	0.905								
CONV	0.762	0.720	0.764	0.691	0.715	0.802	0.868							
TTF	0.791	0.772	0.812	0.785	0.754	0.816	0.814	0.900						
CONF	0.777	0.773	0.798	0.741	0.757	0.809	0.788	0.833	0.906					
FLOW	0.684	0.660	0.738	0.747	0.661	0.687	0.682	0.737	0.764	0.880				
SAT	0.771	0.745	0.795	0.729	0.739	0.808	0.801	0.864	0.889	0.761	0.909			
PV	0.759	0.739	0.780	0.700	0.728	0.806	0.810	0.863	0.855	0.692	0.869	0.904		
TRUST	0.760	0.756	0.798	0.729	0.748	0.797	0.805	0.865	0.880	0.751	0.882	0.870	0.903	
CI	0.722	0.696	0.732	0.651	0.674	0.748	0.767	0.792	0.822	0.668	0.874	0.826	0.823	0.927

Table 4 Tested results

Hypothesis	Relationship	Original Sample	T Statistics	P Values	Tested results
H1a	CRR—> TTF	0.199***	3.692	0.000	Supported
H1b	CRR—> CONF	0.083	1.247	0.212	Unsupported
H2a	TMT—> TTF	0.129**	2.302	0.021	Supported
H2b	TMT—> CONF	0.112**	2.013	0.044	Supported
H3a	AW—> TTF	0.318***	6.441	0.000	Supported
H3b	AW—> CONF	0.110**	2.190	0.029	Supported
H4a	EMP—> TTF	0.313***	6.764	0.000	Supported
H4b	EMP—> CONF	0.140**	3.082	0.002	Supported
H5a	PER—> CONF	0.212***	4.066	0.000	Supported
H5b	PER—> PV	0.102**	2.051	0.040	Supported
H6a	INT—> CONF	0.128**	2.797	0.005	Supported
H6b	INT—> PV	0.009	0.224	0.823	Unsupported
H7a	CONV—> CONF	0.202***	3.916	0.000	Supported
H7b	CONV—> PV	0.163**	3.366	0.001	Supported
H8a	TTF—> PV	0.359***	5.392	0.000	Supported
H8b	CONF—> PV	0.338***	5.902	0.000	Supported
H9a	CONF—> SAT	0.739***	22.268	0.000	Supported
H9b	CONF—> FLOW	0.764***	32.741	0.000	Supported
H9c	FLOW—> SAT	0.196***	5.479	0.000	Supported
H10a	TTF—> TRUST	0.274***	5.671	0.000	Supported
H10b	SAT—> TRUST	0.389***	6.284	0.000	Supported
H10c	PV—> TRUST	0.295***	4.620	0.000	Supported
H11	PV—> CI	0.214***	3.517	0.000	Supported
H12	TRUST—> CI	0.134**	2.153	0.031	Supported
H13	SAT—> CI	0.569***	7.823	0.000	Supported

CRR: course resource, TMT: teaching method and technology, AW: appropriate workload, EMP: empathy, INT: interaction, PER: personalization, CONV: convenience, TTF: task-technology fit, CONF: confirmation, FLOW: flow, SAT: satisfaction, PV: perceived value, TURST: trust, CI: continuance intention.

correlation in our research, as shown in Table 3. Based on this, the discriminant validity was supported.

5.3 Structural model and hypothesis test

After validating the reliability and validity of the measurement model, we assessed the model fit by the standardized root mean square residual (SRMR). The SRMR represents the discrepancy between the empirical and model-implied (theoretical) correlation matrix which is a goodness-of-fit measure for PLS (Henseler et al., 2014). Our model's SRMR is 0.063 which is lower than the recommended threshold value of 0.08 (Hu & Bentler, 1999). Thus, our structural model has a good fit.

Upon assessing the model fit, we then conducted the significance tests of our research hypotheses by means of a bootstrapping procedure with 5000 samples. The results are displayed in Table 4. All hypotheses were confirmed except for two: course resource and confirmation(H1b), interaction and perceived value(H6b). That implies that course resource doesn't have effect on users' confirmation about MOOCs and the interaction will not influence their perceived value of MOOCs.

All of the teaching-based quality have impacts on TTF and confirmation except for course resource which only affects TTF. More specifically, course resource can positively influence task technology fit which supported H1a ($\beta=0.199$, $t=3.692$, $p<0.000$) and has no effect on confirmation. Teaching method and technology has significant and positive effect on task technology fit and confirmation which supported H2a and H2b ($\beta_{\text{TTF}}=0.129$, $t=2.302$, $p=0.021$; $\beta_{\text{CONF}}=0.112$, $t=2.013$, $p=0.044$). Appropriate workload has similar results and supports H3a and H3b ($\beta_{\text{TTF}}=0.318$, $t=6.441$, $p<0.000$; $\beta_{\text{CONF}}=0.110$, $t=2.190$, $p=0.029$). Empathy also has positive effects on TTF and confirmation and thus supports H4a and H4b ($\beta_{\text{TTF}}=0.313$, $t=6.764$, $p<0.000$; $\beta_{\text{CONF}}=0.140$, $t=3.082$, $p=0.002$).

Also, four elements of the platform-based quality have significant influence on confirmation and perceived value except for interaction. Interaction only has effects on confirmation and shows no impacts on perceived value which only supports H6a ($\beta_{\text{CONF}}=0.128$, $t=2.79$, $p=0.005$; $\beta_{\text{PV}}=0.009$, $t=0.224$, $p=0.823$). Personalization can both affects confirmation and perceived value ($\beta_{\text{CONF}}=0.212$, $t=4.066$, $p<0.000$; $\beta_{\text{PV}}=0.102$, $t=2.051$, $p=0.040$) supporting H5a and H5b. H7a and H7b are also supported which implies that convenience can influence them as well ($\beta_{\text{CONF}}=0.202$, $t=3.916$, $p<0.000$; $\beta_{\text{PV}}=0.163$, $t=3.366$, $p=0.01$).

Moreover, TTF and confirmation can both significant influence perceived value supporting H8a and H8b ($\beta_{\text{TTF}}=0.359$, $t=5.392$, $p<0.000$; $\beta_{\text{CONF}}=0.338$, $t=5.902$, $p<0.000$). ECM and flow theory are also validated and supported H9a, H9b and H9c: confirmation has a significant effect on satisfaction in MOOCs (H9a: $\beta=0.739$, $t=22.268$, $p<0.000$), confirmation has a positive impact on flow experience (H9b: $\beta=0.764$, $t=32.741$, $p<0.000$), flow can also positively influence satisfaction (H9c: $\beta=0.196$, $t=5.479$, $p<0.000$). TTF, satisfaction and perceived value can affect trust in MOOCs as hypothesized in H10a, H10b and H10c (H10a: $\beta=0.274$, $t=5.671$, $p<0.000$; H10b: $\beta=0.389$, $t=6.284$, $p<0.000$; H10c: $\beta=0.295$, $t=4.620$, $p<0.000$).

According to these results, approximately 76.2% of the variance in TTF, 76.7% of the variance in confirmation, 81.8% of the variance in perceived value, 58.4% of the variance in flow, 80.5% of the variance in satisfaction and 83.6% of the variance in trust were explained by the antecedent (exogenous) variables.

Lastly, perceived value positively enables users to continuously use MOOCs ($\beta=0.214$, $t=3.517$, $p<0.000$) which supported H11; trust will also significantly influence continuance intention in MOOCs ($\beta=0.134$, $t=2.153$, $p=0.031$) supporting H12. Satisfaction will improve the continuance intention as well ($\beta=0.569$, $t=7.823$, $p<0.000$). Overall, the structural model can explain about 78.4% variance of the continuance intention.

6 Discussion

Continuance intention is beneficial for both students to keep acquiring knowledge and for platform to hold users. Thus, continuance intention has attracted lots of scholars' attention, and is now a critical topic in online learning research field. Extant research has highlighted the importance of quality. However, existing literature mainly stressed the general significance of quality, the fine-grained quality elements and their effect mechanism still need further exploration. To have a deeper and better understanding of the detailed effects and the mechanism of the nuanced quality elements, from the perspective of teaching-based quality and platform-based quality, our study proposes and empirically validates a research model that addresses the continuance intention in MOOCs based on ECM, TTF and flow theory. This research explores how teaching-based quality and platform-based quality impact continuance intention in MOOCs, adding more knowledge to the extant research on online learning in general and on quality effect and continuance intention in specific. We examine and verify effects of quality elements based on ECM, flow theory and TTF. Moreover, we introduce perceived value and trust to our model. We comprehensively disclose the complicated relationships and effect mechanism of quality elements on continuance intention through task technology fit, confirmation, satisfaction, flow, perceived value and trust in MOOCs.

Firstly, the results indicate that the teaching-based quality has a positive influence on users' task technology fit. Course resource, teaching method and technology, appropriate and instructors' empathy can largely improve students perceived task technology fit. This implies that if MOOCs have comprehensive and enough course resource and multiple teaching method and technology, they will have a higher perception of the match between the systems and themselves. Besides, whether the amount of workload is moderate to students is also important to increase their feelings of the fit. Teachers' empathy can also enhance their perception of the match between themselves and courses. In total, the task-technology fit will finally increase their perceived value and trust of MOOCs. And then they would be more likely to continue using MOOCs.

Secondly, the teaching-based quality also shows a significant effect on users' confirmation except for course resource. The results demonstrate that teaching method and technology, appropriate workload and empathy could improve students' confirmation in MOOCs. For example, Xing (2019) has validated that students would have different performance due to the design of the courses, including the course duration, the number of quizzes and so on. Therefore, our results are aligned with it and corroborate the fact that those teaching-based quality elements will make students have a high level of confirmation about learning in MOOCs. The confirmation will increase perceive value which is complied with Qi et al. (2021), and improves satisfaction and flow which is consistent with the ECM (Bhattacharjee, 2001) and the results of Mulik et al. (2019). Then those will finally increase students' intention to persist in MOOCs. However, course resource has no effect on students' confirmation. We primarily infer that students always do not have a wide knowledge of the course resource and they may focus more on the course content instead. Most of the

researches have already validated the importance of course content (Choi & Jeong, 2019; Hone & El Said, 2016). Thus, we can conclude that MOOCs users aim for knowledge-seeking instead of resource-seeking.

Thirdly, the platform-based quality is more related to the system and it has a significant and positive impacts on users' confirmation and perceived value. This finding suggests that personalization, interaction and convenience can strengthen users' perceived value. The results are aligned with the research of Komalawardhana et al. (2021), Qi et al. (2021), Al-Adwan (2020). Besides, personalization and convenience will augment students' confirmation about MOOCs. Compared to offline learning, individuals will have a higher expectation of the convenience and personalization. However, we surprisingly observe that interaction of the system has no effect of confirmation. This may be induced due to the nature of MOOCs. The interaction between the humans may be more important to them instead of the system. For example, findings of Zhao et al. (2020) suggested that sociability can enhance the continuance intention to use MOOCs. Also Hone and El Said (2016) discovered that the interaction between instructors and students can improve their perceived effectiveness in online learning. Therefore, interaction of the system will not influence users' confirmation in MOOCs.

Lastly, we consolidate that task technology fit, satisfaction and perceived value can enhance trust in MOOCs. Also, perceived value, trust and satisfaction can positively influence continuance intention in MOOCs not surprisingly. Similar to other e-service, online learning trust is also influenced by satisfaction and perceived value which is aligned with the findings of recent literature (Jin, 2020). Moreover, task technology fit can induce individuals' match between the courses and themselves. Therefore, this kind of perceived compatible will increase their gratification and lead to higher trust in MOOCs.

6.1 Theoretical implication

This research examines how teaching-based quality and platform-based quality influence continuance intention in MOOCs through ECM, TTF, flow theory. This study contributes to previous researches mainly in three folds.

First, this research integrates ECM, TTF and flow together to illustrate the effect mechanism of quality on continuance intention. From the literature summary, it can be seen that ECM, TTM and flow are widely applied to explain human behavior. Extant research has highlighted the significance of quality in online learning (Yang et al., 2017). However, how quality affect students' behavior and shape their continuance intention still need more exploration. Our research proposes a comprehensive effect model and validate the effects, extending the understanding about the quality effect mechanism in a deeper manner. We provide an alternative view to elaborate the effects of quality on continuance intention, adding more knowledge about the quality effect in the context of online learning.

Second, this research augments prior research in depth by investigating the nuanced quality elements. Recent literature has begun to focus not only on the whole quality, but on more detailed quality elements, for example, Cheng (2021) investigated

course quality by taking insight into course content quality and course design effect, and Faisal et al. (2020) focused on the online learning information system quality like the appearance quality, the information quality in the webpage. Our research explores the effects of detailed quality elements under both the teaching-based quality and platform-based quality, disclosing the internal effect mechanism a further step in depth on the basis of extant literature. Our research enriches the extant literature on online learning and makes a comprehensive examination on fine-grained quality, deepening the understanding of the effect of quality on continuance intention.

Third, our paper sheds light on the difference of online learning platforms compared to other online systems. To details, our research shows that interaction between the system and users in MOOCs isn't as important as other platforms. For e-commerce platform, interaction between system and users is critically prominent and is quite an important driver for continuance intention (Esteves et al., 2021). However, online learning platforms own some difference from e-commerce platforms in essence, that is, users largely pay more attention to the interaction between instructors or peers and themselves, as Zhao et al. (2020) argued. Therefore, distinct from e-commerce platform, interaction is not so vital for e-learning platform. Our research adds evidence on the heterogeneity between different kinds of platforms, which reflects that factors may generate different effects under different platform environment. Supported the particularity of MOOC platform, our results are helpful to draw deeper insights on online learning platform.

6.2 Practical implication

The results of our research can provide several feasible strategies with MOOCs platform developers and instructors who are concerned about the participants' dropout.

Our results show that teaching-based quality has a significant influence on users' task technology fit and confirmation in MOOCs. Therefore, instructors need to pay more attention to the course design. For example, they can evaluate their participants' ability and needs about courses and design a suitable and acceptable course syllabus relevant to the volume of assignments. Also, it's necessary for instructors to employ multiple teaching methods and offer sufficient course resources. Moreover, they may need to take more efforts on students' development in the future and increase the interaction between instructors and students.

For platform developers, they need to provide more personalized information with users. They can recommend similar and appropriate courses to users based on users' platform using experience. It's also beneficial to send different information to different learners according to their identities (workers or students) and majorities. Although the interaction between the system and users is not as significant as in other e-services, developers still need to take this into consideration in case individuals drop out due to the poor interaction of the service. Convenience is already very mature in online learning environment. However, there is still some space.

For instance, developers can invest more efforts in improving the quality of mobile applications due to the widely adoption of mobile devices.

7 Conclusion

Our research explores how teaching-based quality and platform-based quality affect continuance intention based on ECM, TTF, flow theory and trust in online learning environment. The results indicate that teaching-based quality factors will improve learners' task technology fit and confirmation, while platform-based quality can enhance the confirmation and perceived value. Then these will further arise users' satisfaction and trust and improve the using experience in MOOCs. Finally, they will have higher intention to continuously participate in online learning. Although our study has examined the effect of quality, there is still some limitations. First, most of our respondents are students. Secondly, we only detect the intention instead of the actual behavior. Further studies can include more diversified samples to examine the continuous behavior in online learning environment.

Authors' contributions SS conceptualized and designed research, interpreted data, supervised the research team, WF collected and analyzed data, drafted the manuscript, SS interpreted data and reviewed and edited the manuscript. The authors read and approved the final manuscript.

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Declarations

Competing interests The authors declare that they have no competing interests.

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