Learner control, user characteristics, platform difference, and their role in adoption intention for MOOC learning in China

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Massive open online course (MOOC) learning attracts more and more attention in both the practice and the research field. Finding out what factors influence learners' MOOC adoption is of great importance. This study focuses on learner control, user characteristics and platform difference. Hypotheses and a research model are proposed by incorporating perceived learner control, e-learning self-efficacy, and personal innovativeness in information technology (PIIT) into the original technology acceptance model (TAM). With the empirical data from 214 MOOC learners, the effects of perceived learner control on perceived usefulness and perceived ease of use are confirmed. E-Learning self-efficacy is found to have positive influence on perceived learner control and ease of use. While the effect of PIIT on perceived learner control is not supported, PIIT influences learners' perception of usefulness and ease of use. Furthermore, a comparison between foreign and native MOOC platforms shows the former should emphasize ease of use more, and the latter should emphasize usefulness more, to enhance their attractiveness.

Introduction

Massive open online courses (MOOCs), are a development in the area of distance education, and a progression motivated by open education ideals (Yuan & Powell, 2013). Unlike the traditional online teaching and learning systems, which usually allow limited enrolments, MOOCs provide the opportunity for massive participation, the tools of discussion, and the ways of interaction (Pappano, 2012). Thus, students learning in MOOC courses are provided with a greater level of control than they might typically experience in a traditional face-to-face classroom course (Chou & Liu, 2005; Fisher, Wasserman, &Orvis, 2010). Learners now have many MOOC platforms to choose from: Coursera and EdX from North America; Future Learn from England; Iversity from Germany; and XuetangX and ICourse163 from China. In academia MOOCs have also gained wide attention from researchers.

A literature review published by Liyanagunawardena, Adams and Williams (2013) divided MOOC research into several research branches including: case studies. introduction of MOOCs, concept of MOOCs, discussion of the education theory, technology details, provider focus, participant focus, and others. Another similar study published by Gasevic, Kovanovic, Joksimovic and Siemens (2014) revealed the main focus for future MOOC research and posited that student motivation, attitude, engagement, and learning success are the foremost current research topics. Extant literature about MOOCs is divided into four categories according to main themes, a) education technology improvement and MOOC platform design, b) learner's motivation, attitude, and behavioral patterns, c) learner's performance and learning success, and d) communities and social network learning. Despite the breadth of literature in this area, three critical gaps exist that represent fruitful opportunities for research.

First, the reasons why students choose MOOC learning as a new form of e-learning and factors that influence MOOC learners' adoption intention should be studied further. In the past, researchers concentrated on student retention (Adamopoulos, 2013) and learner intent and behavior (Campbell, Gibbs, Najafi, & Severinski, 2014), but the reason why students adopt or refuse MOOCs is neglected. This is essential for improving education quality. Second, few researchers focus on the effects of learner's characteristics, especially for learner control, on MOOC acceptance behavior. Research about the relationship between learner control and learning outcomes (Hughes et al., 2013; Karich, Burns, & Maki, 2014), provide a reference for us. Third, comparison research on different MOOC platform characteristics are relatively rare. Foreign platforms usually contain courses taught in English or their native language, and the interface design may be unfamiliar to Chinese students. Website design differences (website layout, spatial features, use of certain colors, preferences for multimedia elements, representation of language and script) existed among different countries (Cyr & Trevor−Smith, 2004). These design differences and language problems may cause different perceptions about MOOC learning and affect students' MOOC adoption intention. The purpose of this research is to investigate the user characteristics of MOOC learners, their role in the adoption process, and analyze the difference between foreign MOOC platforms and native MOOC platforms. Our research model can be seen in Figure 1.

Theoretical background

Technology acceptance model

Proposed by Davis (1989), the technology acceptance model (TAM) is a process for understanding the acceptance of information technology. TAM suggests perceived usefulness (the degree to which using a particular technology would enhance job performance) and perceived ease of use (the degree to which using the system would be free of effort), are the two main perceptions that influence the attitude, intention, and usage behaviour toward a new technology. TAM is one of the most widely used technology acceptance theories, and also the most commonly used theory in e-learning acceptance studies. Šumak, Heričko and Pušnik (2011) found that 86% of the e-learning acceptance studies reviewed employed TAM as their theoretical basis.

Researchers differentiated types of e-learning adoption users into professionals, for example nurses (Cheng, 2014), and employees, teachers, students, and working mothers (Kibelloh & Bao, 2014). In the field of e-learning, TAM could not only be used for predicting adoption behavior, but also for measuring the learning satisfaction, continuous intention to use e-learning (Pereira, Ramos, Gouvêa, & Costa, 2015), loyalty to e-learning (Sánchez-Franco, Peral-Peral, & Villarejo-Ramos, 2014), course outcomes, and academic performance using e-learning (Arbaugh, 2014). The features of technology: interactivity, personalisation, accessibility, mobility, and the choice of media to present the contents (Agudo-Peregrina, Hernández-García, & Pascual-Miguel, 2014); individual characteristics such as personal innovativeness in information technology, computer self-efficacy, and demographic variables (Chow et al., 2013; Thatcher & Perrewe, 2002);the course characteristics of learning resources, course content, tutor quality, and course quality (Persico, Manca, & Pozzi, 2014; Teo, 2014); and other variables such as social influence (or social norm) and flow (Wu & Zhang, 2014), are incorporated into TAM to enhance the understanding of adopting. In summary, TAM has been widely used in predicting e-learning adoption and proved to be robust.

Learner control

Shyu and Brown (1992) defined learner control as the degree to which students can direct their own learning experiences. Reeves (1993), and Orvis, Fisher and Wasserman (2009)described learner control as an element of learning that allows learners to make important decisions about various features of the learning activity. Although shifting control over the learning process has long been discussed in the pedagogy of teaching and learning, it is not until the information technology and social network become prevalent that the practice of students' self-controlled learning and personalising learning come into action.

The first introduction of learner control in computer-adapted instruction was to explain student performance, and it was assumed that the degree of control the learner was positively related to student performance (Merrill, 1975). A survey by Marshall et al. (2009) found that a great number of teachers thought personalising learning with the help of technology, giving the students more control over the learning process, was very important.

Behrend and Thompson (2012) studied the influence of full control and customisation of the designed pedagogical agent (animated characters, in place of the teacher, to inspire motivation and learning in computer-based tutoring systems) in contrast to no choice of designed pedagogical agent and found learner control to be of benefit to learning outcomes. However, research findings seem to be inconsistent when it comes to learning outcomes. Some other studies found no effects on learning outcomes (Lahti, Hätönen, & Välimäki, 2014; Means, Toyama, Murphy, Bakia, & Jones, 2009), or even negative effects of learner control on learning outcomes (Jaggars & Bailey, 2010; Xu & Jaggars, 2014).

Despite the inconsistent findings in the relationship between learner control and learning outcomes, leaner control seems to have a positive effect on the perception of the learning process. When conducting a meta-analysis on learner control, Karich, Burns and Maki (2014) identified that learner control within educational technology does not directly lead to increased outcomes for students and had a somewhat higher effect on behaviour variables than the outcome variables. Students would feel competent and be more interested in those activities in which they are allowed to make choices. Kraiger and Jerden (2007) identified learner control as a useful factor high level learning engagement and for e-learning superiority. Orvis et al. (2009) found that learner control has a positive impact on learning satisfaction, and that high-level learner control over the learning environment features would influence the learners' affective and utility-based reactions to these features.

Learner characteristics

Vast bodies of psychology and sociology research have explored and identified the role of user characteristics in differentiating the effects on cognitive, affective and behavioural reactions. There are various aspects from which we can have a good understanding of user characteristics when studying the adoption of information technology, such as: the Big Five personality inventory, which includes openness, conscientiousness, extraversion, agreeableness, and neuroticism as five dimensions of personality (Barrick & Mount, 1991); demographic characteristics (age, gender, culture, education level, and social class), personal innovativeness in information technology (PIIT) (Agarwal & Prasad, 1998); and computer self-efficacy (Compeau & Higgins, 1995).

The Big Five is used widely in the individual performance, satisfaction and organisation outcome research (Barrick, Mount, & Judge, 2001; Wagerman & Funder, 2007).Orvis, Brusso, Wasserman and Fisher (2010) examined three of the factors and their moderate effects in the relationship between degree of learner control and learning performance. Generally, the Big Five is used to explain the difference in learning performance. Though it has been used to explain the behaviour toward information technology use, small sample sizes delivered varying results. While McElroy, Hendrickson, Townsend and Demarie. (2007) found only openness influenced internet use, the study by Devaraj, Easley and Crant (2008) indicated all the factors except openness mattered in explaining technology acceptance. Venkatesh, Sykes and Ventkatraman (2014) found openness, conscientiousness, and extraversion affected website usage.

Karich et al. (2014) suggested a somewhat stronger effect for students in K-12 compared with college students or adult learners. Xu and Jaggars (2014) found that certain kinds of students are more negatively affected in e-learning, especially males, younger students, students with lower level academic skills, and African-American students. The demographic characteristics of gender, age, and education level are often studied to get a better understanding of learning effectiveness. In Xu and Jaggars' (2014) research, the survey subjects were similar in the demographic characteristics of age and education level.

However, as for the adoption behavior intention, the user characteristics concerned with information technology of PIIT, and computer self-efficacy are more often used and their effects are more consistent in the computer technology context. PIIT is a conception that describes one's willingness to give any new information technology a try (Agarwal & Prasad, 1998). Compeau and Higgins (1995) defined computer self-efficacy as a judgment of an individual's possible ability to use a computer when he or she uses it in the future. It is developed from the self-efficacy in the social cognition theory. Doubtless, such factors are closely related to the acceptance of new computer related technology. Thatcher and Perrewe (2002) studied the relationship between PIIT and computer self-efficacy as user related features in the context of using computers. Lewis, Agarwal and Sambamurthy (2003) proposed that individual influence was one of the three main aspects that influence one's belief about technology acceptance. The study surveyed knowledge workers from a university about their perceptions of using course websites in their work, and identified the positive effects of PIIT and computer self-efficacy as individual factors. Ke, Sun, Yang and Sun (2012) differentiated external variables into user characteristics and system characteristics when they studied the acceptance of an e-learning system, and used PIIT and computer self-efficacy as main user features to influence perception of usefulness and ease of use.

Hypotheses development and research model

Hypotheses from the original TAM model

Based on Davis (1989), an individual's perception of usefulness and ease of use toward the system are positively related to the attitude toward usage, and the attitude has a positive effect on the intention to use, which influences the actual usage behavior. To keep the model parsimonious, we modified the original relationships a little. As Heijden (2004) did when incorporating enjoyment in TAM, and Gefen, Karahannaand and Straub (2003) did when including trust in TAM, we removed attitude and studied the relationships among perceived usefulness, perceived ease of use, and intention to use. Thus, we have the hypotheses 1, 2 and 3.

H1: Perceived usefulness of MOOC learning has a positive effect on the intention to use MOOC learning.
H2: Perceived ease of use of MOOC learning has a positive effect on the intention to use MOOC learning.
H3: Perceived ease of use of MOOC learning has a positive effect on perceived usefulness of MOOC learning.

Hypotheses from perceived learner control

Learner control which helps form a respective learning experience should aid learning because it increases interest and motivation to learn (Scheiter & Gerjets, 2007). Gerjets, Scheiter, Opfermann, Hesse and Eysink (2009) conducted a test between learner control and time spent in e-learning, and found that learners with a high level of control tended to devote more time to the e-learning environment than those with a low level of control. Hence, one's perception of learner control (PLC) can cause different levels of engagement, motivation and attitude toward MOOC learning. Justifiably, an individual perception of MOOC learning including its usefulness, ease of use, and intention may be different because of his/her distinct perception of learner control of MOOC learning. Thus, we developed the hypotheses 4, 5 and 6.

H4: Perceived learner control of MOOC learning has a positive effect on perceived usefulness of MOOC learning.
H5: Perceived learner control of MOOC learning has a positive effect on perceived ease of use of MOOC learning.
H6: Perceived learner control of MOOC learning has a positive effect on the intention to use MOOC learning.

Hypotheses from PIIT

PIIT as a variable measuring one's possible positive attitude toward new information technology has been studied in many circumstances. For example, Lu, Yao and Yu (2005) studied the adoption of mobile wireless Internet services and confirmed the effect of PIIT on user's perception of usefulness and ease of use to accept the new technology. As for the e-learning technology, Raaij and Schepers (2008) found a positive effect of PIIT on perceived ease of use when accepting a virtual learning environment. Tan, Ooi, Leong and Lin (2014) studied the influence of PIIT on perceived ease of use and intention, and only found the hypothesis on perceived ease of use to be true. Therefore, it is quite necessary to incorporate PIIT as a determinant variable under the new circumstances of MOOC learning. Besides the effect of PIIT on perceived usefulness and ease of use, we think the positive attitude caused by PIIT will have some influence on the new construct perceived learner control. Thus, we have the hypotheses H7, H8, H9.

H7: PIIT has a positive effect on perceived learner control of MOOC learning.
H8: PIIT has a positive effect on perceived ease of use of MOOC learning.
H9: PIIT has a positive effect on perceived usefulness of MOOC learning.

Hypotheses from e-learning self-efficacy

Vijayasarathy (2004) studied the factors that influence the usage of the online shopping and employed a factor, internet self-efficacy, that describes "a consumer's self-assessment of the capabilities to shop online" (Vijayasarathy, 2004; p.751)to substitute computer self-efficacy. As computer technology has become an indispensable part of our lives, we think it is improper to use computer self-efficacy as a factor to influence the perception of MOOC learning. Roca, Chiu and Martínez (2006) studied the effects of computer self-efficacy and internet self-efficacy on perceived ease of use (PEOU), and found that the former had much less influence than the later. Thus we develop a more learning concerned factor, namely e-learning self-efficacy, to replace computer self-efficacy. We define e-learning self-efficacy (ESE) as a learner's self-assessment of one's ability to learn online. E-learning self-efficacy is an important individual characteristic, and it is reasonable to assume people with different levels of e-learning self-efficacy will have a different perceptions of perceived learner control. Thus, we have the hypotheses H10 and H11.

> H10: E-learning self-efficacy has a positive effect on perceived learner control of MOOC learning.
> H11: E-learning self-efficacy has a positive effect on perceived ease of use of MOOC learning.

The TAM model and its extended models have demonstrated robustness in much research, but these relationships may be significant or not significant. Even the significant relationships will not stay the same among different users and technologies. Venkatesh and Morris (2000) conducted research on acceptance and usage behavior toward new technology and compared gender difference among the relationships. They found that the relationships were proven solid among all samples, all male samples, and all female samples, but there existed differences in the strength of the proven relationships. As in the MOOC context, for Chinese learners there are not only domestic platforms such as XuetangX and ICourse163, but also platforms from other countries, such as Coursera and EdX from America, and Future Learn from England. These foreign platforms usually contain courses taught in English or their native language. Generally, these platforms have similar functions. Learners can retrieve a course based on the classified catalogue, or by using the search engine. They choose to participate in a course, and then complete the course by learning from the teacher and other classmates, completing homework and tests. However, a platform like Coursera has an interface that is usually in English, with courses taught in English. Retrieving courses and learning in English is always hard for Chinese learners, even if they have learned English for several years in school. Besides, the website layout, usage of certain colors, and the logic of process varies across different countries. Chinese learners are more familiar with the design features of their own platforms. All these things indicate that Chinese learners probably find their own platforms easier to use and understand than foreign ones. So it is fair to say, for Chinese learners, perceived usefulness affects intention more when using native platforms, and perceived ease of use affects intention more when using foreign platforms. Thus, we have the last hypothesis.

> H12: The model is robust across different platform, but the strength of the relationship will differ. Specifically, perceived usefulness matters more when domestic platforms are used, and perceived ease of use matters more when foreign platforms are used.

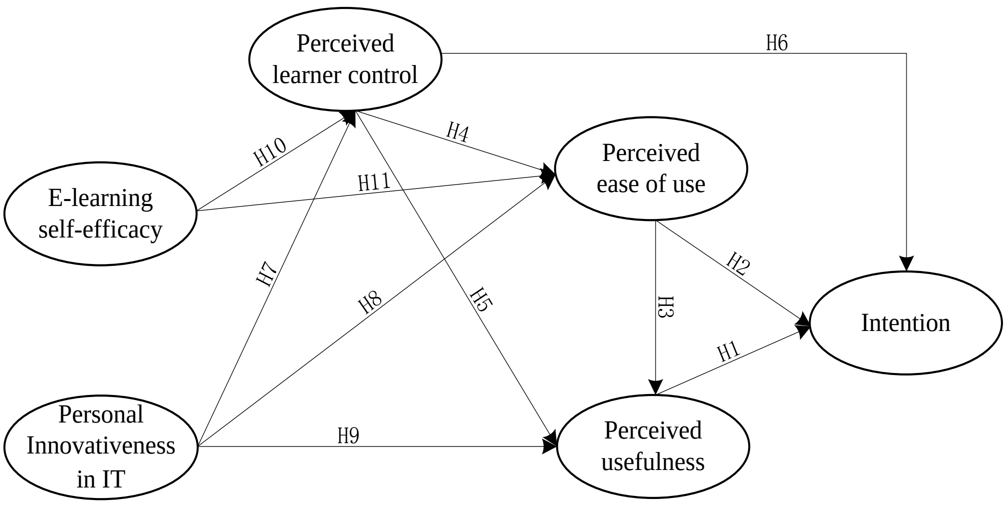

Figure 1. Proposed model

Study design and survey sample

Questionnaire design

This research employed a questionnaire survey to acquire data and test the proposed hypotheses. The questionnaire was divided into two parts. The first part asks for basic information of the survey sample and the second part measures the construct from our model. The entire construct is measured using a 7-point

Likert scale, with 1 indicating *strongly disagree* and 7 indicating *strongly agree*.

Measurements of the variables are listed in Table 1. To avoid the ambiguity and inaccuracy, experts in social surveying and MOOC learning examined all the measurement items. All items were modified and reviewed to agree with the MOOC learning context. Table 1 summarizes the latent variables, their measurement items, and references. All these measurements were originally in English, and developed into Chinese using a forward-backward translation.

Table 1
Measurement item

Construct	Item	Description	Reference
Perceived learner control	PLC1	I feel in control when searching for courses on this site.	Kim, Ferrin, & Rao, 2008
	PLC2	I feel in control with the process of participating in courses on this site.	
	PLC3	I feel in control when learning courses on this site.	
	PLC4	Overall, I feel in control when I'm using this website.	
Personal innovativeness in information technology	PIIT1	If I heard about a new information technology, I would look for ways to experiment with it.	Agarwal & Prasad, 1998;Tan et al., 2014
	PIIT2	Among my peers, I am usually the first to try out new information technologies	
	PIIT3	Overall, I like to experiment with new information technologies	
E-learning self-efficacy	ESE1	I feel confident using the e-learning system	Roca, Chiu & Martínez, 2006
	ESE2	I feel confident using the internet for learning.	
	ESE3	I feel confident that I have rich experience in e-learning.	
Perceived usefulness	PU1	Using the website for learning improve my quality of e-learning.	Davis,1989; Lee et al.,2005
	PU2	Using the website for learning improves my efficiency of e-learning.	
	PU3	Using the website for learning is useful.	
Perceived ease of use	PEOU1	Learning to use the website is easy for me.	Davis,1989; Lee et al., 2005
	PEOU2	My interaction with the website is clear and understandable.	
	PEOU3	Overall, it's easy to use the website for me.	
Intention to use	INT1	I intend to use the website for learning to pursue personal interests or hobbies.	Davis, Bargozzi, & Warshaw,1989; Lee et al., 2005
	INT2	I intend to use the website for learning to expand upon my formal learning.	
	INT3	I intend to use the website for learning frequently.	

Data collection and sample description

Coursera is one of the most used MOOC learning platforms around the world and attracts learners from many countries, including China. Besides foreign platforms, learners from China can also use native platforms such as ICourse163 and XuetangX. We chose Coursera (https://www.coursera.org/) and ICourse163 (http://www.icourse163.org/) as our survey platforms, because they resemble each other with their courses are mainly from universities, and both are popular among Chinese learners. We sent emails to learners in the two platforms to invite them to participant in the survey.

The subjects of this research are MOOC learners. To obtain effective subjects, this research used the QQ group tool, which is the most popular Chinese instant messaging service. For better learning and communication, MOOC learners studying the same course on Coursera often spontaneously build a QQ group. Chinese MOOC platforms often provide official QQ groups. Sample QQ groups were discovered by keyword searching in QQ, and examining the discussion forum as calls for building a QQ group always happens here. To avoid possible interference, similar courses were selected across the two platforms. After asking for permission to join the QQ groups, ethical approval was obtained from the QQ group administrator. Emails containing the survey link were sent to group members to invite them to participate in the survey. Academic usage and information privacy principles were introduced before survey questions were presented.

We had 245 learners respond to the questionnaire. During the process of data cleaning, this research deleted 15 as invalid, from the sample data. Of the 230 sample data was left, and were Chinese learners. A group of 116 used Coursera more often and answered the measurements of latent variables based on their experience of using Coursera. The remaining 98 used ICourse163 more frequently and answered the measurements of latent variables based their experience of using ICourse163. Most of them had heard about two or more MOOC platforms. The detailed demographic data can be seen in Table 2.

Table 2
Demographic Data

Measurement	Item	Frequency	Percentage
Gender	male	134	62.62%
	female	80	37.38%
Education Background	junior college or lower	8	3.74%
	undergraduate	129	60.28%
	postgraduate or higher	77	35.98%
Age	<=18	4	1.87%
	18-22 (included)	111	51.87%
	23-28 (included)	63	29.44%
	>28	36	16.82%

Data analysis

The tests of both measurement model and structural model were conducted through the partial least squares (PLS) approach (Ringle, Wende, & Will, 2007). Different from covariance-based structural equation modeling method, PLS is a variance-based method and has some relative advantages. It is less strict on the size of the sample and the distribution of the sample data (Hair, Ringle, & Sarstedt, 2013). As our total sample size in the separate platforms is relatively small, the PLS method was used to process data.

Measurement model test

The factor loadings, average variance extracted (AVE), composite reliability, and Cronbach's alpha of the measurement model for all sample and separated samples are shown below in Table 3 and Appendix A. The composite reliability for all constructs in the entire sample exceeded 0.90.In the sample from ICourse163 all exceeded 0.80 and in the sample from Coursera all exceeded 0.90. According to Fornell and Larcker (1981), all samples demonstrate a reasonable reliability. An AVE for each construct above the recommended threshold of 0.50 indicated over 50% of the variance observed can be explained by the latent constructs, which shows the reliability of the constructs (Hair, 2009). Clearly, the smallest AVE (0.748), which was for PIIT in the sample from ICourse163, reaches the recommended value.

Additional evidence on reliability can be obtained by comparing Cronbach's alpha with the recommended value of 0.7. If Cronbach's alpha is above 0.7, then the construct possesses adequate reliability. The lowest score of Cronbach's alpha was 0.829 for PIIT in the sample from ICourse163 and this is much larger than the recommended value. Hence, our data shows adequate reliability.

Table 3
Results of reliability

		ALL			
		Loading	AVE	CR	α
PLC	PLC1	0.880	0.829	0.951	0.931
	PLC2	0.927			
	PLC3	0.908			
	PLC4	0.927			
ESE	ESE1	0.949	0.842	0.941	0.906
	ESE2	0.963			
	ESE3	0.836			
PIIT	PIIT1	0.879	0.805	0.925	0.879
	PIIT2	0.884			
	PIIT3	0.928			
PU	PU1	0.915	0.839	0.940	0.905
	PU2	0.918			
	PU3	0.916			
PEOU	PEOU1	0.945	0.912	0.969	0.952
	PEOU2	0.970			
	PEOU3	0.950			
INT	INT1	0.933	0.856	0.947	0.916
	INT2	0.906			
	INT3	0.937			

Notes: The ALL column presents all data together. Loading refers to factor loading, AVE refers to average variance extracted, CR refers to composite reliability and α refers to Cronbach's alpha.

The validity of the measurement items consists of convergent validity and discriminant validity. Convergent validity describes the highly correlated relationships within a latent variable. Factor loading scores greater than 0.7, together with AVE greater than 0.5, demonstrate adequate convergent validity (Wixom & Watson, 2001). With the lowest factor loading being 0.791, and the lowest AVE 0.748, all the constructs are adequate in terms of convergent validity.

Discriminant validity means that latent variables are distinct from each other and much less correlated. This means variables should relate much more strongly to themselves than to others. The discriminant validity can be examined by comparing the square root of the AVE with the correlation between constructs (Fornell & Larcker, 1981). If the square root of the AVE of a construct is larger than any of the correlations between the construct and other constructs, then the discriminant validity is conformed. According to Table 4, all the values on the diagonal were larger than the corresponding value off diagonal, so the discriminant validity is proved to be adequate. Thus, our measurement model was reliable, valid, and suitable for the test of the structural model.

Table 4
Results of validity

		ESE	INT	PLC	PEOU	PIIT	PU
ALL	ESE	**0.918**					
	INT	0.495	**0.925**				
	PLC	0.566	0.514	**0.911**			
	PEOU	0.601	0.718	0.556	**0.955**		
	PIIT	0.538	0.481	0.325	0.500	**0.897**	
	PU	0.566	0.724	0.629	0.673	0.552	**0.916**
G1	ESE	**0.901**					
	INT	0.502	**0.867**				
	PLC	0.529	0.590	**0.903**			
	PEOU	0.609	0.672	0.549	**0.950**		
	PIIT	0.387	0.427	0.213	0.351	**0.865**	
	PU	0.546	0.728	0.542	0.577	0.513	**0.906**
G2	ESE	**0.926**					
	INT	0.490	**0.956**				
	PLC	0.584	0.476	**0.919**			
	PEOU	0.606	0.748	0.564	**0.958**		
	PIIT	0.624	0.508	0.393	0.596	**0.921**	
	PU	0.567	0.724	0.677	0.744	0.574	**0.919**

Notes: Column ALL represents all samples together. G1 represents samples from ICourse163. G2 represents samples from Coursera.

Hypotheses test

The hypotheses were tested employing the bootstrapping method. Chin (1998) recommended 500 times sampling for significance testing of the estimated path coefficient. As more sampling times is usually better, we employed 1000 times sampling for all the calculations.

The R^2 value in the intention construct is an indicator of the explanatory power of our proposed model. The acceptance level depends on the research context (Hair et al., 2013). Venkatesh, Morris, Davis and Davis (2003) compared several models in terms of user acceptance of IT, and found the range of explained variance in user intention was from 17% to 69%. Using the empirical data collected, our model showed a desirable explanation of the intention to use a MOOC platform for learning. As we can see in Figure 2, in the entire sample, 62.2% of variance of the intention was explained by perceived learner control, perceived ease of use, and perceived usefulness. As for the separate samples, Figure 3 and Figure 4 showed that 64.3% of the variance was explained in ICourse163 sample, 62.5% of the variance was explained in Coursera sample. The results show that the proposed model was powerful in explaining learners' intention. Therefore, the analysis of path coefficient and significance makes sense.

The testing result of the entire sample can be seen in Figure 2. In the entire sample, the hypotheses from the original TAM model were all supported. Perceived learner control was found to affect perceived usefulness ($\beta = 0.350$, $p < 0.001$) and perceived ease of use ($\beta = 0.308$, $p < 0.001$), whereas its direct effect on intention was not supported ($\beta = 0.007$, ns). Appling the mediation analysis suggested by Kenny (2015), complete mediation was found in the path from perceived learner control to intention by perceived usefulness and perceived ease of use.

E-learning self-efficacy significantly influenced perceived learner control ($\beta = 0.549$, $p < 0.001$), while the influence of PIIT on perceived learner control was not significant ($\beta = 0.029$, ns). PIIT was confirmed as an important indicator of perceived usefulness ($\beta = 0.266$, $p < 0.001$) and perceived ease of use ($\beta = 0.242$, $p < 0.01$). The variances of perceived usefulness and perceived ease of use were explained respectively 60.0% and 47.0% by their antecedents. Perceived learner control was explained by e-learning self-efficacy of 32.0% in its variance. In summary, except for H6 (perceived learner control on intention) and H7 (PIIT on perceived learner control), the rest of the hypotheses were supported with our empirical data.

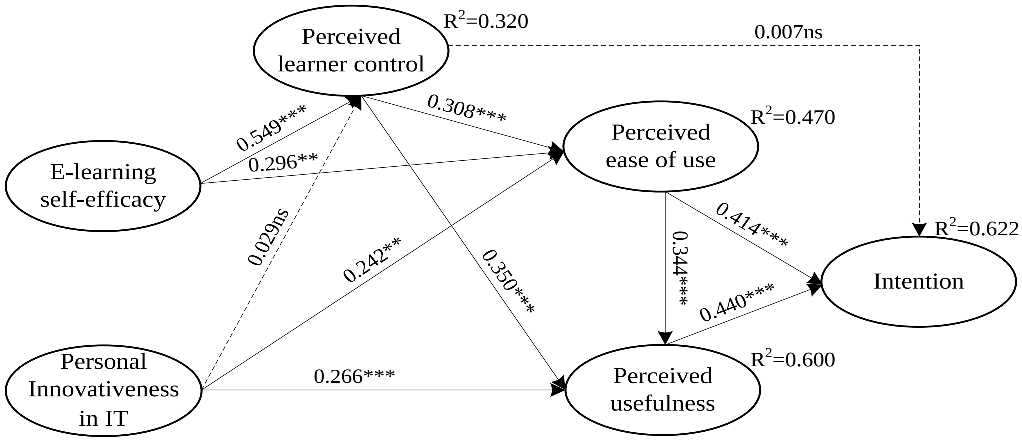

Figure 2. Entire sample

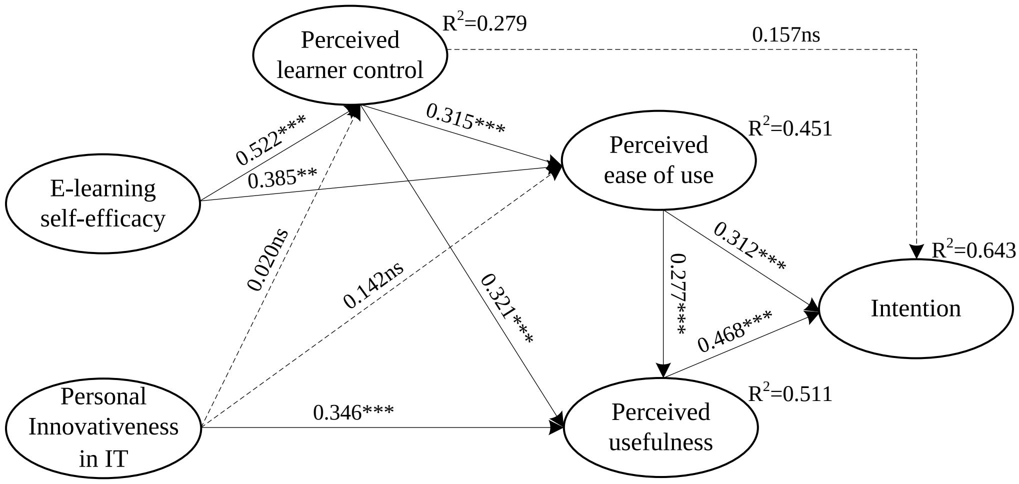

Figure 3. Sample from ICourse163

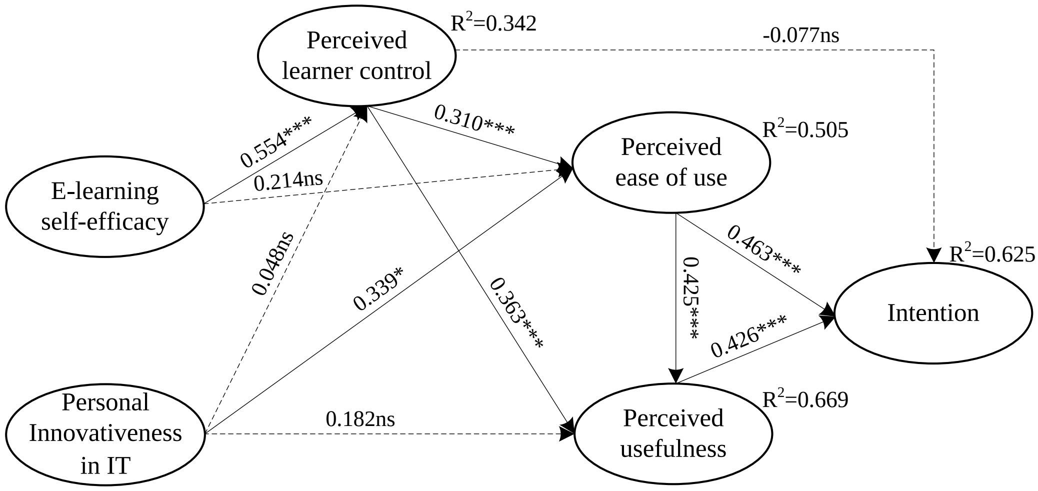

Figure 4.Sample for Coursera
Note: **p* < 0.05, ***p* < 0.01, ****p* < 0.001, ns = non-significant

For H12, a comparison of the supported hypotheses and a test of the difference in paired path coefficient were conducted. Figure 3 and Figure 4 show the different results of our two samples. For the sample from ICourse163, besides H6 and H7, the influence of PIIT on perceived ease of use (H8) were not supported. The variances of perceived usefulness and perceived ease of use were explained respectively as 51.1% and 45.7% by their antecedents. Perceived learner control was explained by e-learning self-efficacy of 27.9% in its variance. For the sample from Coursera, besides H6 and H7, the influences of PIIT (H9) and e-learning self-efficacy on perceived usefulness were not supported. The variance of perceived usefulness and perceived ease of use were explained respectively as 66.9% and 50.5% by their antecedents. Perceived learner control was explained by e-learning self-efficacy of 34.2% in its variance. Overall, the proposed model was robust and provided powerful explanation for the variance in the predicted variables.

Testing of the difference of the path coefficient of the two sub-samples was conducted using the method recommended by Keil et al. (2000). The calculation process is displayed in Figure 5-below.

$S_{pooled} = \sqrt{\{[(N_1 - 1)/(N_1 + N_2 - 2)] \times SE_1^2 + [(N_2 - 1)/(N_1 + N_2 - 2)] \times SE_2^2\}}$

$t = (\beta_1 - \beta_2) / [S_{pooled} \times \sqrt{(1/N_1 + 1/N_2)}]$

Where S_{pooled} = pooled estimator for the variance

t = t-statistic with $(N_1 + N_2 - 2)$ degrees of freedom; N_i = sample size of dataset for group i

SE_i = standard error of path in structural model of group i

Figure 5. The calculation process

Table 5 and Appendix B display the hypotheses testing results. According to the results, the difference of H5 (perceived learner control on perceived ease of use) and H7 (PIIT on perceived learner control) are not significant. Though the difference of H6 is significant, it should be explained carefully since H6 is not supported in the proposed model. Except H5, H6 and H7, the rest of the hypotheses all are significantly distinct. In particular, the influence of perceived usefulness on adoption intention was stronger in ICourse163 user group than in Coursera user group (β_{G1}-$\beta_{G2} > 0$, $p < 0.05$). As to perceived ease of use, the effect on adoption intention and perceived usefulness was stronger in Coursera user group than in ICourse163 user group (β_{G1}-$\beta_{G2} < 0$, $p < 0.0001$).That is to say, perceived usefulness affected intention more when using native platforms, and perceived ease of use affected intention more when using foreign platforms. Hence, it's reasonable to proclaim H12 is supported based on the empirical data.

Table 5
Results of hypotheses test

	ALL			
	β	SE	*t* value	*p*
H1	0.440	0.085	5.143	***
H2	0.414	0.085	4.926	***
H3	0.344	0.096	3.614	***
H4	0.350	0.069	5.095	***
H5	0.308	0.084	3.697	***
H6	0.007	0.059	0.091	
H7	0.029	0.077	0.370	
H8	0.242	0.088	2.718	**
H9	0.266	0.071	3.769	***
H10	0.549	0.064	8.590	***
H11	0.296	0.111	2.680	**
R^2_{PLC}	0.320			
R^2_{PU}	0.600			
R^2_{PEOU}	0.470			
R^2_{INT}	0.622			

Notes: Column All represents all samples together.*p<0.05, **p<0.01, ***p<0.001

Discussion and implication

Discussion of the results

In this study, the intention to use a MOOC platform for learning was predicted using the extended TAM model. A new construct named *perceived learner control*, together with two user characteristics (ESE and PIIT), were incorporated into the TAM model. H1, H2 and H3 were supported. The support of all hypotheses among perceived usefulness, perceived ease of use, and intention demonstrated the robustness of the TAM.

H4 and H5 were supported, while H6 was not. According to the data analysis, perceived learner control was an important antecedent for both perceived usefulness and perceived ease of use. Previous researchers have studied how learner control could influence the learning engagement, performance and outcome, but few have identified its influence on attitude and intention to use the technology. The more personalized one perceives an e-learning environment to be, the more control of such environment he/she perceives (Wu & Zhang, 2014). The positive influence of perceived learner control of MOOC learning on cognition of the MOOC learning indicates that giving leaners more choices about their learning process makes learners more positive about the technology or service. This is consistent with the underlying motivation of personalization. However, in terms of perceptions toward MOOC learning, the positive influence of perceived learner control on intention was not direct and fully mediated by PU and PEOU.

H8, H9, H10 and H11 were supported, while H7 was not PIIT, consisting with previous studies, had a positive effect on both perceived usefulness and perceived ease of use, but its influence on perceived learner control was not supported. Since PIIT describes the willingness to try out a new information technology, its weak relation with the control perception about the learning process is quite reasonable. As for ESE, a more e-learning concerned factor, its positive effect on perceived learner control was supported. A learner more confident in his/her ability to learn online is likely to feel the learning process is more controllable. Consisting with the demonstrated influence of computer self-efficacy and internet self-efficacy on perceived ease of use, the effect of e-learning self-efficacy, a more specific self-efficacy factor on perceived ease of use was also confirmed.

H12 was supported. Though the proposed model showed its robustness across different platforms, there existed some differences regarding the path coefficients. For ICourse163 from China, the positive influence of PIIT on perceived ease of use was not significant ($\beta = 0.142$, ns). This may be explained by familiarity with the platform. Since the samples are Chinese, they don't have the potential language problem when using the platform for learning. Hence, the positive attitude caused by high level PIIT didn't influence the perceived ease of use, for it had already been easy to use. Compared with Coursera from America, larger path coefficients were found on the paths from e-learning self-efficacy to perceived ease of use, from PIIT to perceived usefulness, and from perceived usefulness to intention. This further confirmed the effect of perceived usefulness in predicting the intention. Learners studying on native platforms, put more attention on perceived usefulness of the platform. For Coursera from America, both the positive influence of PIIT on perceived usefulness ($\beta = 0.182$, ns) and e-learning self-efficacy on perceived ease of use ($\beta = 0.214$, ns) were not significant. Raaij and Schepers (2008) indicated that non-significant relationship between PIIT and PU could be explained by the type of system studied or variable like voluntariness. Path coefficients related to perceived ease of use (H2, H3 and H8) were larger than the other platform. Learners studying on foreign platforms might feel difficulty in using the platform and emphasised the effect of perceived ease of use. Wang and Baker (2014) found students who were English native speakers were more confident in completing the course than non-native speakers. The lack of confidence was likely to be associated with emphasis on ease of use. Chinese learners on foreign platforms have to put more effort into using the platform, because they have to understand the indications and instructions before actually learning. Compared with learners on domestic platforms, they are more concerned with perceived ease of use. Also, it is reasonable that the effect of e-learning self-efficacy on perceived ease of use is shadowed.

Theoretical implications

From the insights of students, this study provides a different perspective on perceived control. Control in IT/IS acceptance research is mainly related to external control, which influences the perceived ease of use, for example facilitating conditions and organisational support. In the e-learning context, there is another source of control namely learner control. Learner control has been studied regarding its influences on the learning outcomes in the education field. Hence, our study researched the perceived learner control and its effect on perception toward MOOC learning. Furthermore, the perceived learner control is found to influence the intent through cognition of the MOOC learning, that is, perceived usefulness and perceived ease of use.

This paper also gives deeper insight into the inner mechanism of learners' MOOC adoption intention, by combining two learner characteristics (ESE and PIIT) into the TAM model. The effects of learner characteristics (ESE and PIIT) on MOOC adoption intention are mediated by platform characteristics (PEOU and PU). This means that, when it comes to MOOC adoption intention, students will take both their own personal characteristics and platform's characteristics into consideration.

Last but not least, to test the model's robustness and its different relationship strength, a comparison study of different countries' MOOC platforms was implemented. Because of familiarity with the native platform, the positive influence of PIIT on perceived ease of use was not significant. When learning on the native MOOC platform, students put more attention on perceived usefulness of the platform. With the international or foreign MOOC platforms, Chinese students felt difficulty in using the platforms, and emphasising the effect of perceived ease of use.

Practical implications

For MOOC learning platforms providers should focus on the perception of learner control so as to extend their adoption and take into consideration that students have different usage experiences with foreign MOOC platforms and native platforms. For international platforms providers, ease of use is of more importance to keep their attractiveness for students from different countries who may use different languages and be unfamiliar with the platform. Providing a technologically, linguistically, and culturally neutral platform is very important for the globalisation of the MOOC platform. Hence, the providers should pay attention to keep their platform simple, understandable, and easy to use, which includes translation of language, layout, symbols, navigation, the use of color, and so on. For platforms mainly serving native students, it is important to enhance the usefulness of the platform, such as providing courses that are unique and peculiar to native culture. It does help for them to compete with the international platforms in high quality courses.

Further, MOOC platforms or researchers and teachers should cultivate or enhance students' e-learning self-efficacy. According to our results, e-learning self-efficacy has a positive influence on perceived ease of use, sequentially improving MOOC's acceptance. ESE is an important student characteristics factor. Some foundational training for teachers, or introduction videos displayed on the platform's homepage about how to use the MOOC correctly and efficiently is necessary and feasible.

Last but not least, the MOOC platform should pay attention to stimulating students' personal innovativeness in IT and inner learning initiative. PIIT positively affects perceived ease of use and perceived usefulness, and then promotes MOOC adoption intention indirectly. In this paper, PIIT measures one's possible positive attitude toward MOOCs, as a new digital technology. For students with high levels of innovativeness, the MOOC platform designer or manager should meet their need for innovativeness and maintain their learning enthusiasm by providing more innovative functions and novel courses. For students whose personal innovativeness in IT is relatively low, the MOOC platform manager or operator should communicate with them, listen to them, and strengthen the platform's interest and interactivity to motivate them, improving their personal innovativeness in IT. For instance, the MOOC platform can encourage students to participate in community discussion or course learning, either by encouragement or as compulsory participation.

Conclusion and future work

The TAM model has been adapted for various application contexts, and e-learning is definitely an important one. Previous studies have researched the TAM model extended by factors such as perceived enjoyment (Lee, Cheung, & Chen, 2005), social influence (Cheung & Vogel, 2013), and perceived playfulness (Liao, Huang, Chen, & Huang, 2015) in e-learning related technology acceptance. This study introduces a new construct, perceived learner control into the TAM model, and identifies its positive influence on perceived usefulness and ease of use. Though both e-learning self-efficacy and PIIT are learner characteristics, the former influences perceived learner control, while the latter does not. As is confirmed in previous studies, ESE as one kind of self-efficacy, positively influences perceived ease of use in the context of MOOC learning, as does PIIT on perception of usefulness and ease of use. Differences exist during the process of deciding between the different MOOC learning platform because learners weigh perceived ease of use and usefulness differently in distinct situations.

There are limitations of this article need to be further researched. More foreign and domestic platforms need to be researched to further investigate the generalisation of platform differences. As in this study, the sample learners tended to have high education levels, the generalisations of the results may be reduced. In addition, more work needs to be done to further investigate the antecedent of perceived learner control. As perceived learner control is important in predicting learners' adoption intention, it is necessary to find out what kind of system characteristics can influence learner's perception of control.

Acknowledgments

The authors are grateful to the editors and the referees for their constructive comments. The authors were supported by the National Natural Science Foundation of China [Grant 71203166], and the Fundamental Research Funds for the Central Universities [Grant 2016 Wuhan University project of Humanities and Social Science" Humanities Computing & Semantic Mining"].

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Please cite as: Zhang, M., Yin, S., Luo, M., & Yan, W. (2017).Learner control, user characteristics, platform differences, and their role in adoption intention for MOOC learning in China. *Australasian Journal of Educational Technology, 33*(1), 114-133. https://doi.org/10.14742/ajet.2722

Appendix A
Results of reliability

		G1				G2			
		Loading	AVE	CR	α	Loading	AVE	CR	α
PLC	PLC1	0.890	0.815	0.946	0.924	0.883	0.845	0.956	0.939
	PLC2	0.926				0.932			
	PLC3	0.870				0.933			
	PLC4	0.923				0.928			
ESE	ESE1	0.930	0.812	0.928	0.883	0.958	0.858	0.948	0.917
	ESE2	0.942				0.973			
	ESE3	0.827				0.843			
PIIT	PIIT1	0.791	0.748	0.898	0.829	0.923	0.849	0.944	0.912
	PIIT2	0.879				0.903			
	PIIT3	0.918				0.937			
PU	PU1	0.892	0.821	0.932	0.891	0.924	0.844	0.942	0.908
	PU2	0.914				0.918			
	PU3	0.912				0.914			
PEOU	PEOU1	0.948	0.903	0.966	0.946	0.944	0.918	0.971	0.955
	PEOU2	0.959				0.976			
	PEOU3	0.945				0.953			
INT	INT1	0.876	0.751	0.900	0.833	0.958	0.914	0.970	
	INT2	0.821				0.955			0.953
	INT3	0.902				0.955			

Notes: G1 presents data from ICourse163 learners. G2 presents data from Coursera learners. Loading refers to factor loading, AVE refers to average variance extracted, CR refers to composite reliability and α refers to Cronbach's alpha.

Appendix B
Results of hypotheses test

	G1				G2				Test for H12		
	β	SE	*t* value	*p*	β	SE	*t*value	*p*	Difference (β_{G1}-β_{G2})	*t*value	*p*
H1	0.468	0.115	3.940	***	0.426	0.133	3.153	**	0.042	2.442	*
H2	0.312	0.090	3.525	***	0.463	0.137	3.513	***	-0.151	-9.320	***
H3	0.277	0.135	2.105	*	0.425	0.130	3.366	***	-0.148	-8.136	***
H4	0.321	0.131	2.383	*	0.363	0.081	4.486	***	-0.042	-2.860	**
H5	0.315	0.106	2.954	**	0.310	0.118	2.567	*	0.005	0.323	
H6	0.157	0.096	1.778		-0.077	0.078	1.004		0.234	19.632	***
H7	0.020	0.108	0.092		0.048	0.121	0.390		-0.028	-1.767	
H8	0.142	0.118	1.127		0.339	0.136	2.514	*	-0.197	-11.188	***
H9	0.346	0.098	3.533	***	0.182	0.089	1.912		0.164	12.796	***
H10	0.522	0.078	6.702	***	0.554	0.100	5.542	***	-0.032	-2.569	*
H11	0.385	0.121	3.243	**	0.214	0.183	1.179		0.171	7.888	***
R^2_{PLC}	0.279				0.342						
R^2_{PU}	0.511				0.669						
R^2_{PEOU}	0.457				0.505						
R^2_{INT}	0.643				0.625						

Notes: G1 represents samples from ICourse163. G2 represents samples from Coursera. *p<0.05, **p<0.01, ***p<0.001