A meta-analysis of the moderating role of prior learning experience and mandatory participation on factors influencing MOOC learners' continuance intention

Min Zhang, Sihong Li
Wuhan University, China

Yan Zhang
University of the Chinese Academy of Sciences, China

Retaining learners has been an important issue for massive open online course (MOOC) platforms. Given the different, and even contradictory, conclusions in studies on the continuance intention of MOOC learners, this study selected 53 highly correlated empirical studies published from 2008 to 2022 and constructed a research model based on visual knowledge map analysis. Meta-analysis was applied to identify the key factors, and subgroup analysis was conducted to explore the moderating effect of mandatory participation and prior learning experience. The results show that attitude and satisfaction play the most significant role. Perceived usefulness, perceived ease of use, confirmation, social influence, perceived enjoyment, outcome expectation, self-efficacy and task-technology fit all play essential functions, while the direct impact of social presence requires further research. Prior learning experience and mandatory participation have moderating effects on perceived usefulness. MOOC developers should make more efforts and improvements in content quality, social quality and service quality.

Implications for practice or policy:
- Learners' continuance intention can be enhanced by improving individual perceived positive feelings related to MOOCs and individual satisfaction with MOOC platforms.
- Directors of mandatory courses in MOOCs should place greater emphasis on improving learners' perceived ease of use of MOOC platforms.
- Superintendents of MOOC platforms need to be aware of the role of perceived usefulness of learners with less prior learning experience in their continuance intention.

Keywords: MOOC learners, continuance intention, prior learning experience, mandatory participation, meta-analysis

Introduction

Massive open online courses (MOOCs) refer to learners' network learning based on MOOCs' online learning information systems (ISs; Kizilcec et al., 2013). The outbreak of the novel coronavirus disease (COVID-19) has increased the demand for online education (Zayapragassarazan, 2020), indicating new opportunities for educational reform. In such a context, MOOCs, as the core of the international strategic action of educational digitisation, have attracted increasing attention because they can provide an efficient and effective alternative solution for the long-term sustainable development of traditional classroom education during the pandemic.

However, for some people, MOOC learning may be a trend. The latest statistics show that the dropout rate of MOOCs is as high as 90% (Gu et al., 2021), which is why scholars have begun to pay increasing attention to learners' continuous use behaviour. Alemayehu and Chen (2021) recommended that more attention should be paid to investigating learners' intentions. Therefore, it is of great theoretical value and practical significance to study the continuance intention (CI) of learners with MOOCs. After a systematic literature review of existing studies, three research gaps were identified as follows:

First, despite the accumulation of various theories and models on the continuation of technological innovation, such as the expectation confirmation model (ECM) and the technology acceptance model (TAM), the literature abounds in diverse but often contradictory findings. Research includes contradictions on whether the perceived usefulness (PU) of and satisfaction (SAT) with MOOCs are significantly related (Alraimi et al., 2015; Lu et al., 2019). There is also controversy about whether self-efficacy (SE) directly impacts MOOC continuation (Jung & Lee, 2018; Wu & Chen, 2017). It is necessary to review and summarise research and explore the framework of CI in MOOCs to offer insights into overcoming these issues through its influencing factors.

Second, the impact of whether the course takes strict measures to control participation has not been sufficiently studied. IS research attributes mandated and voluntary use to two separate information technology (IT) usage environments (Du et al., 2022). According to mandatory participation, MOOC types are divided into mandatory and self-paced extracurricular tasks. A mandatory course in MOOCs is an online course arranged by the school, which requires students to attend and participate in assessments to obtain college credits. Correspondingly, a self-paced course in MOOCs refers to learners' active learning of an online course based on their own will, which is a non-mandatory out-of-classroom task. According to the theory of planned behaviour, perceived social pressures (or subjective norms) may make learners carry out a behaviour (or not) (Cheon et al., 2012). However, M. Zhou (2016) suggested that external pressure or demand did not interfere with students' decisions to opt in or out of a MOOC. Due to the unsystematic study of MOOC course types, it is necessary to deeply study learners' behaviour in relation to different subdivided course types and explore the influencing factors of learners' CI of different MOOC types to provide targeted insights for personalised services.

Third, the role of prior learning experience in mediating MOOC CI has not attracted much attention. The transition from traditional classroom learning to online learning cannot be accomplished overnight, because users need time to adjust (Arbaugh, 2004), and users' beliefs and attitudes change over time (Venkatesh, 2000). Prior learning experience helps students actively participate in learning (Milligan et al., 2013), and the more experienced learners are, the more rational they are (Wang et al., 2019). However, with the increase in online learning time, positive as well as adverse experiences will increase simultaneously. Negative events affect learner SA (K.-L. Lin et al., 2011), thereby affecting CI. Due to the lack of in-depth analyses of learning experiences, it is necessary to pay more attention to learning behaviour in the context of these experiences.

Based on the above discussion, two research questions were proposed as follows:

- Given the contradictory conclusions presented in single studies focusing on specific situations and when multiple studies focusing on different situations are regarded as a class of scientific problems, what integrated conclusions can be drawn about the influence of these key factors on MOOC learners' CI?
- How did mandatory participation and learners' prior learning experience moderate their CI?

To answer the first question, this study attempted to use meta-analysis to provide a comprehensive theoretical framework for MOOC learners' CI. The meta-analysis, proposed by Glass (1976), enables statistical analysis of quantitative data from different studies to integrate research results, which draws accurate and credible conclusions and is applied to identify critical factors. Therefore, this study first constructed a visual knowledge map of relationships among factors in existing research based on the selected literature and then obtained a comprehensive model of MOOC learners' CI through meta-analysis. To answer the second question, subgroup analysis was applied to classify the study sample types corresponding to two moderator variables, moderate them to establish cumulative knowledge and provide more accurate and robust action guidelines for practice (Ringquist, 2013).

Background

Factors influencing IS users' CI

CI of IS focuses on influencing factors of the long-term use of ISs (Franque et al., 2020). The TAM and the ECM are the most common models explaining CI in ISs.

The TAM is the most widely recognised behavioural intention model in IS disciplines (Q. Ma & Liu, 2004) and is used to examine the relationship between PU, perceived ease of use (PEOU), and attitude (ATT). PU is the degree to which a particular system is perceived to improve performance (Sánchez & Hueros, 2010). PEOU is the degree to which people think using a particular system would be reasonably straightforward (Saadé & Bahli, 2005). ATT refers to how favourable or unfavourable someone evaluates or appraises the behaviours in question (Fishbein & Ajzen, 1977). However, the TAM concerns only short-term beliefs and attitudes before or after the acceptance of an IS and has limitations in explaining eventual CI (Joo et al., 2018). Thus, the TAM has better explanatory power when combined with more external factors (C. Lin et al., 2012).

Compared with the TAM, the ECM focuses on factors affecting CI (Bhattacherjee, 2001), which theorises evaluations of system usage based on past experiences. The ECM introduces SAT to explain CI. SAT reflects the positive or pleasant emotional state in work evaluation (Locke, 1976), which is easily affected by confirmation of previous PU and IS usage expectations. Confirmation (CON) refers to the agreement between users' expectations and their performance in the IS (Bhattacherjee, 2001), which is the main factor affecting user SAT (Hu & Zhang, 2016).

Factors influencing MOOC learners' CI

The TAM and ECM have been extensively tested to effectively interpret the CI of online education (Daneji et al., 2019; Fang et al., 2019). Learners' PU, PEOU, ATT, CON and SAT of MOOCs have been found to significantly impact CI in MOOCs (Dai et al., 2020; Daneji et al., 2019; Shao, 2018).

Inevitably, as this body of work has grown, the empirical results are scattered and contradictory in some cases, generating puzzles and obstacles to theoretical research and practical application. Exploring the influencing factors of MOOC learners' CI from multiple perspectives is necessary.

In general, social environmental, course-related and learner-related factors are the three most significant factors in studying MOOC learners' behaviour. Social environmental factors can play a significant role in users' IS and IT adoption behaviour (Venkatesh et al., 2003). Social presence (SP) describes the salience of others and interpersonal relationships in interaction (Short et al., 1976), which is necessary to ensure an effective online learning environment (Garrison et al., 1999). Social influence (SI) in MOOCs refers to learners believing that important people would like them to continue learning through MOOCs (Venkatesh et al., 2003). Some MOOC learners, especially new learners, are very concerned about media coverage and advice from the people around them (J. Zhou, 2017).

From the perspective of the course, since the epidemic, MOOCs should meet the teaching needs brought about by the suspension of face-to-face teaching in schools, as well as the functional learning needs of learners. Task-technology fit (TTF) predicts learner performance and CI in MOOCs (Kim & Song, 2022; W.-S. Lin, 2012). TTF refers to a user's subjective assessment of whether a technology assists their tasks (Goodhue & Thompson, 1995).

Including learner-related factors in MOOCs is also significant (L. Ma & Lee, 2019). Perceived enjoyment (PE) refers to the degree to which people find delight without external reinforcement when carrying out missions (Davis et al., 1992). MOOCs provide users with a valuable platform for engaging in learning and serve the hedonic purpose of creating an enjoyable learning experience (Tao et al., 2022). Outcome expectation (OE) means the perceived results of certain actions (Hsu & Chiu, 2004). Outcomes of e-learning include skills-based outcomes, cognitive outcomes and affective outcomes (Yu et al., 2010). SE in social cognitive theory refers to one's confidence in organising and performing a task to achieve expected goals (Bandura, 2005). Learners with higher SE in MOOCs motivate themselves and regulate their learning for success (Komarraju & Nadler, 2013).

The moderating effect of mandatory participation and prior learning experience

It is worth noting that little is known about the relative importance of the various predictors of learners' CI in MOOCs because the results differ across studies and research contexts.

As mentioned above, the impact of course type on learners' CI is evident. In particular, whether the course is mandatory or not has a huge impact. When a MOOC is taken as a mandatory task, it is often regarded as part of the formal learning process and matches the compulsory credit plan. When MOOCs are self-paced extracurricular tasks, students struggle in an open, self-paced learning environment, often leading to low completion rates and procrastination (Dreisiebner et al., 2020). However, the results of a study conducted by Gregori et al. (2018), who believed that the quality of students' participation would be higher in self-paced extracurricular tasks because of their interests, were different.

User experience is an important moderating factor of IS use behaviour (Bhattacherjee & Premkumar, 2004). They found that the duration of learning has the most critical impact on the learning experience in the study of online learning continuation. The index of learning time may be used to reflect the learning experience (K.-M. Lin et al., 2011). Judgements of prior learning experiences are based on the length of time spent using MOOCs. In this study, we divided MOOC learners into a high-experience group and a low-experience group: the former had more than half a year of online learning experience or had participated in at least 1-semester online courses, while the latter refers to those who have participated in MOOCs for less than half a year or a semester. There have been relatively few studies in the literature specifically on low-experience learners. Thus, we classified studies that did not indicate the respondents' experience into the low-experience group.

Identification of factor and relationship network

Based on the analysis of the 53 empirical studies in the collected articles, this paper used Gephi to visually present 170 pairs of structural relationships. The visual knowledge map was developed as shown in Figure 1, where the node size increases with the number of times used in the literature. The label of the node that only appeared once was hidden. The maximum structures are in the centre of the figure, namely SAT, ATT, PU, PEOU, CON, SP, SI, PE, OE, SE, TTF and others. It should be noted that some variables may have different naming methods in different studies. Thus, these names were combined and presented as the same variable and a unified concept was used in this study. Moreover, some variables lacking direct theoretical support or discussed in only a few empirical articles were abandoned.

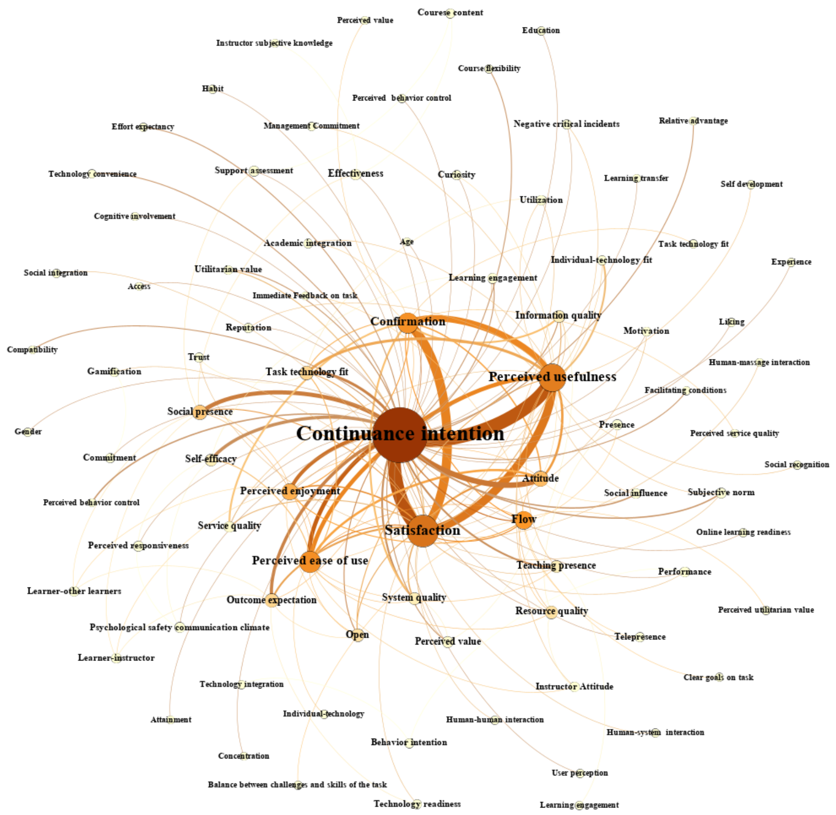

Figure 1. Factor and relationship network

Model construction

The most frequently occurring structures were incorporated into the research framework using the visual knowledge graph tool to construct the MOOC CI research model, as shown in Figure 2.

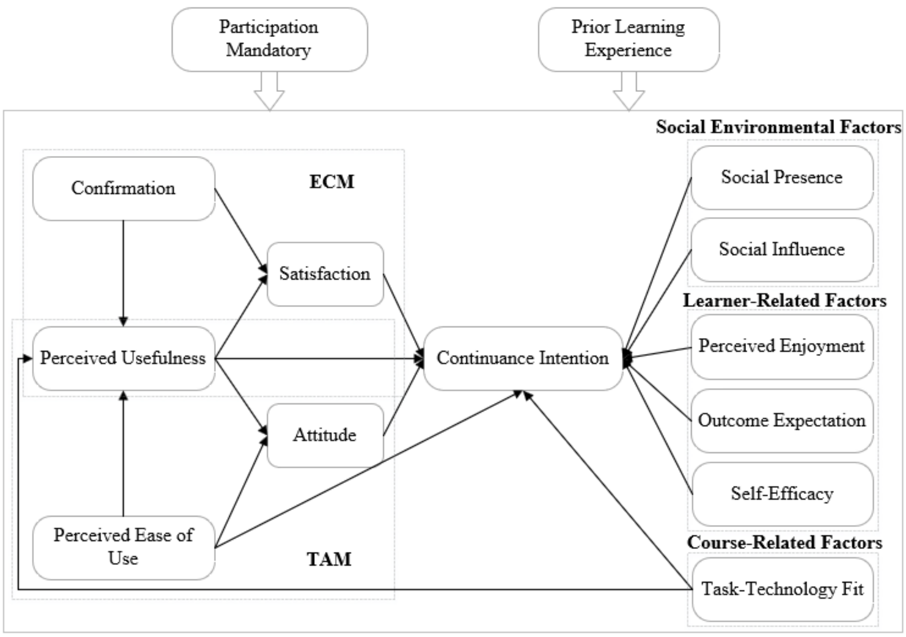

Figure 2. The research model of MOOC learners' CI

Methodology

Meta-analysis was applied to determine the influence of critical factors, and group analysis was conducted to determine the moderating effect of moderators. Previous literature has reported standard procedures of meta-analysis. This study followed the steps suggested by Lipsey and Wilson (2001) and Sabherwal et al. (2006), consisting of (a) searching for individual studies in the literature, (b) coding the identified studies and (c) analysing the accumulated findings. The steps are explained in more detail below.

Search process and eligibility criteria

The term *MOOC* was first created to describe the Connectivism and Connected Knowledge online course run by the University of Manitoba in 2008 (Goldie, 2016). Therefore, this study set the period for selecting the research samples from 2008 to 2022.

First, the following sites were visited: EBSCO, Web of Science, Elsevier, Emerald, Academic Search Complete, IEEE Xplore, ProQuest and Google Scholar to retrieve related studies by using the search formula of "(MOOC OR MOOCs OR e-learning OR online learning) AND (continuance intention OR continuous usage OR continuation)". Unpublished conference papers and proceedings were sought from conference websites, such as the Association for Educational Communications and Technology, the Association for the Advancement of Computing in Education, Sloan-C and the American Educational Research Association. This initial retrieval process identified 1826 studies suitable for meta-analysis.

Then, three experts in the field of online education research were invited to identify those works of literature highly related to the topic of MOOC CI by screening the titles and abstracts. Through this process, 236 studies were selected from the initial papers.

Moreover, we also reviewed the references of the confirmed highly related literature and conducted a forward literature search. Those that were highly relevant to this study but not yet included in the research sample pool were identified and supplemented into the study sample through manual search, which resulted in an additional 10 papers added to the literature search results. Among the 246 articles, 114 articles were empirical studies.

To ensure that all the data samples were suitable for the meta-analysis with predetermined criteria, we carefully read the abstract and appraised the research content of each article. Three screening conditions were adopted to clean the data samples: (a) must be an empirical study that investigated the learners' MOOC CI; (b) must report quantitative information about variables, including sample sizes, correlation coefficients, or other statistical data, such as *t* values, regression coefficients, mean and standard deviation; and (c) investigated subject must be an individual MOOC learner. Figure 3 illustrates the information and selection process of the included studies from published papers. Finally, 52 articles (with 53 studies) satisfied the above requirements and could be used for this meta-analysis because some articles reported more than one study. Studies of different sample sizes and correlation coefficients in the same article were considered different. See Appendices A and B for detailed information on these studies.

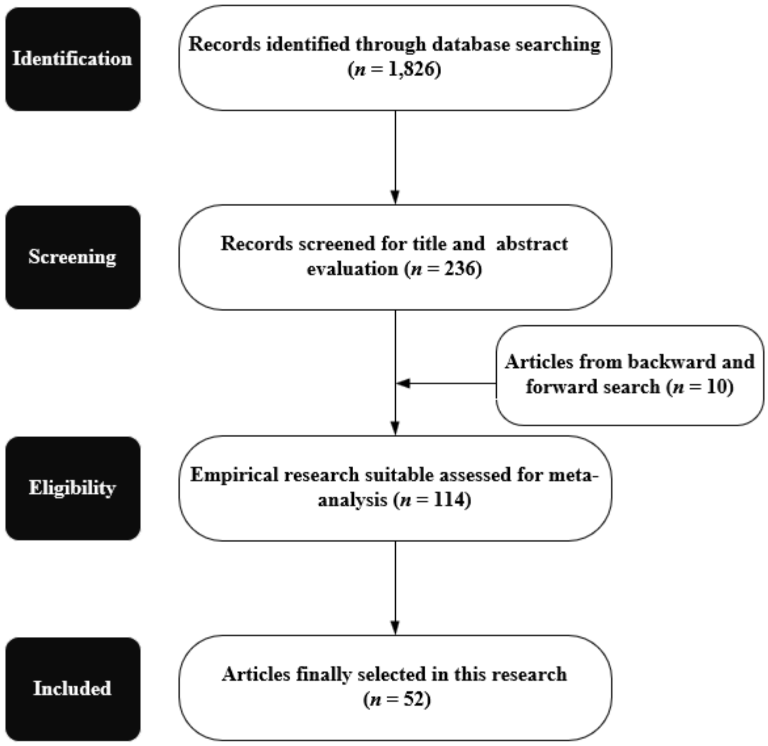

Figure 3. Flowchart of literature search

Coding of the studies

In the process of encoding the literature, we collected the following information: the authors' name, year of publication, title, sample size, type of online learning platform, learning experience, research model or theory, conceptual model, the key variables included and their Cronbach's alpha coefficient or comprehensive reliability value and the effect size. In addition, similar variables were merged into one variable. For instance, both perceived hedonic value and perceived fun meant learners' PE.

Based on the research model, this study conducted descriptive statistics on the collected path relationships in the 53 studies, obtained their correlation coefficients and reliability and tested the consistency and stability of the studies. The correlation coefficient *r* was used as the magnitude of influence in the meta-analysis. The regression coefficient can be used for studies where the correlation coefficient is not given (Wolf, 1986). Some studies took the form of structural equation models, and the following formula was used to convert the *t* value of a path into a correlation coefficient (Fleiss, 1993):

$$\mathrm{r} = \sqrt{t^2/(t^2 + df)} \quad (1)$$

where *t* represents the *t* value of the path and *df* represents the degrees of freedom.

Analysis of the accumulated findings

In the meta-analysis, to avoid measurement errors and sampling errors in different studies, the basic calculation formula in Excel was used to calculate the simple average of the correlation coefficient of each pair of relationships and calculated the adjusted average based on the sample size according to the following formula:

$$r_+ = \Sigma N_i r_i / \Sigma N_i \quad (2)$$

where r_i is the correlation in each Study i, and N_i is the number of samples.

Then, the Fisher *r* to *z* transformation on the path correlation coefficient was performed to obtain the changed correlation coefficient *z* as the merging effect value (Wolf, 1986) to adjust the data deviation caused by sampling variances. The formulas are as follows:

$$z = 0.5 * ln((1 + r)/(1 - r)) \text{ (3)}$$

$$z_{+} = \Sigma N_i Z_i / \Sigma Ni \text{ (4)}$$

$$r_z = Exp(2z_{+} - 1)/Exp(2z_{+} + 1) \text{ (5)}$$

where *r* is the relative correlation and Ni represents the sample size of Study i.

We applied the meta-analysis R software package to complete the correlation analysis in this study. The Metacor and Metabias functions were used to calculate the effect size, with a confidence interval of 95%, *z* test, heterogeneous statistics Q value, heterogeneous index I^2 and Egger's test. The 95% confidence interval was calculated to interpret the significance of the average effect size, and the 95% confidence interval excluding 0 suggests that the mean effect size is significant. The *z* test was used to evaluate the significance of the effect size of the relationship (Cram et al., 2019). The heterogeneity test was used to select a random-effects model or fixed-effects model for meta-analysis. The estimated average effect under the fixed-effects model was often more conservative than that under the random- effects model (Poole & Greenland, 1999). Therefore, the random-effects model was chosen as a theoretical method for the synthesis (Hedges & Vevea, 1998). Egger's test was used to test publication bias; if $p > 0.05$, the sample study had no publication bias and was regarded as reliable (Egger et al., 1997). Finally, a subgroup analysis (Q test) based on uniformity estimation was used to discover potential moderating effects.

Results

Descriptive statistics

Table 1 introduces the path relationship of the variables in the research model and their statistical data, including sample size and correlation coefficient. This study examined 17 pairs of relationships. Among them, SAT-CI was detected the most, with 29 studies, followed by PU-CI (28 studies), while PU-ATT and TTF-CI were detected the least, with only 5 studies. In most of these studies, the significance level was higher than 80%, and the average sample size of the path relationship was more significant than 200.

Table 1
Descriptive statistics

Path relationship	No. of studies	Correlations			Range of correlations		Range of sample sizes		Average sample size	Cumulative sample size
		Significant	Nonsignificant	Significant (%)	Lower	Upper	Lower	Upper		
SE-CI	7	7	0	100%	0.17	0.43	144	397	260.86	1826
PE-CI	8	7	1	87.50%	0.00	0.58	126	456	278.5	2228
SP-CI	7	5	2	71.43%	-0.21	0.44	144	456	315.29	2207
SAT-CI	29	28	1	96.55%	0.04	0.92	48	1347	370.75	10381
PEOU-CI	9	5	4	55.56%	-0.179	0.33	151	456	255.67	2301
PU-CI	28	25	3	89.29%	0.07	0.74	88	1347	375.04	10126
CON-SAT	20	20	0	100%	0.18	0.91	88	1347	449.37	8538
PU-SAT	18	16	2	88.89%	0.04	0.74	88	1347	393.88	6696
PEOU-PU	10	10	0	100%	0.25	0.64	135	2530	467.7	4677
CON-PU	14	14	0	100%	0.17	0.93	88	1347	438.31	5698
OE-CI	7	7	0	100%	0.12	0.50	240	854	389.29	2725
ATT-CI	11	11	0	100%	0.16	0.91	94	2530	527.27	5800
SI-CI	6	5	1	83.33%	-0.06	0.41	151	435	256.17	1537
PEOU-ATT	6	5	1	83.33%	0.02	0.23	135	2530	644.5	3867
PU-ATT	5	5	0	100%	0.18	0.72	230	2530	746	3732
TTF-CI	5	4	1	80%	0.11	0.35	252	854	469.8	2349
TTF-PU	6	6	0	100%	0.163	0.742	88	854	345.67	2074

Reliability statistics

This study also checked and collected Cronbach's alpha or comprehensive reliability values (if Cronbach's alpha is not reported in the literature) to ensure that these variables achieved the desired reliability. As shown in Table 2, the average reliability coefficients of the 12 variables ranged from 0.87 to 0.91, exceeding the recommended threshold of 0.7 (Nunnally, 1994). All variables met the requirements and could be used in the research.

Table 2
Reliability statistics

Variable	Average	Minimum	Maximum	Variance	No. of studies
PU	0.89	0.60	0.99	0.004	33
PEOU	0.88	0.71	0.99	0.004	16
SE	0.89	0.84	0.93	0.001	7
PE	0.89	0.82	0.95	0.002	8
OE	0.88	0.76	1.00	0.007	7
CON	0.88	0.80	0.94	0.002	19
SP	0.91	0.84	0.95	0.002	5
SAT	0.89	0.65	0.97	0.004	31
CI	0.88	0.71	0.97	0.004	50
ATT	0.90	0.83	0.96	0.001	11
SI	0.87	0.67	0.97	0.012	6
TTF	0.90	0.79	0.98	0.003	9

Correlation analysis

Table 3 shows the simple average r of the correlation coefficient, the weighted average r_+ of the correlation coefficient, the effect size r_z after Fisher *r* to *z* transformation and its standard error SE, 95% confidence interval, Q statistics and their *p* values, the *z* score and *p* value of the *z* test, I^2 statistics and *p* values of the Egger's test. Among them, the *z* test is used to evaluate the importance of the impact size of each relationship (Cram et al., 2019). The *z* test results showed that at the $p < 0.05$ level, the effect size of each relationship was statistically significant. The use of the Q value and I^2 for heterogeneity testing helped in choosing a random-effects model or a fixed-effects model for meta-analysis. All relationships were significant for the heterogeneity test, with Q > K-1, where K was the number of corresponding studies, $P_{(Q)} < 0.05$, and $I^2 > 60\%$ (Higgins & Thompson, 2002). Thus, the random-effects model was chosen for this study's meta-analysis.

Table 3
Correlation analysis

Path	r	r_+	r_z	SE	95% Confidence interval	z test	$P_{(Z)}$	Q value	$P_{(Q)}$	I^2 (%)	$P_{(Egger's\ test)}$
SE-CI	0.30	0.29	0.30	0.04	0.21–0.38	6.52	0.000	23.40	0.001	74.4	0.72
PE-CI	0.27	0.23	0.28	0.07	0.14–0.42	3.74	0.000	100.11	0.000	93.0	0.67
SP-CI	0.07	0.08	0.07	0.08	-0.09-0.23	0.87	0.386	77.77	0.000	92.3	0.36
SAT-CI	0.47	0.50	0.51	0.04	0.41–0.60	8.91	0.000	1009.35	0.000	97.2	0.28
PEOU-PU	0.39	0.34	0.40	0.04	0.32–0.48	8.66	0.000	67.06	0.000	86.6	0.07
PEOU-CI	0.10	0.10	0.11	0.05	0.00–0.21	2.04	0.042	49.95	0.000	84.0	0.71
PU-CI	0.29	0.31	0.30	0.04	0.23–0.38	7.38	0.000	392.58	0.000	93.1	0.57
CON-SAT	0.46	0.53	0.50	0.05	0.38–0.61	7.02	0.000	1010.32	0.000	98.1	0.04
PU-SAT	0.36	0.28	0.38	0.05	0.27–0.48	6.50	0.000	372.96	0.000	95.4	0.00
CON-PU	0.49	0.47	0.55	0.06	0.38–0.68	5.63	0.000	1084.31	0.000	98.8	0.60
OE-CI	0.23	0.23	0.24	0.06	0.12–0.35	3.89	0.000	68.78	0.000	91.3	0.84
ATT-CI	0.58	0.67	0.65	0.08	0.45–0.79	5.26	0.000	1276.74	0.000	99.2	0.12
SI-CI	0.21	0.23	0.22	0.08	0.06–0.36	2.70	0.007	55.11	0.000	90.9	0.40
PEOU-ATT	0.16	0.15	0.16	0.03	0.11–0.21	5.99	0.000	8.44	0.134	40.7	0.68
PU-ATT	0.48	0.59	0.51	0.10	0.29–0.68	4.17	0.000	165.47	0.000	97.6	0.25
TTF-PU	0.45	0.45	0.47	0.08	0.30–0.62	4.90	0.000	78.87	0.000	93.7	0.86
TTF-CI	0.18	0.17	0.18	0.05	0.09–0.27	3.82	0.000	20.42	0.000	80.4	0.40

Note. $P_{(Q)}$ is the significance level of the Q test for heterogeneity; $P_{(z)}$ is the significance level of the *z* test.

According to the heterogeneity test results, except for the PEOU-ATT path, the heterogeneity of the other paths' effect sizes was significant. Therefore, the fixed-effects model was selected to analyse the PEOU-ATT relationship. Forest plots are usually employed to visualise heterogeneous test results, and the results are shown in Figure 4. The PEOU-ATT effect value is 0.15, and the confidence interval is 0.12–0.18.

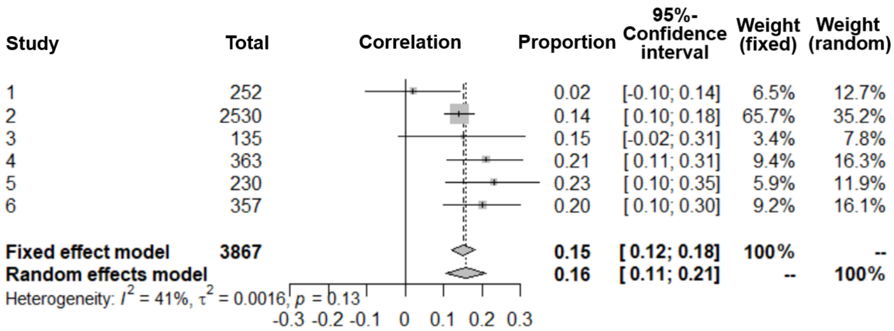

Figure 4. The forest plot of PEOU-ATT

The forest plots can visualise the heterogeneous test results. Figure 5 shows the range of R(z), central tendency and correlation coefficient in the random-effects model. Most of the relationships pass the significance test. However, the SP-CI path includes 0 in the 95% confidence interval, and the *p* value of the *z* test exceeds 0.05, which indicates that the effect size is not significant. Regarding publication bias, when Egger's test value exceeds 0.05, it indicates that the sample study has no publication bias (Egger et al., 1997). The PU-SAT relationship failed the Egger's test, for *P* (Egger's test) = 0.00.

Cohen (2013) pointed out that an effect size close to 0.1 means that the effect on the dependent variable is small. An effect size close to 0.3 indicates a medium effect, while an effect size close to 0.5 indicates a relatively high effect (Cohen, 2013). For central tendency, PU-CI, SE-CI, PEOU-PU and TTF-CI are more concentrated than other relationships. According to the correlation analysis, the effect value of the ATT-CI relationship is the largest at 0.65, revealing that ATT has the most substantial explanatory power for MOOC CI. The effect size of PU-ATT, CON-PU and CON-SAT is also greater than 0.5. The effect size of SE-CI, PEOU-PU, PU-CI, PU-SAT and TTF-PU is between 0.3 and 0.5, indicating strong effects. The effect size of PE-CI, OE-CI and SI-CI is between 0.2 and 0.3, which means a medium effect. The effect size of PEOU-CI is close to 0.1, indicating a low effect.

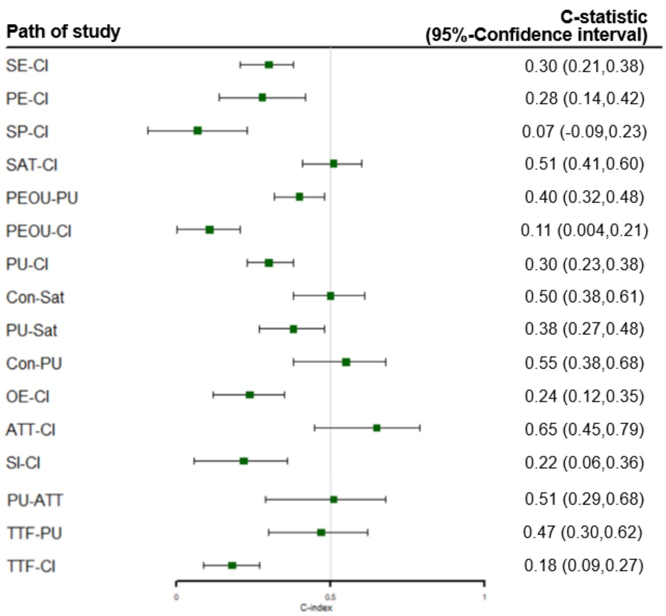

Figure 5. The forest plots of R(z)

Moderator analysis

Table 4 shows the results of the moderator analysis. Concerning the moderating effect of mandatory participation, the PEOU-CI relationship is moderated by MOOC mandatory participation. The effect of the self-paced extracurricular tasks (r_z = 0.23) is greater than the mandatory tasks (r_z = 0.41). Concerning the moderating effect of prior learning experience, the PU-CI and CON-SAT relationships are influenced by prior learning experience. For the PU-CI relationship, the low-experience group's impact size (r_z = 0.37) is higher than the impact size of the high-experience group (r_z = 0.20). For the CON-SAT relationship, the low-experience group's impact size (r_z = 0.60) is higher than the impact size of the high-experience group (r_z = 0.37). Figures 6 (a), (b) and (c) visualise the overall distribution of variable values and feature values through violin plots.

Table 4
Brief results of moderator analysis

Path relationship	Subgroups	k	N	r_z	95% CI	Q_w	Between groups test	
							Q_b	p
			Moderator 1: MOOC mandatory participation					
PEOU-CI	Self-paced	3	692	0.23	0.07-0.38	10.34^{**}	3.76^{*}	0.052
	Mandatory	6	1609	0.41	-0.06-0.14	21.03^{***}		
			Moderator 2: Prior learning experience					
PU-CI	Less	17	7163	0.37	0.26-0.45	237.18^{***}	4.39^{**}	0.036
	More	12	3217	0.20	0.10-0.29	79.31^{***}		
CON-SAT	Less	11	6007	0.60	0.43-0.72	572.45^{***}	4.26^{**}	0.039
	More	8	2421	0.37	0.23-0.50	122.68^{***}		

Note. k is the number of studies; N is the number of observations in each study; r_z means correlation; Q_w is the Q test for homogeneity within subgroups; Q_b is the Q test for homogeneity between subgroups; *p* is the significance level of the Q test for heterogeneity between subgroups. **p* < 0.1. ***p* < 0.05. ****p* < 0.01.

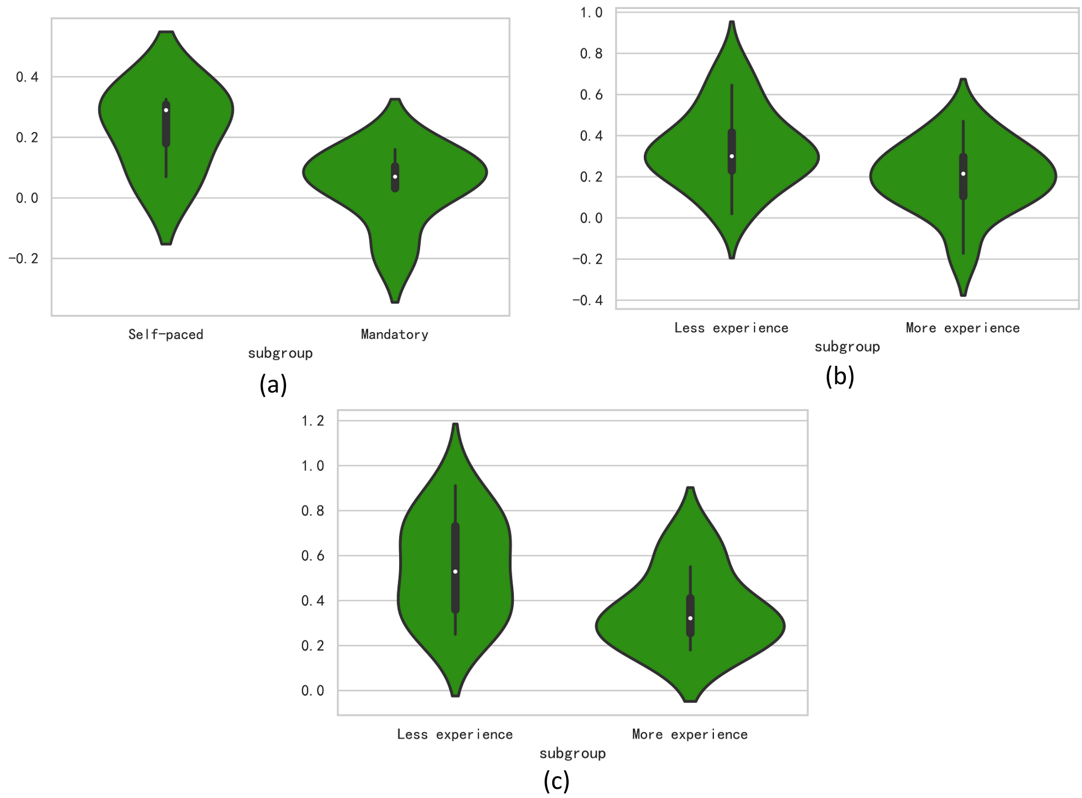

Figure 6. (a) Violin plots of PEOU-CI moderated by mandatory participation; (b) violin plots of PU-CI moderated by prior learning experience; (c) violin plots of CON-SAT moderated by prior learning experience

Discussion

The objective of this study was to clarify the relative importance of the critical factors to learners' MOOC CI, as well as the moderating effect of specific moderators. The final model is shown in Figure 7.

According to the meta-analysis results, traditional CI theories are valid in MOOC CI. This study further confirmed the stability of the TAM and ECM models in research on MOOC CI. ATT and SAT were crucial ways to determine and explain MOOC CI, which is consistent with prior findings (Alraimi et al., 2015; Wu & Chen, 2017). The findings confirmed that CON positively impacted the perceived performance of MOOC platforms, including increased PU and SAT (Gu et al., 2021), which in turn significantly impacted MOOC CI (Alraimi et al., 2015). The path of PU-ATT is also significant. PEOU affected CI in MOOCs directly and indirectly affected CI through PU and ATT, which is consistent with research (Shao, 2018). While there is a publication bias towards PU-SAT, indicating that PU provides limited support for improving MOOC SAT (Alraimi et al., 2015; Daneji et al., 2019). MOOC learners usually care about their personal needs when using MOOC platforms (Olasina, 2018).

Regarding social environmental factors as a new learning experience, SI positively influences learners' MOOC CI. That is, users' MOOC CI is influenced by word of mouth from the media and those around them. In comparison, the path effect of SP-CI is not significant and needs further study. Some studies have concluded that study group members' SP plays a vital role in driving learners' MOOC CI (Dalvi-Esfahani et al., 2020; Luo et al., 2018). Other studies have shown that online interactions negatively influence CI with regard to participation (Chang et al., 2015; Zhang et al., 2012). For course-related factors, TTF is significantly positively correlated with users' PU and MOOC CI (Kim & Song, 2022). Meanwhile, the indirect effect of TTF on MOOC CI is more significant than the direct effect because the effect size of TTF-PU is more significant than that of TTF-CI. That is, assessing the relationship between TTF and MOOC CI will likely highlight other mediators, such as PU, in more detail. Regarding learner-related factors, SE, PE and

OE positively affect MOOC CI. It is essential to properly measure and enhance learners' SE in MOOCs (Lee et al., 2020). PE is emotional arousal. Students may view MOOCs as hedonic systems, in addition to using the platform as a utilitarian system for learning (Tao et al., 2022). For OE, MOOC platforms and teachers should strive to meet learner expectations, enhancing MOOC CI (Bourdeaux & Schoenack, 2016).

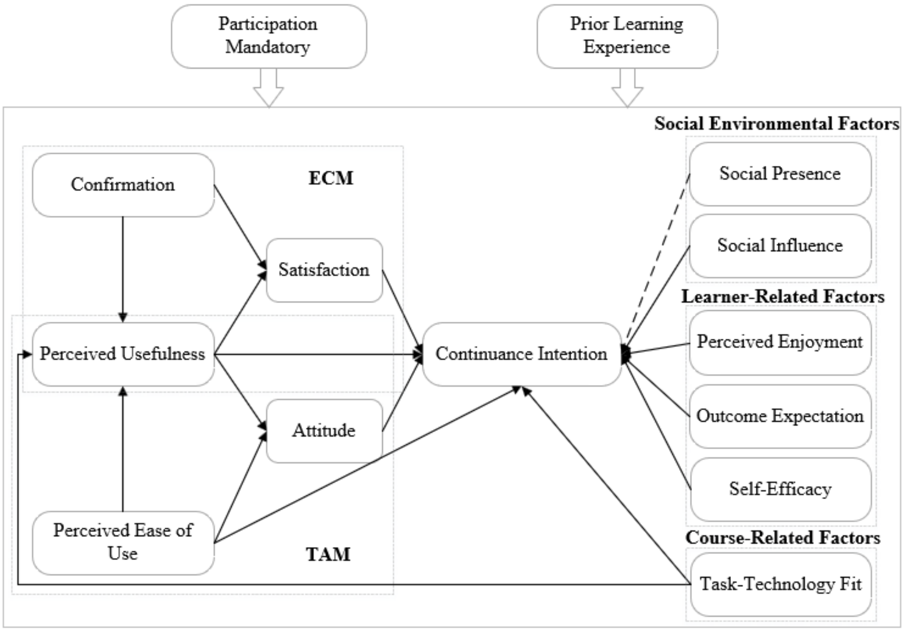

Figure 7. The revised research model of MOOC CI
Note. The significance level is depicted as a solid line, and the nonsignificant line is portrayed as a dotted line.

The moderating effect of mandatory participation and prior learning experience was also confirmed. For the moderating effect of mandatory participation, PEOU plays a more significant role in mandatory tasks than in self-paced tasks. This finding suggests that learners in mandatory tasks may have higher requirements for system perception because they must use it, so they pay more attention to PEOU, while students in self-paced tasks may pay more attention to other factors. For the moderating effect of prior learning experience, the impact of PU-CI in the low-experience group is greater than that in the high-experience group. When the MOOC platform improves the performance of beginners and makes them perceive the usefulness of MOOCs, learners will have positive psychological feedback on the platform, thereby enhancing CI in MOOCs (Gu et al., 2021). In addition, for CON-SAT, the confirmation of the platform by learners with less learning experience has a more significant effect on their SAT. Confirmation changes as the user's experience with a particular technology increases (Chauhan et al., 2022).

Practical implications

The findings are of practical value to MOOC developers, especially when face-to-face teaching is greatly affected by the COVID-19 epidemic.

First, the content quality of the MOOC platform should be improved to match the content needs of students. In designing and promoting MOOC course content, platforms should provide standard and scientific training courses for course developers to help them develop a higher-quality course content system. Subject teachers can upload course-related materials in a targeted manner to facilitate students' learning at different paces. Only in this way can learners' ATT and SA be significantly enhanced. In addition, big data technology can also be used to track individual learning traces and group learning transfer, accurately judge and develop new curriculum systems and eliminate unpopular curriculum systems. Meanwhile, the platforms must be carefully publicised to avoid exaggerating benefits and system costs because recognition is closely related to SAT.

Second, MOOC developers should pay enough attention to improving the platform's social quality to match students' social needs. On the one hand, practitioners should attract more universities and more high-level teachers who are deeply involved in a specific subject domain. Industry experts should provide high-quality courses to enhance the external SI and reputation of MOOC platforms (J. Zhou, 2017). On the other hand, an exciting learning environment should be created by implementing advanced technology (Guo et al., 2016) or gaming elements to improve learners' internal social participation and PE. For instance, gamification elements, such as points, badges or rewards, are displayed on leaderboards and provide a sense of competition between learners and their online classmates (Rohan et al., 2021) to motivate learners to be more actively engaged with MOOCs. In addition, positive feedback on learning outcomes should be provided regularly, with assessments of learning through forums, question-and-answer sessions, quizzes and automatic scoring of papers (Xiong & Suen, 2018) to motivate them to achieve learning goals and meet expectations for outcomes.

Finally, MOOC platforms should strive to meet the individual service needs of learners. As mentioned, personalised, customised services according to platform types and prior experiences are vital. MOOC platforms should establish and maintain close relationships with new learners in MOOCs. MOOC providers can provide convenient feedback channels to follow learners' perceptions. For example, regular questionnaire surveys should be conducted to listen to students' real needs and voices and increase their PU. Moreover, SAT can be promoted by ensuring the confirmation of expectations. In addition, mandatory courses in MOOCs should pay special attention to improving learners' PEOU, enhancing CI and improving teaching efficiency. It is equally important to actively establish instant feedback channels for problem solving through study groups to reduce the use barriers of MOOC platforms.

Limitations and future directions

This study is a meaningful exploration of MOOC learning behaviour research, but there are still some limitations, which leaves space for further research. The quantitative research methods used in this study have specific requirements for the scale of research samples. Although this study included and analysed critical variables in the literature, some significant factors may not be included in this study because of their relative novelty and rare occurrence. In the future, scholars could conduct further empirical research on those variables and relationships to obtain richer research conclusions. As English is the world's most popular language for scientific communication, this study included only studies published in English. Studies written in other languages were not included, which may limit the generalisability of the findings. In future studies, publications in multiple languages could be collected to enrich the application scope of the research conclusions. Moreover, with the maturity of MOOC industry development and the enrichment of the MOOC research system, there will be an increasing number of interesting topics, such as comparative studies of different cultural situations and innovative research on the MOOC metaverse, which may encourage new research topics.

Author contributions

Min Zhang: Conceptualisation, Methodology, Formal analysis, Writing original draft, Writing – review and editing; Sihong Li: Data curation, Analyzing and interpreting the data, Visualization, Writing original draft; **Yan Zhang**: Conceptualisation, Methodology, Writing part of the original draft, Writing – review and editing, revising.

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Corresponding author: Yan Zhang, zhy@ucas.ac.cn

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Appendix A: Overview of conclusions in sample studies

Studies	CON	PU	SAT	PEOU	SP	PE	OE	SE	ATT	SI	TTF
Alraimi et al., 2015	√	×	√			√					
Brahmasrene & Lee, 2012		√									
Chang et al., 2015(1)					×			√			
Chang et al., 2015(2)					×			√			
Chauhan et al., 2022	√	√	√								√
Chen et al., 2018			√				√				
Cheng, 2019	√	√	√								√
Cheng, 2022					√						
Chiu & Wang, 2008		√				√	√	√		×	
Dağhan & Akkoyunlu, 2016	√	√	√								
Dai et al., 2020	√		√						√		
Dai et al., 2022	√		√						√		
Dai, Teo, Rappa, et al., 2020	√		√						√		
Dalvi-Esfahani et al., 2020		√		√	√	×			√		√
Daneji et al., 2019	√	×	√								
de Melo Pereira et al., 2015			√								
Gu et al., 2021	√	√	√								
Guo et al., 2016		√	√			√					
Hsu et al., 2018		√		√			√		√		
Ishak & Malaysia, 2020				√				√		√	
Jo, 2018		√	√								√
Joo et al., 2018		√	√	√							
Jung & Lee, 2018		√		×				√			
Kim & Song, 2022		√		×							√
Lai & Lai, 2014		√					√			√	
M. C. Lee, 2010	√	√	√	√					√		
K. M. Lin, 2011		√	×	×					√		
K. M. Lin et al., 2011		×	√	√					√		
W.-S. Lin & Wang, 2012	√	√	√								
Lu et al., 2019	√	√	√								
Luo et al., 2018					√	√	√				
Najmul Islam, 2011		√		√						√	
Nong et al., 2022	√	√	√								
Nugroho et al., 2019		×	√								
Park et al., 2022			√								
Qi et al., 2020					√	√					
Ramayah & Lee, 2012			√								
Rodríguez-Ardura & Meseguer-Artola, 2016		√		√					√		
Rohan et al., 2021	√	√	√								
Shanshan & Wenfei, 2022	√		√								
Shao, 2018		√		√							

Suriazdin et al., 2022	√	×	√								
Tan & Shao, 2015	√	√	√								
Tawafak et al., 2018		√	√	√			√				√
Tsai et al., 2018						√					
L.-Y.-K. Wang et al., 2019		×		×		√		√			
T. Wang et al., 2021	√	√	√								√
Wu & Chen, 2017		√		×					√		√
Xu & Wang, 2017	√	√	√	√							
Yang et al., 2017		√		√							
Zhang et al., 2012			√		√			√			
J. Zhou, 2017	√		√				√			√	
Zhu et al., 2020									√		
√	20	29	31	12	5	7	7	7	11	4	8
×	0	6	1	5	2	1	0	0	0	1	0

Note. CON: confirmation; PU: perceived usefulness; SAT: satisfaction; PEOU: perceived ease of use; SP: social presence; PE: perceived enjoyment; OE: outcome expectation; SE: self-efficacy; SI: social influence; ATT: attitude. √: The paper studied this factor and found it has a significant effect. ×: The paper studied this factor and found it has an insignificant effect. Numerals (1) and (2) indicate two studies from the same article.

Appendix B: Overview of the articles in meta-analysis

Studies	Sample size	Experience	Mandatory participation
Alraimi et al., 2015	316	Less	Self-paced
Brahmasrene and Lee, 2012	872	Less	Self-paced
Chang et al., 2015(1)	397	Less	Self-paced
Chang et al., 2015(2)	273	Less	Self-paced
Chauhan et al., 2022	396	Less	Mandatory
Chen et al., 2018	854	More	Mandatory
Cheng, 2019	391	More	Mandatory
Cheng, 2022	307	Less	Mandatory
Chiu & Wang, 2008	286	More	Mandatory
Dağhan & Akkoyunlu, 2016	467	Less	Mandatory
Dai et al., 2020	638	More	Self-paced
Dai et al., 2022	439	Less	Self-paced
Dai, Teo, Rappa, et al., 2020	306	More	Self-paced
Dalvi-Esfahani et al., 2020	456	More	Mandatory
Daneji et al., 2019	368	Less	Mandatory
de Melo Pereira et al., 2015	343	More	Mandatory
Gu et al., 2021	550	Less	Self-paced
Guo et al., 2016	244	More	Mandatory
Hsu et al., 2018	357	Less	Self-paced
Ishak & Malaysia, 2020	250	More	Mandatory
Jo, 2018	237	More	Mandatory
Joo et al., 2018	222	More	Mandatory
Jung & Lee, 2018	306	Less	Mandatory
Kim & Song, 2022	252	Less	Mandatory
Lai & Lai, 2014	240	Less	Self-paced
M. C. Lee, 2010	363	More	Mandatory
K. M. Lin, 2011	135	More	Mandatory
K. M. Lin et al., 2011	230	More	Mandatory
W.-S. Lin & Wang, 2012	88	More	Mandatory
Lu et al., 2019	300	More	Self-paced
Luo et al., 2018	258	More	Mandatory
Najmul Islam, 2011	175	Less	Mandatory
Nong et al., 2022	410	Less	Self-paced
Nugroho et al., 2019	48	Less	Mandatory
Park et al., 2022	224	More	Self-paced
Qi et al., 2020	372	Less	Self-paced
Ramayah & Lee, 2012	250	Less	Mandatory
Rodríguez-Ardura & Meseguer-Artola, 2016	2530	More	Mandatory
Rohan et al., 2021	206	More	Self-paced
Shanshan & Wenfei, 2022	555	Less	Self-paced
Shao, 2018	247	Less	Self-paced

Suriazdin et al., 2022	164	Less	Self-paced
Tan & Shao, 2015	1347	Less	Mandatory
Tawafak et al., 2018	295	More	Mandatory
Tsai et al., 2018	126	Less	Mandatory
L.-Y.-K. Wang et al., 2019	170	More	Mandatory
T. Wang et al., 2021	854	Less	Self-paced
Wu & Chen, 2017	252	More	Self-paced
Xu & Wang, 2017	151	Less	Self-paced
Yang et al., 2017	294	More	Self-paced
Zhang et al., 2012	144	More	Mandatory
Zhou, 2017	435	More	Self-paced
Zhu et al., 2020	94	Less	Mandatory

Note. The numerals (1) and (2) indicate two studies from the same article.