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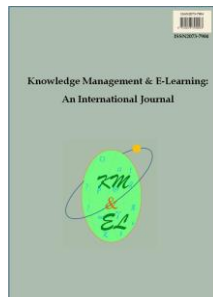
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Chinese MOOC learners' satisfaction and continuance intention: A mixed-method study

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Abstract: Drawing on the technology acceptance model (TAM), self-determination theory (SDT), expectation-confirmation model (ECM), and massive open online courses (MOOCs) design effects, the present work introduced a conceptual model for understanding the fine-grained mechanism underlying learner satisfaction and continuance intention. A structural equation modelling analysis based on 168 MOOC learners' survey data showed that perceived usefulness positively affected satisfaction and continuance intention. Assessment and autonomous motivation positively affected continuance intention; expectation confirmation significantly influenced perceived usefulness and satisfaction. By providing empirical evidence about affecting factors relating to learners' satisfaction and continuance intention, this study shows valuable managerial insight into MOOC design.

Keywords: Learner satisfaction; Continuance intention; Structural equation modelling; MOOC design

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1. Introduction

Advances in Internet technologies have significantly changed how educational services operate and are delivered. Massive open online courses (MOOCs), as a prevalent online education mode, are receiving increasing attention in academia and educational markets for their potential to restructure instruction and learning. As a result, MOOC has developed into a pedagogical innovation that modernizes higher education worldwide (Fang et al., 2019).

In China, MOOCs have undergone rapid development since 2013. Between 2017 and 2019, the number of MOOCs has grown from 3,200 to 12,500, with the number of learners increasing from 55 million to 200 million. At the 2020 World MOOC Conference, it was announced that the number of MOOCs and learners in China surpassed 34,000 and 540 million, respectively, making China the first place in MOOC size. The huge investment in MOOCs in China is driven by the government's expectation of increasing access to higher education, facilitating education equality, and reducing regional and intercollegiate inequalities in educational resources via MOOCs (Dai et al., 2020a).

Learner satisfaction and continuance intention have been important in measuring MOOC success. Satisfaction, as an important psychological factor, can influence learners' motivational levels and learning outcomes. Scholars have reported learner satisfaction's positive relationships with their success, learning motivation, and retention in MOOCs. Driven by the increasing competition in the MOOC market, learner satisfaction has become an important factor for measuring MOOC success (Joo et al., 2018). If learners feel more satisfied with MOOCs, providers tend to extend their products and services to more audiences, construct brands, and promote MOOC usage.

Continuance intention indicates learners' willingness to continue participating in MOOCs. According to Bhattacharjee (2001), continuance intention is also an important determinant of a new technology's success. Understanding learners' continuance intention is thus vital for promoting MOOCs' sustainability (Zhao et al., 2020). According to Wu and Chen (2017), it is essential to identify variables that can influence learners' intention to continue participating in MOOCs besides their initial acceptance. Similarly, Alraimi et al. (2015) suggest that exploring drivers for continuance intention to adopt information systems like MOOCs brings insights into their viability and sustainability. Learners' continuance intention thus plays a significant role in measuring MOOC success because learners have to persevere with learning to reap the intended educational benefits of the learning experiences (Hone & El Said, 2016). Thus, one of the objectives of this research is to reveal factors that affect learners' decision to keep taking MOOCs.

As a result, studies on learners' satisfaction and intention to reuse MOOCs have been an active topic in academia (e.g., Rekha et al., 2023; Nong et al., 2022; Shang & Lyv, 2022; Li & Zhao, 2024; Qi et al., 2023; Shang & Lyv, 2024). For example, Rekha et al. (2023) integrated an expectation-confirmation model (ECM) with perceived openness, reputation, enjoyment, and computer self-efficacy to examine why students continued utilizing MOOCs. Based on survey data from 383 students in India, Rekha et al. (2023) identified confirmation and perceived usefulness's significant effects on satisfaction. Nong et al. (2022) examined the MOOC continuance intention by combining ECM with perceived service quality, revealing perceived service quality's positive impact on satisfaction and continuation intention. Shang and Lyv (2022) investigated quality elements' effects on MOOC continuance intention based on ECM and flow theory, identifying teaching- and platform-based quality's positive influence on confirmation and perceived value. Li and Zhao (2024) analyzed the factors influencing students' continuance intention to adopt MOOCs, showing the unified theory of acceptance and use of technology model's significant and positive influences on MOOC student satisfaction.

MOOCs researchers have attempted to understand drivers for learners' satisfaction and continuance intention according to ECM (Alraimi et al., 2015), self-determination theory (SDT) (Pozón-López et al., 2021), or technology acceptance model (TAM) (Joo et al., 2018). For instance, Joo et al. (2018) focused on examining what motivated college learners to adopt MOOCs in Korea, identifying the positive effects of perceived ease of use and usefulness on satisfaction. However, Joo et al.'s (2018) study focused on Korean MOOCs, which may be different from MOOCs in China. Guided by self-determination and relationship quality theories, Sun et al.'s (2019) analysis of 374 learners participating in Chinese University MOOCs showed the significantly positive influences of autonomy, competence and relatedness on intrinsic motivation. Based on the data collected from 300 subjects, Lu et al. (2019) examined the drivers of learners' satisfaction with MOOCs from an ECT perspective, showing that perceived usefulness, interest, and flow experience significantly mediated the relationship between confirmation and satisfaction. Regarding SDT, Pozón-López et al.'s (2021) analysis of 210 MOOC learners' survey data proved the significant impact of perceived satisfaction and autonomous motivation on use intention. Joo et al.'s (2018) survey study conducted with TAM considerations verified satisfaction's positive influence on continuance intention and satisfaction's role in mediating perceived ease-of-use/usefulness and continuance intention in MOOCs. However, few of the extant studies have provided a comprehensive understanding with joint consideration of the TAM, ECM, SDT, and MOOC design and implementation effects (Hone & El Said, 2016). In addition, as highlighted by Kovanović et al. (2015), there is an increase in recognition of the importance of localizing MOOC research to address cultural and contextual differences.

Thus, there is a need to focus on Chinese learners to provide insights tailored to the Chinese MOOC landscape. To bring a multifaceted and inclusive overview of the distinctive features of Chinese MOOCs, it is essential to extend the existing literature by proposing and empirically verifying a concept model to better understand the fine-grained mechanism underlying Chinese MOOC satisfaction and continuance intention.

Accordingly, the present work proposes a theoretical model which combines TAM, SDT, ECM, and factors regarding MOOC design and implementation to understand how they affect MOOC satisfaction and continuance intention. The model is validated based on a partial least squares-structural equation modelling (PLS-SEM) methodology using the survey data of MOOC learners in China. According to the Ministry of Education of the People's Republic of China (MOE) (2019), MOOCs in China are thought to solve the disparities in the allocation of resources for higher education that exist between colleges and across regional boundaries. However, Chinese MOOCs are challenged by high dropout rates (e.g. 95.5% of 1000 courses provided in XuetangX) (Feng et al., 2019). The present work, focusing especially on Chinese MOOC learners, aims to identify determinants that significantly affect continuance intention to adopt MOOCs. It is expected that the results will offer theoretical and empirical insights to support Chinese educators in creating efficient learning support systems or interventions that encourage students to stick with MOOCs and, ultimately, advance educational equity in China.

2. Theoretical background

2.1. Self-determination model

Motivation refers to the impulses and instincts that make humans act (Pozón-López et al., 2021). In the analysis of motivation, researchers commonly make use of SDT, which differentiates autonomous and controlled motivations regarding the underlying regulation and the extent of self-determination (Deci & Ryan, 2012). Accumulated evidence shows that there are self-determined or non-self-determined behaviours based on triggers from autonomous or controlled stimuli (Pozón-López et al., 2021). Accordingly, in SDT, motivations involve extrinsic and intrinsic motivations (Chen & Jang, 2010). Intrinsic motivation is “the doing of an activity for its inherent satisfactions rather than for some separable consequence” (Ryan & Deci, 2000, p. 72). Extrinsic motivation refers to “a construct that pertains whenever an activity is done to attain some separable outcome” (Ryan & Deci, 2000, p. 71).

Extrinsic motivation can be also described as controlled motivation. Lee (2010) found that subjective norms and perceived behavioural control significantly affect continuance intention. For example, when others surrounding a student have used an online education system, it is more likely that the student will follow them (Pozón-López et al., 2021). Intrinsic motivation and extrinsic motivation are often difficult to distinguish. According to Joo et al. (2018), motivational regulation is helpful in “[understanding] the complex mix and range of motivation among MOOC learners” (p. 263). For example, how external systems (e.g., certificates and credit) affect learners' motivation can be investigated by using external regulation. Similarly, when students are primarily driven by course materials that are considered helpful for their career development and job promotion, they undergo identified regulation. We believe that SDT is crucial for understanding learners' internal drive and engagement in MOOCs. By

considering SDT in this study, we can explore how motivation affects learners' continuance intention.

2.2. Technology acceptance model

Technology acceptance indicates users' willingness to use a technology (Teo, 2011). Different theories, frameworks, and models have been developed to clarify and predict users' intentions and adoption of a given technology. TAM includes "the concept of perceived ease of use and perceived usefulness to explain people's acceptance process when new technology emerges and is adopted" (Joo et al., 2018, p. 262). Perceived usefulness involves "the degree to which a person believes that using a particular system would enhance his/her job performance" (Davis, 1989, p. 320). Perceived ease of use involves "the degree to which a person believes that using a particular system would be free of physical and mental effort" (Davis, 1989, p. 320). Even though scholars have attempted to show that perceived ease of use and usefulness cannot adequately describe users' acceptance intention, TAM remains a flexible model popularly employed to understand users' acceptance of new technologies. By incorporating TAM into this study, we aim to examine how students' perceptions of the usefulness and ease of use of MOOCs affect their continuance intention and satisfaction.

2.3. Expectation-confirmation model

Expectation confirmation refers to how a user perceives the gap between the expectation and actual performance of an information system (Bhattacharjee, 2001). ECM was extended from expectation confirmation theory to examine one's intention to reuse information systems. Many researchers have claimed that a user's confirmation could positively influence their perceived usefulness and satisfaction (Lin et al., 2005). When users believe in the usefulness of technology and their usage experience lives up to their initial expectations, they tend to be more satisfied. Bhattacharjee and Premkumar (2004) also suggested that initial expectations do not significantly affect users' satisfaction and disconfirmation in using information technologies. ECM helps explain how individuals' post-adoption perceptions, specifically confirmation/disconfirmation of expectations, influence their satisfaction and continuance intention. By incorporating ECM into our model, we can investigate how learners' initial expectations of MOOCs align with their actual experiences and how this alignment affects their satisfaction and continuance intention.

Drawing on these theories, the present work proposes a conceptual model that jointly considers TAM, SDT, ECM, as well as MOOC design and implementation effects for a comprehensive understanding of the drivers for MOOC learners' satisfaction and continuance intention. Each of the theories contributes unique insights into different aspects of the learner experience, allowing for a holistic analysis. Moreover, the combination of these theories allows us to capture both the cognitive and motivational aspects of learner behaviour. This enhances the predictive power of our model and offers a nuanced understanding of the underlying mechanisms at play. In practice, the integration of multiple theories enables us to identify various factors that educators and platform designers can leverage to enhance learner satisfaction and engagement in MOOCs. By understanding the interplay between technology acceptance, motivation, and expectation confirmation, stakeholders can make informed decisions to improve the overall MOOC experience.

3. Literature review and hypotheses

3.1. Technology acceptance model

Prior studies on technology-enhanced learning environments have indicated that learners' perceptions of the utility of the environment are significantly affected by its perceived ease of use. The SDT and TAM were used in an effort by Nikou and Economides (2017) to investigate learners' intentions to utilize a mobile assessment system, revealing the perceived simplicity of use's influence on perceived usefulness. Wu and Chen (2017) studied MOOC learners and discovered that perceived usefulness was significantly affected by perceived ease of use. In addition to the original acceptance of new technology, increasing attention is paid to the continuance intention to utilize a given new technology (Joo et al., 2018). For instance, Daneji et al.'s (2017) analysis of 447 Malaysian MOOC students' data revealed perceived ease of use's significant effect on continuance intention. Thus, this study hypothesizes that:

Hypothesis 1. Perceived ease of use is positively associated with perceived usefulness.

Hypothesis 2. Perceived ease of use is positively associated with continuance intention.

According to Joo et al. (2018), when a learner believes a MOOC is useful, he or she is more satisfied and tends to continue. Pozón-López et al. (2021) and Alraimi et al. (2015) have empirically confirmed perceived usefulness's positive influence on MOOC satisfaction and continuance intention. We thus hypothesize that:

Hypothesis 3. Perceived usefulness is positively associated with perceived satisfaction.

Hypothesis 4. Perceived usefulness is positively associated with continuance intention.

As Joo et al. (2018) suggest, satisfaction enables a user "to examine a path from initial acceptance to continuance intention" (p. 263). In MOOCs, learners' satisfaction's positive influence on continuance intention has been reported (e.g., Pozón-López et al., 2021; Lu et al., 2019). We thus hypothesize that:

Hypothesis 5. Perceived satisfaction is positively associated with continuance intention.

3.2. Expectation-confirmation model

MOOC learners' perceptions of MOOCs' usefulness may change with their confirmation experiences (Bhattacharjee, 2001). When a learner confirms that MOOCs' usefulness goes above her or his initial expectation, she or he is more likely to perceive MOOCs as useful. ECT also suggests that users' confirmation is an important antecedent to satisfaction. In MOOCs, learners usually compare expectations with actual experiences (Lu et al., 2019). When a learner perceives that a MOOC's performance lives up to her or his expectation, she or he will experience confirmation and feel satisfied. Thus, the higher the confirmation from experience is, the more a learner will feel satisfied with a MOOC. For example, Ouyang et al., (2017) adopted ECM to study MOOCs and found confirmation's direct influence on both perceived usefulness and usefulness. Dai et al.'s (2020b) study of Chinese university MOOCs identified confirmation's significant effect on satisfaction. We accordingly hypothesize that:

Hypothesis 6. Expectation confirmation is positively associated with perceived usefulness.

Hypothesis 7. Expectation confirmation is positively associated with perceived satisfaction.

3.3. Self-determination model

SDT applies to MOOCs because learners experience autonomous and controlled motivations for course enrolment. According to Zhou (2016), autonomous and controlled motivations can promote and diminish continuance intention, respectively. For example, Xiong et al. (2015) showed a significant role of motivation in predicting learners' engagement in MOOCs. Similarly, Zhou (2016), who adopted SDT to investigate Chinese college learners' acceptance of MOOCs, discovered that students' "autonomous motivation while using MOOCs would have a positive effect on attitudes towards MOOCs" (p. 196). We thus hypothesize that:

Hypothesis 8. Controlled motivation is negatively associated with continuance intention.

Hypothesis 9. Autonomous motivation is positively associated with continuance intention.

3.4. MOOC design and implementation effects

Previous studies have largely investigated the roles of MOOC qualities in affecting satisfaction and continuance intention. For example, Gupta and Maurya (2022) focused on content and instructional qualities' effects on MOOC learners' intention to complete and continue to use MOOCs. Shang and Lyv (2022) investigated how teaching- platform-based quality elements impacted continuance intention. However, in addition to quality elements such as course content, teacher instruction, and platforms, there are other factors related to MOOC design and implementation that also affect satisfaction and continuance intention (Sun et al., 2008), for example, interaction and problem-solving. Therefore, in this study, the use of "MOOC design and implementation" has a larger coverage of "MOOC quality". In other words, in addition to learners' perception of the overall quality of a MOOC or its several quality factors, we also consider other specific and fine-grained aspects of MOOCs. These factors may include course instructors (e.g., Du, 2023; Van Wart et al., 2020), assessment (e.g., Kumar & Kumar, 2020; Hew et al., 2020), content quality (e.g., Suriyapaiboonwattana & Hone, 2023; Pozón-López et al., 2021; 2020), and interaction (e.g., Kuo et al., 2014; Hone & El Said, 2016; Deshpande & Chukhlomin, 2017). By further including these specific dimensions of MOOC design and implementation, we aim to capture the multifaceted nature of learners' experiences and perceptions within the MOOC environment. This enables us to uncover potential areas for improvement and intervention that may have been overlooked in broader assessments of MOOC quality.

3.4.1. Course structure, course quality, and instructor

Many MOOC studies have focused on content structure, course quality, and instructors. For instance, Hew et al. (2020) highlighted course instructors' significance in explaining learner satisfaction. As Mohapatra and Mohanty (2017) stated, content quality and instructors' and course providers' reputations are crucial determinants for learners before

selecting a MOOC. Mohapatra and Mohanty (2017) also highlighted the importance of an institution's content quality and reputation for learners' MOOC usage. Content quality's positive influence on learner motivation and satisfaction is also found by Guo et al. (2014). Yang et al. (2017) identify course quality's significant impact on MOOC continuance intention. Li et al. (2021) indicate that course quality positively affected MOOC continuance intention. Based on the literature, we hypothesize that:

Hypothesis 10. Course structure significantly affects perceived satisfaction.

Hypothesis 11. Course quality significantly affects perceived satisfaction.

Hypothesis 12. The instructor significantly affects perceived satisfaction.

Hypothesis 13. Course structure significantly affects continuance intention.

Hypothesis 14. Course quality significantly affects continuance intention.

Hypothesis 15. Instructor significantly affects continuance intention.

3.4.2. Learning resources and assessment

According to Rekha et al. (2023), providing various resources (assignments, exams, seminars, and instructional materials) to support learning contributed to increasing MOOC satisfaction. Regarding assessment, self-assessment and learnability have been highlighted to help "learners understand where they stand about the learning objectives" (Deshpande & Chukhlomin, 2017, p. 279). Through assessment, MOOC learners can understand how they progress in learning, and the provision of self-assessment tools empowers their autonomy and promotes critical thinking skills and their satisfaction with learning. Yang et al. (2017) and Jordan (2015) also identified assessment's positive influence on MOOC satisfaction. Accordingly, the following hypotheses are proposed:

Hypothesis 16. Learning resource significantly affects perceived satisfaction.

Hypothesis 17. Assessment significantly affects perceived satisfaction.

Hypothesis 18. Learning resource significantly affects continuance intention.

Hypothesis 19. Assessment significantly affects continuance intention.

3.4.3. Other variables

Researchers have also examined the impact of the roles of interaction, support for problem-solving, and instructor feedback on MOOC learner satisfaction. Li et al. (2018) suggested that the amount of "asynchronous discussion significantly predicts learners' satisfaction with MOOCs and that [subject] discipline moderates the relationship between asynchronous discussion and satisfaction" (p. 279). Similarly, Chen et al. (2018) suggest that MOOC learners access materials and participate in discussions and communication activities to share opinions and/or ideas by using "texts, images, or multimedia functions to achieve the purpose of information sharing" (p. 708). Regarding support for problem-solving in MOOCs, Hew (2018) highlighted the significant effects of adopting problem-centred learning strategies on elaborating learners' sense of competency. Hew (2018) also claimed that "students most prefer a problem-centric style of teaching that focuses on meaning-making with relevant examples of how the principles or concepts taught can be applied in the real world" (p. 10). Similarly, Hew (2016) observed an improved engagement during problem-based learning supported by easy-to-understand explanations of concepts. We thus hypothesize that:

Hypothesis 20. Process significantly affects perceived satisfaction.

Hypothesis 21. Relationship significantly affects perceived satisfaction.

Hypothesis 22. Process significantly affects continuance intention.

Hypothesis 23. Relationship significantly affects continuance intention.

There are other types of MOOC variables. For instance, Deng et al. (2019) suggested workload and difficulty of a MOOC as major causalities for completion. Huang et al. (2017) reported that course difficulty could affect the relationship between satisfaction or reuse retention and factors like course content and teacher knowledge. Hew and Cheung (2014) have identified getting a certificate as one of the key drivers of MOOC enrolment. According to Joo et al. (2018), motivational regulation is helpful in “[understanding] the complex mix and range of motivation among MOOC learners” (p. 263). We thus hypothesize that:

Hypothesis 24. Perceived difficulty significantly affects perceived satisfaction.

Hypothesis 25. Perceived workload significantly affects perceived satisfaction.

Hypothesis 26. Certificate and credit significantly influence perceived satisfaction.

Hypothesis 27. Perceived difficulty significantly affects continuance intention.

Hypothesis 28. Perceived workload significantly affects continuance intention.

Hypothesis 29. Certificate and credit significantly affect continuance intention.

3.5. Concept model

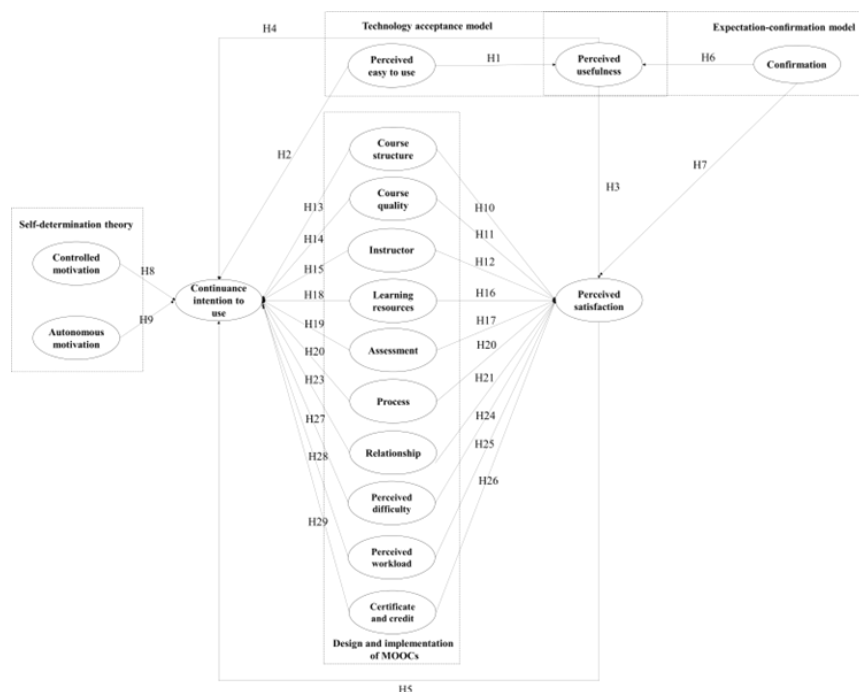


Fig. 1. Concept model

The present work proposes a conceptual model (Fig. 1) for exploratory analysis of the effects of TAM, ECM, SDT, and MOOC design and implementation on Chinese MOOC learners' satisfaction and continuance intention. Previous research has examined MOOC learners' satisfaction or continuance intention based on TAM, ECM, or SDT. However, limited work has systematically investigated MOOC learners' satisfaction and continuance intention with joint consideration of these theories and MOOC design and implementation effects. The integration of TAM, SDT, ECM, and MOOC design effects in our conceptual model offers a robust framework for understanding and predicting learner satisfaction and continuance intention in MOOCs. Particularly, we focus on Chinese MOOCs, which are quite different from that of Western MOOC learners. According to Dai et al. (2020b), MOOCs' success to some extent relies on their ability to offer quality education according to local needs. Kovanović et al. (2015) also highlight the need for MOOC localization. Thus, this study aims to provide important insights into drivers for Chinese MOOC students' satisfaction and continuance intention.

4. Methods

The present work tests the proposed model using a PLS-SEM analysis and a thematic analysis based on the survey data from Chinese MOOC learners, focusing on acquiring a comprehensive understanding of drivers for their satisfaction and continuance intention.

4.1. Instruments

A structured questionnaire was adopted to collect quantitative data, which includes two sections. The first section includes 6 questions on demographics, including gender, age, major, education level, internet experience, and MOOC use frequency. The second section includes 44 items for measuring 16 constructs in the proposed model. Item questions were formatted on a 5-point Likert scale, wherein 5 means strongly agree and 1 means strongly disagree.

To ensure validity, item questions were determined and modified by referring to previous research. The question items for perceived usefulness (3 items) and ease of use (3 items) were determined based on Davis (1989). Perceived satisfaction (2 items) and continuance intention (2 items) were measured with reference to Spreng et al. (1996), Joo et al. (2018), and Zhou (2016) scale design. Three items on confirmation came from Bhattacharjee (2001). The question items for controlled (2 items) and autonomous motivation (4 items) were decided based on Zhou (2016). Items of course structure were modified according to Peltier et al. (2003) and Deshpande and Chukhlomin (2017). Items measuring course quality were determined with reference to Sun et al. (2008) and the instructor came from Manalo (2014). Three items of learning resources were taken from Nie and Hu (2018) and Jing and Zhao (2020). Items measuring assessment were determined based on Manalo (2014) and Jing and Zhao (2020), and the process was adapted from Peltier et al. (2003), Eom and Ashill (2006), and Deshpande and Chukhlomin (2017). The question items for the relationship (4 items) were determined based on Peltier et al. (2003). Two items adapted from Tzovla et al. (2021) were used to measure certificate and credit. Items measuring perceived difficulty and workload were taken from Hew et al. (2020) and Jing and Zhao (2020). Reliability coefficients ranging from 0.73 to 0.98 for these measures were reported in previous studies.

We followed Barclay et al. (1995) to present the questionnaire to educational technology experts to verify the instrument's applicability and readability. Thereafter, a

pilot study with 20 respondents with backgrounds comparable to those of survey respondents was carried out. According to the experts' and respondents' suggestions, minor rewording was done. The detailed measurements and questions are provided in the Appendix I.

4.2. Data collection

Since the present study focuses on learners' satisfaction with MOOCs and their continuance intention, target participants needed to have had experiences of learning in MOOCs before they completed the online survey. Therefore, university students above 17 years old with prior experience in learning via MOOCs were targeted. Invitations were posted on various channels such as WeChat, xMOOC, and XuetangX with links for participants to access the questionnaires. After removing careless cases (e.g., straight-line responses), 168 valid questionnaires were acquired, satisfying Barclay et al.'s (1995) ten times rule of sample size requirement.

Table 1
Demographic information

		Frequency	Percentage
Gender	Male	53	31.55%
	Female	115	68.45%
Age	18—20	35	20.83%
	21—23	62	36.90%
	24—26	34	20.24%
	27—29	20	11.90%
	30 and above	17	10.12%
Education level	Undergraduate	108	64.29%
	Postgraduate and above	60	35.71%
Major	Humanities	46	27.38%
	Social Sciences	37	22.02%
	Science and Engineering	62	36.90%
	Others	23	13.69%
Internet experience	2 years and below	9	5.36%
	3—4 years	7	4.17%
	5—6 years	29	17.26%
	7—8 years	34	20.24%
	9 years and above	89	52.98%
MOOC use frequency per week	2 hours and below	118	70.24%
	3—4 hours	33	19.64%
	5—6 hours	10	5.95%
	7—8 hours	5	2.98%
	9 hours and above	2	1.19%

Table 1 shows the demographic information of the 168 respondents, of whom 68.45% were female, and 56% ranged from 18-year-old to 23-year-old. Regarding education level, 64.29% and 35.71% were undergraduate and postgraduate students, respectively. Most respondents majored in Science and Engineering, followed by Humanities and Social Sciences. Over half of the respondents have used the Internet for over nine years. In addition, over 70% attend MOOCs for only 2 hours or below every

week. This result somewhat is consistent with Shang and Lyv (2022) who reported that 26.1% of participants used Chinese MOOCs less than twice a month and 45.9% used MOOCs between 2 and 5 times. While our sample primarily comprises individuals with limited MOOC engagement, it reflects the current landscape of Chinese MOOCs which are constrained by high dropout rates (Feng et al., 2019). This can explain why most of the Chinese respondents have not developed the habit of using MOOCs regularly. Thus, this study, in alignment with Kovanović et al.'s (2015) suggestions of focusing on MOOC localisation, offers insights into the experiences and behaviours of this demographic, contributing to nuanced understandings of MOOC use patterns in China.

4.3. Quantitative data analysis

The 168 questionnaires were analyzed using PLS-SEM, with a bootstrap sample of 5000 being adopted to assess indicators' contributions to corresponding constructs. The measurement model was estimated using Composite Reliability (CR), Cronbach's alpha, and Average Variance Extracted (AVE) following the criteria of acceptance: CR > 0.60, Cronbach's alpha > 0.70, and AVE > 0.50. The square root of AVE and HTMT ratio of correlations were computed to analyse the constructs' discriminant validity (Henseler et al., 2015). The Standardized Root Mean Square Residual (SRMR) index was adopted to see "how the composites of our model behave within a nomological net rather than as isolated manifest variables" (Sanchez-Franco et al., 2019, p. 491). In addition, a full collinearity test (Kock, 2015) was conducted to assess common method bias. The value of variance inflation factor (VIF) was adopted to check both the measurement and structure models for collinearity. VIF values of 5 or above are indicative of collinearity issues (Hair et al., 1995). The structural model was assessed by looking at constructs' relationships (i.e., path coefficient) and constructs' influence (i.e., effect size). Regarding structural path analysis, a t-test was used to understand the path coefficients' significance.

4.4. Semi-structured interview

An interview is "an interchange of views between two people conversing about a theme of mutual interest" (Kvale, 1994, p. 14). As Hobson and Townsend (2010) state, interviews enable scholars to discover things that cannot easily be discovered via observations since they allow interviewees to reflect on their personal experiences. A semi-structured interview is a common interview approach as it "ensures coverage of the researcher's agenda while also providing opportunities for interviewees to talk about what is significant to them" (Hobson & Townsend, 2010, p. 231). The present work also conducted semi-structured interviews to get an in-depth understanding of students' personal experiences and their perceptions about MOOC (dis)advantages. A total of 11 interviewees were randomly selected from the 168 respondents. Each interview was conducted on a one-to-one basis. The interviewees were encouraged to provide details about learning in MOOCs. Interviews in Chinese were held with randomly selected participants. Interviewees were informed that the interviews would be audio-recorded. Each interview lasted about 30 minutes. There were three interview questions adapted from Cheng (2019).

- 1) What made you try MOOCs?
- 2) What are the benefits and problems of MOOCs?
- 3) What will enable you to continue to participate in MOOCs?

4.5. Qualitative data analysis

Thematic analysis, as “a method for identifying, analyzing and reporting patterns (themes) within data” (Braun & Clarke, 2006, p. 79), was implemented to analyze the interview data. In conducting qualitative analysis, this study has strictly followed procedures in the literature to ensure that the data analysis was carried out consistently and exhaustively and that the findings emerged from the data and not personal predispositions. In this study, Microsoft Excel was used in the thematic analysis to code and thematically analyze the interview data. Three steps were conducted to obtain themes by referring to Braun and Clarke (2006). Firstly, audio recordings were transcribed into written texts. The transcription process enhanced the familiarity with the data through reading, re-reading, and taking notes. Secondly, codes were produced to organize and summarize useful information in the raw data. Finally, concepts that were originally identified from the transcribed data were grouped into conceptual categories and further into basic themes based on similarities. The basic themes are broader and can capture the meanings of a set of codes. For example, the basic theme “interactivity” was inferred from the codes such as “limited interaction”, “discuss with classmates”, and “interact freely”. To answer the first interview question, the codes were grouped into four basic themes: “individual interest”, “supplementary learning for formal study”, “requirement of schools, teachers or employers”, and “self-promotion”. Regarding the second question, nine four basic themes included “allowing self-learning”, “rich curriculum resources”, “economical”, “use of tests and assignments”, “availability of discussion forum”, “low level of interactivity”, “low level of Interactivity”, “low quality of course content”, “instructor feedback”, and “high requirement for self-learning ability”. For the third question, three basic themes were “individual interest”, “need for learning or work”, and “self-promotion”. The identified main themes were subsequently analyzed regarding the results derived from the PLS-SEM analysis. In addition, during the analysis procedure, the codes and themes have been presented to experts of MOOCs who have a lot of experience in MOOC design and instruction for their opinions. Based on experts’ opinions, the initial codes and themes have been modified.

4.6. Ethical issues

Before attending the surveys or interviews, each participant was informed about the research objectives and procedures. Regarding the audio recording of interviews, we explained to the interviewees the reason and procedure and assured the security of audio information. We also guaranteed participants that their identities were protected and that they could stop participating anytime.

5. Results

5.1. Descriptive statistics of participants’ responses

Table 2 presents the descriptive analysis results of the participant responses, with an average rating between 2.25 and 4.95. Items such as LR3 (4.08), PEOU3 (4.08), and IS1 (4.08) have achieved high scores, whereas ratings on CM2 (2.52), CM1 (2.80), and PD1 (2.92) were low.

Table 2
Descriptive statistics

Construct	Items	Mean	Median	Standard deviation	Kurtosis	Skewness
Course structure (CS)	CS1	3.899	4	0.616	3.808	-0.402
	CS2	3.958	4	0.784	3.04	-0.525
Course quality (CQ)	CQ1	3.173	3	0.966	2.546	-0.191
	CQ2	3.536	4	1.002	2.714	-0.438
Instructor (IS)	IS1	4.077	4	0.758	4.217	-0.791
	IS2	3.982	4	0.77	3.5	-0.523
	IS3	3.875	4	0.82	3.647	-0.746
Learning resources (LR)	LR1	4	4	0.819	3.911	-0.853
	LR2	4.018	4	0.738	3.11	-0.476
	LR3	4.083	4	0.738	2.996	-0.491
Assessment (AS)	AS1	3.696	4	0.867	3.297	-0.645
	AS2	3.732	4	0.808	3.751	-0.641
	AS3	3.56	4	0.887	3.393	-0.723
Process (PR)	PR1	3.357	3	0.962	2.513	-0.238
	PR2	3.393	3.5	0.903	2.131	-0.119
	PR3	3.893	4	0.758	2.966	-0.398
	PR4	3.851	4	0.838	3.43	-0.695
Relationship (RE)	RE1	3.649	4	0.91	2.631	-0.447
	RE 2	3.655	4	0.922	2.762	-0.414
	RE3	3.679	4	0.911	2.626	-0.419
	RE4	3.744	4	0.954	3.249	-0.674
Certificate and credit (CC)	CC1	3.208	3	1.237	2.02	-0.191
	CC2	3.506	4	1.158	2.455	-0.583
Perceived difficulty (PD)	PD1	2.917	3	1.075	2.338	0.282
Perceived workload (PW)	PW1	3.369	3	0.982	2.208	-0.069
Perceived ease of use (PEOU)	PEOU1	4.042	4	0.864	3.296	-0.75
	PEOU2	3.929	4	0.755	2.918	-0.385
	PEOU3	4.083	4	0.836	3.646	-0.834
Controlled motivation (CM)	CM1	2.804	3	1.239	1.877	0.112
	CM2	2.518	2	1.184	2.288	0.435
Autonomous motivation (AM)	AM1	3.589	4	0.924	2.893	-0.423
	AM2	4.018	4	0.785	3.209	-0.627
	AM3	3.798	4	0.823	3.218	-0.516
	AM4	3.905	4	0.783	3.055	-0.507
Confirmation (CO)	CO1	3.696	4	0.853	2.959	-0.48
	CO2	3.619	4	0.867	3.363	-0.563
	CO3	3.768	4	0.774	3.818	-0.743
Perceived usefulness (PU)	PU1	3.917	4	0.807	4.991	-1.013
	PU2	3.815	4	0.771	3.175	-0.537
	PU3	3.744	4	0.841	2.671	-0.4
Perceived satisfaction (PS)	PS1	3.815	4	0.763	4.519	-0.812
	PS2	3.827	4	0.804	3.667	-0.718
Continuance intention (BI)	BI1	3.5	4	0.922	2.37	-0.138
	BI2	3.631	4	0.932	2.766	-0.54

5.2. Reliability and convergent validity

Regarding constructs' reliability and convergent validity, the results (Table 3) showed satisfactory internal reliability with Cronbach's alpha ranging from 0.75 to 0.89.

Convergent validity was guaranteed as the AVE ranged between 0.54 and 0.84 (> 0.5) and CR ranged between 0.826 and 0.918 (> 0.6), and cross-loading scores exceeded 0.70. The VIF values of less than 5 indicate no collinearity issues. Discriminant validity was also ensured as the square root of AVE exceeded correlation values (Table 4) and the HTMT (Heterotrait-Monotrait Ratio) (Table 5). In addition, the model's SRMR index was acceptable (i.e., lower than 0.08).

Table 3
Reliability and validity of constructs in the measurement model

Construct	Item	Factor loading	VIF	Cronbach's alpha	CR	AVE
Perceived ease of use	PEOU1	0.86	1.927	0.82	0.891	0.732
	PEOU2	0.866	1.671			
	PEOU3	0.841	2.007			
Perceived usefulness	PU1	0.852	1.877	0.844	0.906	0.763
	PU2	0.904	2.448			
	PU3	0.863	2.004			
Controlled motivation	CM1	0.92	1.529	0.741	0.883	0.791
	CM2	0.858	1.529			
	AM1	0.774	1.686			
Autonomous motivation	AM2	0.809	1.894	0.835	0.89	0.67
	AM3	0.857	2.173			
	AM4	0.832	2.029			
Perceived satisfaction	PS1	0.907	1.772	0.795	0.907	0.83
	PS2	0.915	1.772			
Course structure	CS1	0.869	1.56	0.749	0.887	0.798
	CS2	0.917	1.56			
Course quality	CQ1	0.852	1.485	0.727	0.878	0.783
	CQ2	0.916	1.485			
Instructor	IS1	0.865	2.221	0.836	0.902	0.754
	IS2	0.935	2.901			
	IS3	0.8	1.736			
Learning resources	LR1	0.793	1.585	0.718	0.843	0.644
	LR2	0.905	2.012			
	LR3	0.694	1.368			
Assessment	AS1	0.859	1.871	0.744	0.855	0.665
	AS2	0.859	1.903			
	AS3	0.72	1.241			
Process	PR1	0.736	1.789	0.718	0.825	0.542
	PR2	0.79	1.911			
	PR3	0.708	1.268			
Relationship	PR4	0.707	1.299	0.824	0.883	0.653
	RE1	0.763	1.642			
	RE 2	0.792	1.682			
Certificate and credit	RE3	0.825	1.826	0.712	0.867	0.767
	RE4	0.851	1.825			
	CC1	0.936	1.44			
Confirmation	CC2	0.81	1.44	0.849	0.909	0.768
	CO1	0.878	2.069			
	CO2	0.879	2.144			
Continuance intention to use	CO3	0.873	1.995	0.821	0.918	0.848
	BI1	0.921	1.943			
	BI2	0.921	1.943			

Note. PD and PW with one measure item each were not considered

Table 4
Discriminant validity

	PEOU	PU	CM	AM	PS	CS	CQ	IS	LR	AS	PR	RE	PD	PW	CC	CO	BI
PEOU	0.856																
PU	0.511	0.873															
CM	-0.069	-0.05	0.89														
AM	0.591	0.726	-0.1	0.819													
PS	0.668	0.777	-0.061	0.753	0.911												
CS	0.531	0.48	-0.065	0.668	0.576	0.893											
CQ	0.336	0.459	0.061	0.389	0.483	0.467	0.885										
IS	0.496	0.514	-0.052	0.537	0.586	0.533	0.449	0.868									
LR	0.464	0.57	-0.088	0.568	0.605	0.553	0.414	0.665	0.802								
AS	0.377	0.538	-0.08	0.527	0.561	0.47	0.477	0.531	0.595	0.815							
PR	0.388	0.559	0.079	0.511	0.561	0.508	0.452	0.486	0.504	0.604	0.736						
RE	0.38	0.539	0.154	0.504	0.505	0.342	0.34	0.395	0.418	0.491	0.623	0.808					
PD	-0.063	0.053	0.361	0.037	0.023	-0.075	0.216	-0.078	-0.063	0.018	0.177	0.168	1				
PW	-0.064	-0.061	0.429	0.084	-0.051	0.019	0.063	0.003	0.002	0.077	0.156	0.075	0.466	1			
CC	0.104	0.109	0.324	0.051	0.134	0.042	0.19	0.097	0.063	0.144	0.209	0.265	0.495	0.319	0.876		
CO	0.64	0.758	0.008	0.727	0.807	0.552	0.507	0.558	0.535	0.62	0.578	0.549	0.034	-0.032	0.174	0.877	
BI	0.516	0.733	-0.064	0.703	0.734	0.487	0.444	0.47	0.489	0.579	0.487	0.524	0.049	-0.05	0.092	0.756	0.921

Table 5
HTMT

	PEOU	PU	CM	AM	PS	CS	CQ	IS	LR	AS	PR	RE	PD	PW	CC	CO	BI
PEOU																	
PU	0.599																
CM	0.139	0.142															
AM	0.705	0.864	0.174														
PS	0.81	0.948	0.08	0.923													
CS	0.67	0.6	0.083	0.844	0.738												
CQ	0.398	0.585	0.12	0.499	0.624	0.627											
IS	0.588	0.612	0.11	0.641	0.711	0.67	0.569										
LR	0.601	0.719	0.163	0.722	0.797	0.749	0.563	0.867									
AS	0.47	0.68	0.188	0.67	0.73	0.632	0.646	0.667	0.812								
PR	0.479	0.715	0.203	0.651	0.74	0.692	0.626	0.617	0.683	0.831							
RE	0.437	0.638	0.201	0.605	0.613	0.44	0.419	0.474	0.535	0.622	0.811						
PD	0.139	0.105	0.418	0.101	0.026	0.084	0.254	0.089	0.116	0.076	0.251	0.195					
PW	0.097	0.083	0.499	0.117	0.057	0.041	0.074	0.049	0.06	0.096	0.187	0.085	0.466				
CC	0.142	0.174	0.476	0.127	0.168	0.1	0.235	0.131	0.218	0.182	0.283	0.337	0.57	0.394			
CO	0.752	0.896	0.069	0.861	0.981	0.686	0.641	0.659	0.68	0.786	0.741	0.649	0.049	0.034	0.199		
BI	0.611	0.88	0.081	0.848	0.907	0.615	0.567	0.563	0.629	0.742	0.633	0.628	0.084	0.055	0.142	0.905	

5.3. Hypotheses testing

The VIF values below 5 (see Table 6) for the structural model suggest no collinearity issues. The proposed model separately explained 57.6%, 74.5%, and 66.4% of the variance in perceived usefulness, perceived satisfaction, and continuance intention (Table 6 and Fig. 2). Confirmation significantly influenced perceived usefulness (H6) and satisfaction (H7) with effect sizes of 0.739 and 0.219, respectively. Perceived usefulness

significantly affected perceived satisfaction (H3) and continuance intention (H4) with effect sizes of 0.137 and 0.064, respectively. Assessment (H19), perceived satisfaction (H5), and autonomous motivation (H9) also significantly affect continuance intention with effect sizes of 0.059, 0.045, and 0.044, respectively.

Table 6
Results of hypothesis testing

Hypothesis	Path	VIF	Path coefficient	Effect size	t-value	Hypothesis supported?
H1	PEOU→PU	1.697	0.044	0.003	0.578	No
H2	PEOU→BI	2.016	0.022	0.001	0.295	No
H3	PU→PS	2.768	0.311	0.137	3.609***	Yes
H4	PU→BI	3.315	0.267	0.064	2.49**	Yes
H5	PS→BI	4.094	0.25	0.045	2.517**	Yes
H6	CO→PU	1.697	0.729	0.739	10.582***	Yes
H7	CO→PS	3.181	0.422	0.219	4.652***	Yes
H8	CM→BI	1.428	0.005	0	0.076	No
H9	AM→BI	3.886	0.241	0.044	2.45**	Yes
H10	CS→PS	1.89	0.1	0.021	1.403	No
H11	CQ→PS	1.688	0.006	0	0.098	No
H12	IS→PS	2.141	0.073	0.01	0.941	No
H13	CS→BI	2.452	-0.012	0	-0.169	No
H14	CQ→BI	1.724	0.053	0.005	0.761	No
H15	IS→BI	2.183	-0.024	0.001	-0.332	No
H16	LR→PS	2.368	0.105	0.018	1.429	No
H16	LR→BI	2.363	-0.085	0.009	-0.959	No
H17	AS→PS	2.224	-0.028	0.001	-0.39	No
H17	AS→BI	2.183	0.207	0.059	2.681**	Yes
H20	PR→PS	2.378	0.024	0.001	0.291	No
H21	RE→PS	1.926	-0.005	0	-0.075	No
H22	PR→BI	2.437	-0.082	0.008	-0.912	No
H23	RE→BI	2.058	0.107	0.017	1.331	No
H24	PD→PS	1.808	0.026	0.001	0.446	No
H25	PW→PS	1.369	-0.032	0.003	-0.643	No
H26	CC→PS	1.445	-0.007	0	-0.104	No
H27	PD→BI	1.845	0.028	0.001	0.478	No
H28	PW→BI	1.646	-0.067	0.008	-1.054	No
H29	CC→BI	1.473	-0.009	0	-0.115	No

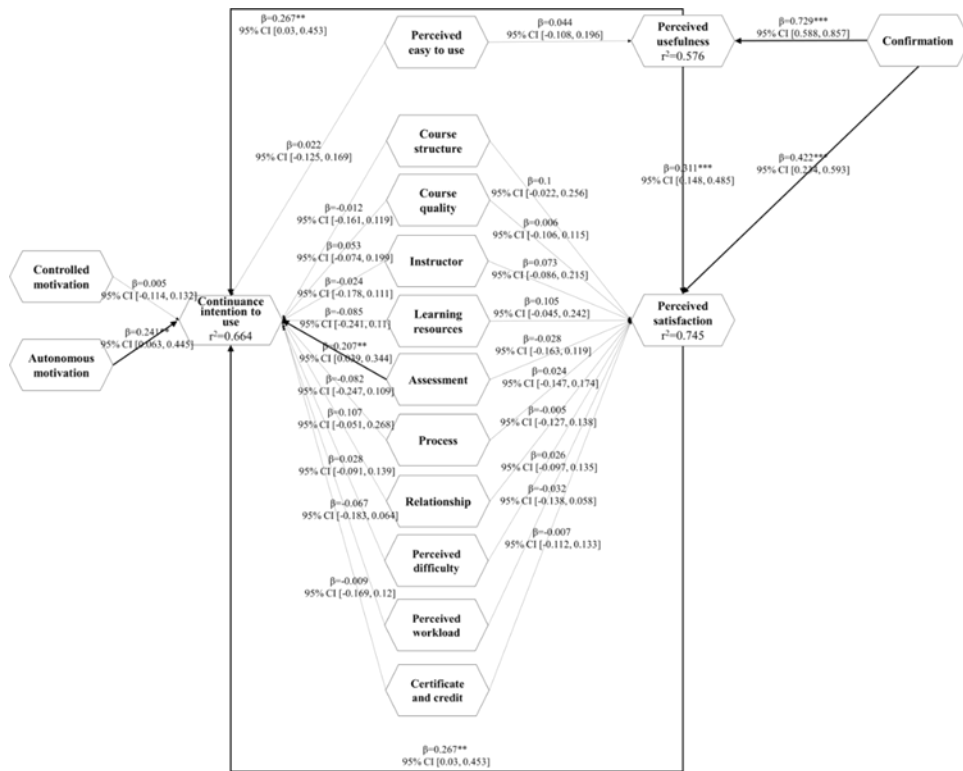


Fig. 2. Results of structural model analysis

5.4. Qualitative analysis of interview data

The interview data were examined from the perspectives of learning motivation, MOOCs' benefits and problems, and intention for future use.

Motives for MOOC use. Four types of motivations were identified, including individual interest (7 interviewees), need for supplementary learning (6), requirements of schools, teachers, or employers (5), and eagerness to promote academic and job performance (2). Such results somewhat confirm the PLS-SEM results in highlighting the importance of autonomous motivation and perceived usefulness in motivating learners' learning in MOOCs. The following quotes demonstrate the four types of motivations:

"At that time, artificial intelligence was too popular, and many of my former lab partners were learning AI. Then I felt that it was fun, and I wanted to learn" (Individual interest, Interviewee 1).

"When I'm taking a course, I usually want to see how other teachers teach this course, for example, the instructional methods and see if there is any gap in my learning that can be filled" (Supplementary learning for formal study, Interviewee 6).

"I took my first MOOC because of a mandatory learning requirement by my employers, and I had to complete the course to earn the required credits" (Requirement of schools, teachers or employers, Interviewee 10).

“The second is to search for courses to learn things that I previously didn’t know and see if it can help me make up for my current knowledge shortcomings” (Self-promotion, Interviewee 6).

Perceived benefits of MOOCs. Most interviewees mentioned that MOOCs empower them to learn whenever and whatever they want and that they could attend courses taught by instructors whose teaching styles fit them the most. There are also interviewees reporting the rich curriculum resources (4 interviewees), charging no or very low fees (3), the use of tests and assignments (3), and interaction via discussion forums (3). Other benefits include rich lecture resources and video repeating and re-watching. The following excerpts illustrate some of the benefits.

“You can take MOOCs when you have time and when you want, and then choose what you want to learn” (Allowing self-learning, Interviewee 4).

“Such a platform can really give learners the opportunity to get in touch with the better courses or teachers of those very top universities. There is a team to prepare the lessons which are then delivered in the form of a series of MOOCs, which is very systematic” (Rich curriculum resources, Interviewee 6).

“If we have the Internet, we can choose courses to learn according to our own needs and interests. The cost is actually very low” (Economicalness, Interviewee 6).

“The advantage is that it has a detailed arrangement of testing, with specific grading criteria, corresponding tests in the middle of the course, homework, and final exams” (Use of tests and assignments, Interviewee 4).

“It allows students to discuss in the discussion forum, and you can see what others are paying attention to” (Availability of discussion forum, Interviewee 7).

Perceived problems of MOOCs. Most interviewees complained about a lack of interaction (9 interviewees), followed by poor-quality content (5), and insufficient instructor feedback (4). Other disadvantages include high requirements for self-learning abilities, poor course outlines, and instructional methodologies. See the following examples for the above complaints:

“The interaction is poor. It is not like offline. In MOOCs, there is no emotional connection between teacher and students” (Low level of interactivity, Interviewee 1).

“Some courses are fragmented, and you have no or limited understanding about the subject you are going to learn” (Low quality of course content, Interviewee 3).

“Teaching feedback or classroom interaction is not timely. The MOOC seems to be following the script in advance” (Instructor feedback, Interviewee 10).

“I think the MOOC requires too high [motivation] for students to learn independently” (High requirement for self-learning ability, Interviewee 6).

Motives for future use of MOOCs. Three types of motivations were identified, including individual interest (8 interviewees), requirements of schools/employees (6), and eagerness for self-promotion (2). Such results corroborate the PLS-SEM results as they both demonstrate the significance of perceived usefulness and autonomous motivation in promoting continuance intention. The following excerpts illustrate these motivations:

“If content happened to be something I wanted to learn, and I found that the MOOC happened to have the course taught by a well-known researcher, then I would take it” (Individual interest, Interviewee 10).

“I may search relevant MOOCs because I have some needs at work recently, but the specific choice of courses depends on whether there is a suitable course” (Need for learning or work, Interviewee 1).

“I will take MOOCs when I want to improve myself” (Self-promotion, Interviewee 11).

6. Discussion

The present study proposed and tested a conceptual model with joint consideration of TAM, ECM, SDT, and course design and implementation effects for a fine-grained understanding of MOOC learners' satisfaction and continuance intention. The PLS-SEM analysis of questionnaire data collected from 168 Chinese MOOC learners showed the model's satisfactory explanation power for perceived usefulness (57.6%), perceived satisfaction (74.5%), and continuance intention (66.4%). Seven hypotheses were proved: PU→PS (H3), PU→BI (H4), AM→BI (H9), PS→BI (H5), AS→BI (H19), CO→PU (H6), and CO→PS (H7). These results provide important insights into effective MOOC design and operation.

6.1. Effects of SDT on continuance intention

H8 and H9, regarding controlled and autonomous motivations' influences on continuance intention, were partly supported by the empirical data. H8 about the relationship between controlled motivation and continuance intention (H17) was not significant. Such a result has been reported by Zhou (2016), who identified indirect relationships between controlled motivation and intention and the insignificant effects of social influence known as a type of controlled motivation on behavioural intention, respectively. However, some researchers have reported the opposite findings. For example, Xu (2015) showed the direct effects of subjective norms, known as a type of social influence, on learners' behavioural intention. Xiong et al. (2015) suggested that social motivation can influence MOOC learners' retention through intrinsic and extrinsic motivations. An explanation for the insignificant of controlled motivation may be that individuals' decisions to attend a course can be affected by social pressure or influence (Pozón-López et al., 2021).

The present work confirmed the positive effect of autonomous motivation, referring to a set of internal incentives driving learners' behaviours, on continuance intention (H9). Such a result has been reported by Pozón-López et al. (2021) and Xiong et al. (2015). We can also find supporting evidence from the interview data as most interviewees demonstrated individual interests and eagerness for self-improvement as the key drivers for their MOOC learning and continuance intention. Such a finding highlights that individual motivation significantly affects learners' intention to reuse MOOCs, which echoes previous research. For instance, Milligan and Littlejohn (2017) reported that most learners used MOOCs as a means to prepare for careers or as a supplementary source for formal learning, while professionals took MOOCs due to current and future needs for promoting job performance. The results also confirm several researchers' findings of intrinsic motivations like learners' interests in course content and courses' utility values as major motives for online learning enrollment. Similarly, de Barba et al.

(2016) demonstrated the important roles of learners' situational interests, achievement goals, and value beliefs in motivating them to participate in MOOCs.

Our result concerning autonomous motivation's significance echoes SDT, which suggests that if a task satisfies a person's needs, then he or she is more likely to persist and show better performance (Pozón-López et al., 2021). In MOOCs, learners' needs are commonly related to eagerness to learn new skills and knowledge for self-improvement or job promotion. The concept of "autonomy needs", as basic psychological needs in SDT, reflects MOOC learners' needs to make options and have freedom of choice. In MOOCs, learners' autonomy needs can be satisfied when they are allowed to choose what and when they want to learn (Fang et al., 2019). According to SDT, perceived autonomy support can enhance intrinsic motivation. Fang et al. (2019) also suggested that when learners' autonomy needs are satisfied, their enjoyment and engagement in learning and interaction with instructors and peers can be enhanced, thus promoting their continuance intention. The significance of autonomy needs satisfaction has also been demonstrated by interviewees.

"The time of class is not fixed. It can be at home or in a dormitory. It is not compulsory as you do not have to go to school to take classes" (Interviewee 11).

"The advantage is the fast-forward function. If there is something that you don't think you are very interested in or that you are more familiar with, then you can quickly skip it" (Interviewee 7).

To promote learners' motivation to learn in MOOCs, Interviewee 1 suggested the use of course recommenders to recommend MOOCs in accordance with individuals' needs and requirements.

"It would be useful if MOOCs can recommend courses through big data analysis or correlation analysis or some recent popular courses".

6.2. Course design and implementation effects on satisfaction and continuance intention

Regarding course design and implementation effects, only H19 pertaining to assessment's effect on MOOC learners' continuance intention was empirically supported, whereas other hypotheses were not confirmed. These results have also been reported in the literature. For instance, Dai et al. (2020a) suggested that interaction could not significantly affect online learners' engagement and satisfaction. Hew et al. (2020) reported that interaction played no significant role in affecting learners' satisfaction.

We identified course quality as an insignificant variable. This is inconsistent with Fianu et al. (2018). The difference is mainly caused by measurement differences. This study compared MOOCs' quality with that of offline courses, whereas Fianu et al. (2018) used information and content quality as indicators. It is also possible that content's effect on satisfaction or continuance intention should be measured via the mediation of perceived effectiveness (Hone & El Said, 2016). Regarding the insignificance of course structure, one probable reason is provided by Hone and El Said (2016), who suggested that "course structure may to some extent be a solved problem within the major MOOC platforms" (p. 166). The insignificant effect of learning resources referring mainly to the lecture videos is because the video is only a medium used by instructors to present the course content (Hew et al., 2020); therefore, the use of videos is unlikely to influence MOOC learners' satisfaction. Certificates and credits are unlikely to affect satisfaction and retention because learners enrolling in MOOCs are mainly driven by individual

interests or needs for self-improvement. Perceived difficulty does not influence satisfaction or continuance intention directly, but it might affect satisfaction/retention's relationship with variables such as instructor knowledge. For instance, students would expect instructors to be knowledgeable when facing course content that is difficult to understand. The insignificance of perceived workload is mainly because most students consider MOOCs a "just-in-time" resource to get what they want (Davis et al., 2017). The reasons for the instructor's insignificance can be obtained from the interview data. According to interviewees, they mainly took top courses rated by MOOC providers. Also, most of them would check previous learners' comments on MOOCs to choose those rated high regarding the quality of instructors and content to enrol. Regarding perceived ease of use, its insignificant influence is mainly because most learners are familiar with Internet and technology use; thus, it is less likely that they would have difficulties using MOOCs.

Regarding the insignificance of interaction and feedback, one explanation is that Chinese students have been customized to such types of instructor-led courses with limited interaction. As Cortazzi and Jin (1996) stated, for most Chinese learners, "the best use of class time is for the teacher to explain things" (p. 30). Also, most interviewees consider the insufficient interaction/feedback acceptable because it is difficult for an instructor to pay attention to every learner in large classes. Thus, learners usually have low expectations about interaction and feedback.

While factors such as course structure, course quality, learning resources, instructor influence, and interaction did not exhibit significant direct influence on continuance intention in our study, they may show indirect and contextual influences within the Chinese MOOC context. For example, while course structure and quality may not directly impact continuance intention, they may play crucial roles in shaping learners' initial satisfaction and perceptions of the course, thereby indirectly influencing their likelihood of continued engagement. Similarly, the influence of instructors and interaction may be mediated by cultural preferences for self-directed learning or alternative modes of knowledge acquisition. Therefore, future work may consider exploring the indirect and contextual influences of these factors within the Chinese MOOC context.

The significant effect of assessment on continuance intention aligns with the emphasis placed on academic performance and credentialing within the Chinese educational system. In China, assessments are often closely linked to academic advancement and professional opportunities, thereby influencing learners' decisions to continue their engagement with MOOCs. Furthermore, the prominence of assessment in driving continuance intention may reflect Chinese learners' motivations for seeking tangible outcomes and recognition of their efforts, particularly in a competitive educational environment. Such a result is supported by prior research. Bali (2014) highlighted assessments' potential to allow learners to apply learned knowledge and skills. Hew (2016) also suggested that active learning and knowledge application play important roles in promoting engagement. According to Littlejohn et al. (2016), most learners value assessment's importance in keeping themselves informed about their progress and performance. To improve assessment quality in MOOCs, interviewees have suggested including problem-solving processes in learning evaluation and using unexpected questions:

"When evaluating students' assignments or tests, some students could quickly grasp and implement the optimal methods taught by the teacher; some only use stupid methods. Although the task could also be completed, the effectiveness and efficiency of the methods were different. It is thus suggested to distinguish different

levels of certificates of completion, for example, qualified and excellent” (Interviewee 1).

“Teachers can use some unexpected questions, like those questions that students generally don’t think will be asked. In this way, students will have to be more concentrated throughout the whole course” (Interviewee 7).

6.3. Effects of TAM and ECM on satisfaction and continuance intention

As for the effects of TAM and ECM, the results showed that perceived usefulness significantly affects satisfaction (H3) and continuance intention (H4). Such a result is supported by Teo and Dai (2022), who also reported that perceived usefulness significantly influenced satisfaction and continuance intention, indicating that usefulness is critical for promoting MOOC learners’ satisfaction and retention (Lu et al., 2019). When students perceive MOOCs to be useful, they tend to be satisfied and would continue to learn (Hone & El Said, 2016). The significant influence of perceived satisfaction on continuance intention (H5) is supported by Lu et al. (2019), who suggested it is essential to make students satisfied with their first MOOC course to motivate them to reuse MOOCs (Joo et al., 2018). We additionally identified confirmation as a significant variable in promoting learners’ perceived satisfaction (H7) and usefulness (H6). Such a result confirms Alraimi et al. (2015) and is in line with ECM’s postulation of the positive effect of usage confirmation of information systems on perceived satisfaction and usefulness.

However, consistent with Teo and Dai (2022) and Pozón-López et al. (2021) perceived ease of use does not significantly affect perceived usefulness (H1) and continuance intention (H2). One explanation originates from the prevalence of learner-friendly designs and ubiquitous technologies (Teo & Dai, 2022). According to Mendoza et al. (2017), when learners do not regard MOOCs as difficult to use, they are not worried about technical challenges. As the interview data shows, almost all students have lots of experience in using technologies; thus, it is unlikely that they would have technical difficulties in using MOOCs.

6.4. Implications

Our study offers several practical implications for educators, course providers, and policymakers involved in the design and operation of MOOCs, particularly within the Chinese context. First, by identifying assessment as a significant factor influencing MOOC learners’ continuance intention, our findings emphasize the importance of incorporating well-designed assessment strategies into MOOC courses. Educators and course providers can enhance learner engagement and retention by implementing assessments that align with learners’ needs and promote meaningful learning experiences.

Second, our study underscores the importance of recognizing learners’ autonomous motivations, such as individual interests and eagerness for self-improvement, in promoting continuance intention. Educators and course providers can leverage these intrinsic motivations by designing courses that cater to learners’ interests and provide opportunities for personal growth and skill development. Third, by confirming the positive influences of perceived usefulness and confirmation on learner satisfaction, our research highlights the significance of meeting learners’ expectations and delivering valuable learning experiences. Course providers can focus on enhancing course utility, relevance, and effectiveness to ensure learner satisfaction and promote continued

engagement with MOOCs. In addition, our findings provide valuable insights for policymakers tasked with shaping the future of MOOC development and implementation in China. By understanding drivers for MOOC learners' satisfaction and continuance intention, policymakers can support initiatives that foster a conducive environment for online learning and promote the widespread adoption of MOOCs as a valuable educational resource.

Several theoretical implications are also presented. First, by integrating multiple theoretical frameworks, including TAM, ECM, SDT, and considerations of course design and implementation effects, our study offers a comprehensive model for understanding MOOC learners' behaviours. This integrated approach enriches existing theoretical perspectives and provides a nuanced understanding of the mechanisms underlying learner satisfaction and continuance intention. Second, our focus on Chinese MOOC learners contributes to the growing literature on cultural and contextual differences in online learning. By addressing the unique characteristics and needs of Chinese learners, our study enhances the generalizability and applicability of theoretical frameworks within diverse cultural contexts. In addition, through empirical validation of our conceptual model using PLS-SEM analysis, the present work offers empirical support for the relationships proposed within the theoretical framework. This validation strengthens the theoretical foundation of our study and contributes to the cumulative knowledge base in online learning research.

6.5. Limitations and future work

The present study has limitations. First, the survey was performed based on self-reporting scales. According to Bayeck (2016), it can be difficult to evaluate participants' actual experiences from self-reported responses. Although interviews were conducted, there were only 11 interviewees. Thus, triangulation with additional sources like behavioural indicators (e.g., log-in data and click data) and interviews with more participants can be considered in future research. Second, there might have been other factors that were not considered. For instance, Bornschlegl and Cashman (2019) reported entertainment level's positive correlation with satisfaction. Future work should consider investigating the effects of other determinants, for example, perceived reputation and enjoyment. Third, this study does not explore the relationships between the constructs over time. Further analysis is needed to validate the conceptual model, particularly by using longitudinal studies to understand the variables' causality and interrelationships. Moreover, a larger sample can be considered in future research to verify the results. Also, as the survey was carried out in Mainland China, future work can consider including data collected from more research settings. In this way, the sample and thus the results can be more representative.

Regarding the usage of single-item indicators for some of the PD and PW variables in our proposed conceptual model. The decision was based on empirical evidence from prior research (e.g., Hew et al., 2020; Jing & Zhao, 2020). For example, in Hew et al. (2020), PD was measured by rating the perception of the difficulty level of the MOOC content, while PW was assessed by inquiring about learners' perceptions of the value or worthiness of the course. To further validate the reliability and robustness of our measures, we conducted statistical analyses such as reliability tests (e.g., Cronbach's alpha) and validity checks (e.g., discriminant validity) using the collected data; the results confirm the satisfactory psychometric properties of these single-item measures according to Loo (2002). However, future work may consider using multiple-item measures for PD and PW constructs to examine their relative strengths and weaknesses.

In addition, unbalanced distributions of respondents' demography (for example gender) are observed, which may introduce potential bias. This limitation is also reported in other survey studies (e.g., Ho et al., 2017; Deb et al., 2024). Nevertheless, the findings are generalizable as the data was collected via various channels and targeting a wide range of MOOC and social media platforms (e.g., WeChat, xMOOC, and XuetaangX). In future work, researchers can expand the current study to include a broader geographical area and respondent categories to gain more insight into Chinese MOOCs.

7. Conclusion

The present study sets a precedent by investigating the driving factors for MOOC learners' satisfaction and continuance intention with joint consideration of TAM, SDT, ECM, and MOOC design and implementation effects. A PLS-SEM methodology was implemented to analyze survey data collected from 168 MOOC learners in Mainland China to empirically examine MOOC sustainability and fulfil China's mission for MOOCs. Results showed that the conceptual model explains 74.5% variations in learners' satisfaction and 66.4% variations in their continuance intention. Perceived usefulness that has a positive influence on satisfaction and continuance intention is a dominant driver for MOOC success. Assessment and autonomous motivation have positive effects on continuance intention; the associations between confirmation of learners' expectations, perceived usefulness, and satisfaction are significant. Our study reveals learners' interests and eagerness for self-improvement are the key motives for their enrollment in MOOCs. Findings are expected to inform instructors and course providers about the effective design and operation of Chinese MOOCs to promote learners' continuance intention and satisfaction.

The contributions of this study can be summarized as follows. First, this study offers a novel approach by integrating multiple theoretical frameworks, including TAM, ECM, and SDT, along with considerations of MOOC design and implementation effects. This comprehensive model allows for a nuanced understanding of the mechanisms underlying MOOC learners' behaviours, which has not been extensively explored in the existing literature. Second, this study specifically targets Chinese MOOC learners, a population with distinct characteristics and needs compared to Western counterparts to address cultural and contextual differences. By focusing on Chinese learners, we contribute to this call for localization and provide insights tailored to the Chinese MOOC landscape. Beyond theoretical contributions, the findings have practical implications for educators and policymakers involved in MOOC development and implementation in China. By identifying significant determinants influencing learners' intentions to continue MOOC participation, we offer actionable insights for designing effective learning assistance and interventions.

Author Statement

The authors declare that there is no conflict of interest.

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Appendix I

Survey questionnaire

The objective of this survey is to identify the factors that influence MOOC learners' satisfaction and continuance intention. I would appreciate it if you could complete the following table. I assure you that the information you give will be considered confidential and will not be shared with any other party.

1. What is your sex

A. Male B. Female

2. What is your age

A. 18 and below B. 19 to 22 C. 23 to 25 D. 26 to 28 E. 29 and above

3. What is your educational level

A. Below undergraduate B. Undergraduate C. Postgraduate and above

4. What is your major

A. Humanities B. Social Sciences C. Science and Engineering D. Others

5. What is your experience of Internet use

A. 2 years and below B. 3 to 4 years C. 5 to 6 years D. 7 to 8 years E. 8 years and above

6. How many hours per week can you spend on MOOCs

A. 2 hours and below B. 3 to 4 hours C. 5 to 6 hours D. 7 to 8 hours E. 9 hours and above

7. Using a scale of 1 to 5, where 1 means "Strongly agree", 2 means "Agree", 3 means "Neutral", 4 means "Disagree", and 5 means "Strongly disagree", please select the rating that best describes your experience of MOOCs learning.

Construct	Questionnaire items	1	2	3	4	5
Course structure	CS1: The structure of the modules was well-prepared and well-organized					
	CS2: Learning objectives of each module in the iMOOC are quite (obvious) clear to the learner					
Course quality	CQ1: The fact that MOOCs are conducted via the Internet means they are of better quality than other (offline) courses					
	CQ2: I do not think the quality of a MOOC is influenced by the fact that it is undertaken via the Internet					
Instructor	IS1: I found the instructors to be knowledgeable in the subject matter					
	IS2: I believe instructors are credible in teaching the subject matter					
	IS3: I was comfortable with the pace of instruction					
Learning resources	LS1: The video definition of the course meets my visual requirements.					
	LS2: The teaching materials are well-organized and presentable					

	LS3: Learning resources of the curriculum are diverse						
Assessment	AS1: The mini-projects, quizzes, and assignments deepen my understanding						
	AS2: I feel the difficulty of the test is moderate.						
	AS3: I believe the evaluation criteria and methodology are reliable to adequately measure my learning						
Process	PR1: The instructor provided helpful timely feedback on assignments, exams or projects						
	PR2: Faculty or staff are actively helpful when students have problems						
	PR3: Real-life scenarios, relevant examples and real-world cases used in the teaching process are helpful in facilitating my understanding						
	PR4: MOOCs had weekly synchronous activities such as guest presenters, live weekly recaps, Q&A sessions, and projects help sessions to stimulate learning						
Relationship	RE1: Student interaction was an important learning component of MOOCs						
	RE2: This course provided an opportunity to learn from other students						
	RE3: The instructor contributed to the discussions in MOOCs						
	RE4: MOOCs provide an opportunity to share progress and interact with others on the discussion forum or via social media and email						
Certificate and credit	CC1: Certificate of attendance plays an important role in my decision to take a MOOC						
	CC2: Credit plays an important role in my decision to take a MOOC						
Perceived difficulty	PD1: I feel the learning tasks of MOOCs are difficult for me to complete						
Perceived workload	PW1: Using MOOCs can take up too much of my time when performing many tasks.						
Perceived easy to use	PEOU1: I find MOOCs easy to use.						
	PEOU2: It is easy to get MOOCs to do what I want them to do.						
	PEOU3: It is easy to become skilful at using MOOCs.						
Controlled motivation	CM1: I use MOOCs because other people say I should						
	CM2: I feel under pressure from my friends/family/spouse to use MOOCs						
Autonomous motivation	AM1: I think using MOOCs is important for learning						
	AM2: I value the benefits of using MOOCs						
	AM3: I think it's important to make an effort to use MOOCs to learn						
	AM4: I think using MOOCs can satisfy my diverse educational needs (e.g., academic and job-related)						
Confirmation	CO1: My experience with using MOOCs was better than I expected.						
	CO2: The service level provided by MOOCs was better than I expected.						
	CO3: Overall, most of my expectations from using MOOCs were						

	confirmed.					
Perceived usefulness	PU1: The use of MOOCs can help me understand the knowledge learned.					
	PU2: Using MOOCs would improve my learning performance.					
	PU3: Using MOOCs would improve my learning productivity.					
Perceived satisfaction	PS1: I was very satisfied with the MOOC course.					
	PS2: Learning in MOOCs is a very delightful experience					
Continuance Intention to use	BI1: I intend to spend more time on using MOOCs					
	BI2: I will use MOOCs on a regular basis in the future					