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Understanding MOOC continuance: An empirical examination of social support theory

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ABSTRACT

Learning outcomes is mediated by multi-channel learning environment and social engagement. Both factors may play a significant role in understanding motivation to learn in massive open online courses (MOOCs). The goal of this study was twofold: a. to compare behavior intention patterns of traditional e-learning platform and MOOCs participants; b. to examine relationships between behavior intention and perceived social support. Therefore, this study applies the concepts of technology acceptance model and social support theory to examine the underlying the determinants of learners' continuance intention factors for MOOCs in Taiwan. In addition, this study adopts perceived convenience, computer self-efficacy, sense of community, and perceived gains as the constructs of social support perspective. Our examination reveals that sense of community, and perceived gains influence learners' behavior intention of both general e-learning platform and MOOCs. However, perceived convenience and computer self-efficacy did not influence learners' behavior intention for traditional e-learning platform, but still have efforts for MOOCs. In summary, our results show that the social support theory and technology acceptance model could be the suitable examination model to investigate the behavioral intentions for MOOCs. These findings have significant theoretical and managerial implications.

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1. Introduction

With the development of IT and communication technologies, many resources tend to be cloud based, such that online resources could be duplicated, obtained, shared, used, and time and space unlimited with lower cost. In Taiwan, Institute for Information Industry indicates the internet access and mobile application population is increasing in Taiwan (Institute for Information Industry, 2016). Their survey also indicated Taiwan people spend an average of 205 min a day sliding mobile phone, almost twice the time watching TV, while the top three activities on the phone are using instant messaging (90%), read news / life information (72%), and online video (71%), showing that mobile audio and video has leapt to the mobile application of Top3.

Nowadays, learners can adopt and use the open educational resources (OER), open courseware (OCW), and massive open online courses (MOOCs) applications to assist their online learning (Bonk, Lee, Kou, Xu, & Sheu, 2015). MOOCs are the technical concept towards online courses that enable learning organizations to access free, high-quality instructional programs and have relevant visibility on the Internet (Johnson et al., 2013; Pellas, 2014). MOOCs is a network platform that allows millions of learners to access a variety of educational materials and resources without time and place constraints, such as Coursera, Udacity, edX, KHAN academy, Udemy, and Lynda.com

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(Chang & Wei, 2016). MOOCs use social networking services (SNS) such as instant messaging (IM), Facebook and Twitter to become increasingly popular to promote increased social interaction and attract millions of teachers, learners and parents (Lin, 2010). As a result, the MOOCs concept and its application have already gained attention from the academic scholars and e-learning industry.

However, while MOOCs are rapidly applying and gaining popularity, there are still exist some drawbacks and need to solve. First, most literatures of current MOOCs researches pay more attention on qualitative research (Clarke, 2013; Kay, Reimann, Diebold, & Kummerfeld, 2013; Leber, 2013). Although there are few quantitative researches investigating the user intention to use the MOOCs (Alraimi, Zo, & Ciganek, 2015; Deale, 2015; Wu & Chen, 2017), unfortunately, they were purely documenting the results of the systemic functional perspective and lack of open educational content (Bonk et al., 2015; Iiyoshi & Kumar, 2008). Second, latest researches found the most learners hard to focus on learning materials and cause the disappointing learning efficiency and effectiveness (Bonk et al., 2015; Chang & Wei, 2016). This phenomenon happens because most MOOCs designs lack of providing an attractive or superior experience for learners. Some scholars have suggested that MOOCs have to improve learners' digital participation, referring to learners' learning and daily interactions with existing technologies in learning ecology, including everyday life and school background (Gurung & Rutledge, 2014). Therefore, it is very important to improve the participation of learners in the development of MOOCs.

Based on the above literature discussion, the social support theory can be adopted and used to solve these two weakness. Shumaker and Brownell (1984) pointed out the "Social support is an exchange of resources between two individuals perceived by the provider or the recipient to be intended to enhance the well- being of the recipient". This relationship helps individuals confront challenges, pressures and difficulties, and enhances their ability to adapt to the environment (Caplan & Killilea, 1976). Based on the concept of social support, it can be used to enhance the cognitive processes and improve the engaging experience for learners. In this study, it is desired to provide references for related educational units that are either building information system or digital learning promotion by studying factors that influence learners in using MOOCs platform. Therefore, this study proposes the research model based on social support theory and technology acceptance model. Related educational units are expected to consider learners in creating and operating digital learning platforms in order to improve learning effect of MOOCs for students. Also, users are expected to join learning autonomously and long, such that related educational units could develop autonomous and persistent learning behaviors of learners through MOOCs, so that more superior high level talents are developed.

2. Literature review

In this section, the MOOCs concepts and developments were introduced in Section 2.1. Then, the main two research theories of this study were technology acceptance model and social support theory also discussed in Section 2.2 and 2.3, respectively.

2.1. Massive open online course

MOOC was proposed by Alexander and Cormier in 2008 and it was an extended approach and tool of flipped classroom model. In September of the same year, Siemens and Downes applied this concept to open the first authentic MOOC course - CCK08. Its concept is mainly based on connectivism learning theory, also referred to as cMOOC. The curriculum model of cMOOC focuses on knowledge construction and creation, emphasizes on creation, autonomy and social network learning, and supports learners to participate in learning with various forms, such as YouTube, Facebook and Twitter etc. In 2012, another new type of open courseware rose - xMOOC, which intends to "extend" learning resources for more people to obtain education online. The curriculum model of xMOOC is closer to traditional teaching process and idea. It focuses on knowledge dissemination and duplication,

emphasizes on video, assignment and test learning methods. By using xMOOC, autonomous learning model and flipped classroom model could be designed on teaching model. Course indexing, appraisal, recommendation functions could be provided on learning support. xMOOC constructs a learning ecosystem composed of technical environment, social environment and teaching environment, which brings innovative and new research issues for open education.

With Taiwan OCW consortium and popularity of global learning through MOOCs in 2012, Taiwan system also recognized the change of educational circle. In January, 2013, Department of Information and Technology, Ministry of Education started to plan "Taiwan MOOCs" in order to improve the trend of autonomous learning. For Taiwan MOOCs, case request is directed to various major Taiwan colleges and universities to encourage them to open MOOCs courses that could attract learners all over the world according to characteristics of each school. Currently, many colleges and universities have joined MOOCs Project in Taiwan, and exclusive MOOCs course platforms are designed in accordance with need of each of the schools, such as NTU MOOCs, NTHU MOOCs, NCHU MOOCs and National Taiwan Normal University ShareCourse etc. In addition, in response to the demand of learning Chinese language, Coursera platform not only invites Chinese language based universities to join the team, but also provides Chinese subtitles for many courses in order to benefit learners. The intention is to allow unlimited number of learners by breaking time and space constraints through internet. In other words, learners could learn courses from top international universities charge of free simply by means of one computer which is capable of networking.

The trend of digital learning (e-learning, m-learning and u-learning) remains, which is supported by many country governments under software and hardware support strongly. Indicator of better learning effect depends mainly on learning outcomes of students, so that cognitive perception of learners for learning system is the key factor of system success. If the digital learning system still focuses on instructors from a single point of view as traditional, it cannot consider learners to satisfy requirement and expectation of learners, so that the learning outcomes and motivation of learners will be limited considerably. On the other hand, digital learning requires learners to arrange learning schedule, learning steps, learning contents by themselves flexibly and autonomously. It is a learner centered teaching model. In view of above, based on learners with higher education, this study will investigate factors that influence learners with respect to use of massive open online courses, and understand how to obtain higher learning outcomes in using MOOCs and how to achieve long-term influence under persistent use.

2.2. Technology acceptance model

Davis, Bagozzi, and Warshaw (1989) proposed technology acceptance model and it is applicable to explain and predict behavioral intention model of users with respect to acceptance of information system. TAM synthesizes expectancy theory, self efficacy theory, cost efficiency norm, innovation adoption theory, evaluation of information report, channel arrangement model and other researches other than information management to develop two important major perspectives in TAM, "perceived usefulness" and "perceived ease of use". Six perspectives are included in the architecture of TAM. They are "perceived usefulness", "perceived ease of use", "attitude", "behavior intention", "actual use", and "external variables", through which factors affecting use of information technology are explained or predicted. The research model of the theory is as shown in Figure 1.

There are many researches were applied TAM to investigate the learners' behavior intention to continue use the e-learning system. Chow, Herold, Choo, and Chan (2012) investigated the famous virtual e-learning environment - Second Life as the research platform, and they found perceived usefulness and perceived ease of use can influence the learning motivation for the healthcare education. The same as Najmul Islam (2013) and Ali, Asadi, Gasevic, Jovanovic, and Hatala (2013), they adopted TAM to investigate the outcomes of e-learning systems adoption, the results indicated perceived usefulness and perceived ease of use can influence the learning outcomes. Recently, King and He (2006) used a meta-analysis to incorporate 88 research papers and reported high credibility of TAM. The

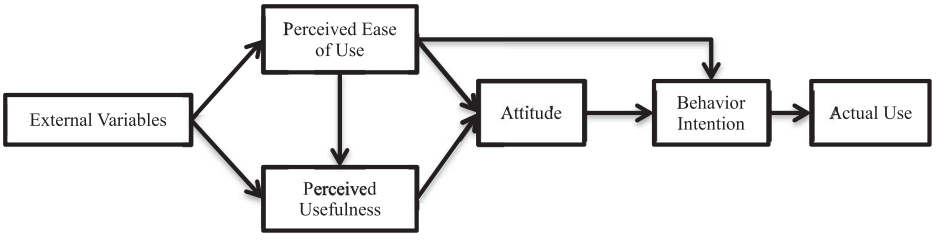

Figure 1. Technology acceptance model.

results showed "TAM to be a valid and robust model". Abdullah and Ward (2016) also collected 107 papers covering the last ten years of e-learning adoption, the results show the perceived usefulness and perceived ease of use have been studied across a range of e-learning technology types and e-learning user types. In addition, Chen and Tsai (2017) also adopted TAM to investigate the users' behavior intention to continue use the personalized location-based mobile tourism app on the YouBike. Therefore, this study is adopted TAM as a ground theory to investigate the behavior intention for MOOCs which incorporates the social support theory as the external factors of the proposed model.

2.3. Social support theory

Traditional social support research mainly investigates on the relationship between individuals, family, and owned friends. In addition, it is a communicative action that leads to effective comfort, information, knowledge, and material exchange (House & Kahn, 1985). In the past, the social support research classifies social support as informational, tangible, emotional, and belonging (Cutrona & Russell, 1990; Uchino, 2004; Wills, 1991). The informational support is the provision of advice, guidance, suggestions, or useful information to someone (Wills, 1991). The *tangible support* is the provision of financial assistance, material goods, or services (House & Kahn, 1985). The *emotional support* is the offering of empathy, concern, affection, love, trust, acceptance, intimacy, encouragement, or caring (Langford, Bowsher, Maloney, & Lillis, 1997). Finally, the *belonging support* is the type of support that gives someone a sense of social belonging. This can be seen as the presence of companions to engage in shared social activities (Wills, 1991).

Nowadays, because of the electronic commerce and social network sites popular, many researchers applied the social support theory to blogs, and social commerce and investigate the user behavior. The, the online social support was be proposed and focused on the relationship between recipients and providers, including online friends or strangers (Chang, 2009; Coulson, 2005). The empirically study showed the informational and emotional support were the most request supports in online social networks (Lin, Hsu, Cheng, & Chiu, 2012). However, the tangible support has the low need in the online social networks (Liu & Hung, 2016). The reasonable explanation is tangible support is difficult to be achieved without face-to-face interactive environment. However, it can be realized in online social networks environment by acted as the social media of providing related commercial goods, or information services (Chen & Lin, 2017). Finally, the belonging support is not significant influence and hard to evaluate in the real world. However, it is became easy to access and obviously observed in the online environment, especially on the social commerce and blogs (Nykvist & Mukherjee, 2016). Therefore, we synthesize social support as fourfold for this study: informational, emotional, tangible, and belonging support.

3. Research methodology

In this section, the research model was proposed based on the TAM and social support theory firstly. Then, the research hypotheses were derived and discussed in Section 3.2. Finally, the

participants' background and data collection process were also described and explained in Section 3.3.

3.1. Conceptual model

This study adopts the technology acceptance model proposed by Davis et al. (1989) and social support theory proposed by Shumaker and Brownell (1984) to explore the influencing factors between traditional e-learning platform and MOOCs platform. The research model is shown in Figure 2. It includes 8 dimensions and 13 hypotheses. Furthermore, the 4 factors as external variables including perceived convenience, computer self-efficacy, sense of community, and perceived gains according to literatures of formers and digital learning related literatures. Then, these four external variables are divided into informational, emotional, tangible, and belonging support factors in accordance to the classification of online social support. Perceived convenience belong to tangible support, computer self-efficacy is viewed as emotional support, sense of community belong to belonging support, and perceived gains belong to information support.

3.2. Research hypotheses

In the following hypotheses, H_1-H_4 are derived from TAM, H_5-H_7 are related with perceived convenience, H_8-H_9 are related with computer self-efficacy, H_{10}-H_{11} are related with sense of community, whereas H_{12}-H_{13} are related with perceived gains. These hypotheses are given below.

3.2.1. TAM

According to Davis (1986), Davis et al. (1989), Venkatesh and Morris (2000), Moon and Kim (2001), and Chen, Chang, Chen, Huang, and Chen (2012), users will have higher behavioral intention and actual use to use a specific IT if they trust it will increase their performance, or they think that the use of the technology will be free of effort. Therefore, the following four hypotheses are proposed:

H_1: Perceived ease of use of learners for digital learning platform has significant positive effect on their perceived usefulness.

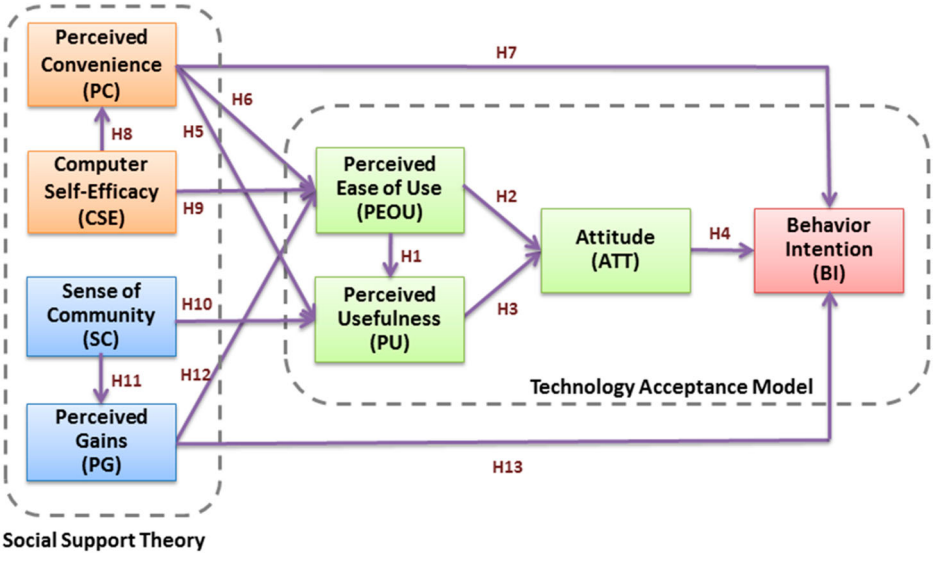

Figure 2. Conceptual model.

H_2: Perceived ease of use of learners for digital learning platform has significant positive effect on their attitude.

H_3: Perceived usefulness of learners for digital learning platform has significant positive effect on their attitude.

H_4: Attitude of learners for digital learning platform has significant positive effect on their behavior intention.

3.2.2. Perceived convenience

According to Merriam-Webster Dictionary, Brown (1989) thought convenience is not only "time saving". Therefore, Brown distinguished convenience into five major categories for study, including: (1) time perspective: product is provided at convenient time regarded by the consumer; (2) place perspective: product is provided in a convenient place regarded by the consumer; (3) obtaining perspective: vendors provide financial or other channels for consumers to buy their products easily. (4) Using perspective: users feel convenient when using the product (5). Execution perspective: convenience to select to do by oneself or by asking for others.

In the society with advancing and innovative information technologies, a swirl of epochs in which time is money, "convenience" is always what consumers' desire. It is indispensable not only in mobile commerce and technical product fields, but also in digital learning field. Learning cost includes not only money, but also time. Therefore, some scholars regard "convenience" as non-monetary cost of consumers. New generations of learners are hungry for knowledge. The rise of knowledge economy allows learning to escape from campus, and allows time and space unlimited access to learning information through any terminal equipment. In this study, we assume that the perceived convenience can be explained that the digital learning platform can provide more flexible service especially for the time saving and cost reduce. Therefore, the perceived convenience can be belonged to the tangible support. Several researchers claimed that perceived convenience have a significant positive impact on perceived usefulness, perceived ease of use, behavior intention (Carter & Campbell, 2012; Mangin, Guerrero, Bourgault, & Egea, 2013; Tsai, 2011). Therefore, the following hypotheses are proposed:

H_5: Perceived convenience of learners for digital learning platform has significant positive effect on their perceived usefulness.

H_6: Perceived convenience of learners for digital learning platform has significant positive effect on their perceived ease of use.

H_7: Perceived convenience of learners for digital learning platform has significant positive effect on their behavior intention.

3.2.3. Computer self-efficacy

Bandura (1977) regarded self-efficacy as determination of organization, action ability for individuals to achieve specific assignment. The self-efficacy theory influenced later research about computer efficacy (Kinzie & Delcourt, 1991; Murphy, Coover, & Owen, 1989). Murphy et al. (1989) thought computer self-efficacy is a determination of ability of using computer. Torkzadeh and Koufteros (1994) thought computer self-efficacy pays attention to the ability perceived by individuals in scenarios that are different from but related to computer. Compeau and Higgins (1995) defined computer self-efficacy as determination of individuals for their computer ability. They emphasized that computer self-efficacy reflects an ability of individuals who perceive that tasks are completed by using their computer abilities, instead of some actual computer operation skills. Therefore, the computer self-efficacy is mainly to allow users in the psychological and emotional, feel confident and problem-solving ability for the use of digital learning platform. In this study, we believe the computer self-efficacy can be belonged to the emotional support. Several researchers have indicated that the computer self-efficacy significantly affects the perceived ease of use (Kilic, 2014; Lee, 2006). Gu, Lee, and Suh (2009) indicated that computer self-efficacy can influence perceived ease of use, perceived

usefulness, and behavior intention in mobile banking. Therefore, this study proposes the following hypothesis:

H_8: Computer self-efficacy of learners for digital learning platform has significant positive effect on their perceived convenience.

H_9: Computer self-efficacy of learners for digital learning platform has significant positive effect on their perceived ease of use.

3.2.4. Sense of community

Draves (2007) though that features of online learning courses should not be limited to teaching contents themselves, but should focus on interaction between contents and learners. Sims (1997) also showed that designers of digital learning courses should not consider only human machine interactivity (e.g. menus, clickable objects etc.). Sense of community was found as critical influential factor of this MOOC study group (Chen & Chen, 2015). Sense of community, as defined by McMillan and Chavis (1986), is "a feeling that members have of belonging, a feeling that members matter to one another and to the group, and a shared faith that members' needs will be met through their commitment to be together". These features are not sufficient to help learners obtain new knowledge, develop understanding and criticism capabilities. Also, in modern teaching technology field, other scholars think the interactivity of the community should be reviewed continuously, and some newer, more concrete criteria should be provided for online course designers in order for learners to develop internet learning systems that are more flexible, helpful for students to learn, and more interactive.

In summary, the degree of sense of community may be improved, if digital learning systems can satisfy interaction requirement between learners and teaching contents, instructors, other learners and platform interfaces timely. According to Pituch and Lee (2006), interactivity was found to be positively related to perceived usefulness and behavior intention. Thus, the following hypothesis is proposed:

H_{10}: Sense of community of learners for digital learning platform has significant positive effect on their perceived usefulness.

Some researchers found that is a positive relationship between sense of community and perceived gains (Chen & Chen, 2015; Ertmer & Stepich, 2005; Trespalacios & Perkins, 2016). Thus, the following hypothesis is proposed:

H_{11}: Sense of community of learners for digital learning platform has significant positive effect on their perceived gains.

3.2.5. Perceived gains

Liao and Lu (2008) thought that how to attract learners to use digital learning system is a great challenge under the trend of digital learning. With respect to selection of learning subjects, there is more autonomy for digital learning in comparison to traditional classroom learning system. From their research result, it is also found that compatibility and comparative advantage are major factors that influence behavior intention on online learning websites. In addition, for learners with experiences in using online learning websites, the factors that influence their use intention are feeling benefits and result demonstration for them. Thereby, it may be inferred that perceived gains is one of the important factors that influence behavior intention of users.

According to Chen and Chen (2015), perceived gains relates to the level of compliance of values due to innovation and values perceived by current users, that is, the level that innovative information technology could meet current requirement, various previous experiences, values and life style of users. In their researches, the students' perceived gains of MOOCs environment from the study groups can be thematically organized into: cognitive gains, affective gains, and

enhanced action tendencies. Therefore, from research results of the two literatures of Chen and Chen (2015), Hackbarth, Grover, and Yi (2003), it is discovered that perceived gains and system experience will influence behavioral attitude through perceived usefulness and perceived ease of use, respectively. Accordingly, the research thinks that the perceived ease of use of learners for digital learning platforms would rise respectively if the level that the use of digital learning platforms could meet current requirement, previous various experiences, values and learning styles is higher.

H_{12}: Perceived gains of learners for digital learning platform has significant positive effect on their perceived ease of use.

H_{13}: Perceived gains of learners for digital learning platform has significant positive effect on their behavior intention.

3.3. Participants and data collection

In the research, after questionnaires issued through network, collected data are arranged for statistical analysis, wherein "Likert 5-point scale" is used for response form of questionnaire content. The study objects were users who have used traditional e-learning platforms. Adoption intention factors for use of e-learning platforms and MOOCs platform were surveyed. Total 463 questionnaires were returned. Total 106 invalid samples were rejected through the filter mechanism in the questionnaire design. Total 357 valid questionnaires remained. The effective sample rate is 77.1%. For subsequent analysis, IBM SPSS Statistics 22 and AMOS 21 were the main analysis tools for research. Wherein, reliability analysis, validity test and correlation analysis are performed for various perspectives. Finally, the questionnaire is listed in the Appendix A and these items is designed from the TAM and social support theory.

For descriptive statistics of personal data, sample distribution is presented in the forms of frequency distribution and percentage. In the research, gender, age, education background, whether digital learning platform has been used or not and whether Taiwan MOOC has been used or not are discussed for basic data of study objects, and basic characteristics of sample data are investigated through SPSS statistical software. Analysis of demographic information for effective samples is as listed in Table 1.

4. Methodology

In this section, the research model and questionnaires were evaluated through the reliability and validity analysis, discriminant and convergent validity, and structural equation analysis.

Table 1. Demographic Information of the respondents ($n = 357$).

Category Item	Variable	Sample Size	Percentage
Gender	Male	188	52.7%
	Female	169	47.3%
Age	Below 18	40	11.2%
	19–25	259	72.5%
	26–30	27	7.6%
	Above 31	31	8.7%
Education Background	Below high school	9	2.5%
	Above College and University	348	97.5%
Digital Learning Platform Usage Experience (Year)	Below 1	129	36.1%
	1–3	142	39.8%
	4–6	60	16.8%
	Above 6	26	9.3%
MOOCs Platform Usage Experience	Yes (Ever Used)	180	50.4%
	No (Never Used)	177	49.6%

4.1. Reliability and validity analysis

According to expression of Nunnally (1978), the recommended value of Cronbach's α shall be above 0.7 as high reliability value. According to initial analysis, Cronbach's α value of all measurement variables in the research reach above 0.7, so that good reliability is achieved. The reliability analysis for detailed revised items are as listed in Table 2.

In the research, convergent validity and discriminant validity are used for evaluation of construct validity analysis. Fornell and Larcker (1981) proposed test of each of the perspectives for existence of convergent validity by evaluation of Average Variance Extracted (AVE) for each of the perspectives. Fornell and Larcker (1981) thought that there is sufficient convergent validity between question items for the perspective as Average Variance Extracted (AVE) is greater than 0.5. In the research, among AVE for each of the perspectives, AVEs of the group using MOOC platform are all higher than 0.6518, AVEs of the group using traditional e-learning platform are all higher than 0.6657, so that it may be inferred that there is good discriminant validity for the questionnaire scale designed in the research. Validity analysis of question items for each of the perspectives is as listed in Table 3.

4.2. Discriminant and convergent validity

In the research, correlation degree between these variables is tested through Pearson correlation analysis. If related coefficient is too high, there would be collinear issue in regression analysis. The tested criterion would be compared with Pearson correlation coefficient by calculating the value of $\sqrt{\text{AVE}}$; it indicates that there is discriminant validity if $\sqrt{\text{AVE}}$ is greater than Pearson correlation coefficient. From Tables 4 and 5, positive correlation exists between all perspectives, and all related coefficients are smaller than the value of $\sqrt{\text{AVE}}$. It indicates that there is no collinear issue and all of them achieve significance level.

4.3. Structural equation analysis

Structural equation analysis is a multivariate analysis, including factor analysis and path analysis, and adopts goodness-of-fit model to assess the proposed research structural model. Table 6 shows the result of goodness of fit test of research model. In Figures 3 and 4, we can learn whether or not the hypotheses proposed are valid and their significance.

In the test results for users of MOOC platform and traditional e-learning platform, the perceived ease of use with respect to perceived usefulness are 0.243, 0.136, respectively. Then, the hypothesis H_1 is supported. The standardized path coefficients of perceived ease of use with respect to using attitude are 0.196, 0.315, respectively. So that hypothesis H_2 is supported. The standardized path coefficients of perceived usefulness with respect to using attitude are 0.720, 0.940, respectively, both of which have *p*-values reaching significance levels smaller than 0.001, so that hypothesis H_3 is supported. The standardized path coefficients of using attitude with respect to using attitude are 0.498, 0.714, respectively, both of which have *p*-values reaching significance levels smaller than

Table 2. Reliability analysis results.

	MOOC Platform		Traditional e-Learning Platform	
Perspective	Items	Cronbach's α	Items	Cronbach's α
Computer Self-Efficacy	6	0.951	6	0.934
Perceived Convenience	2	0.842	2	0.823
Perceived Gains	2	0.814	2	0.841
Sense of Community	3	0.846	3	0.920
Perceived Usefulness	5	0.911	5	0.948
Perceived Ease of Use	4	0.931	4	0.933
Attitude	3	0.889	3	0.900
Behavior Intention	2	0.904	2	0.796

Table 3. Confirmatory factor analysis.

Research Perspective and Measurement Question		Factor Loading (MOOC Platform)	Factor Loading (General Platform)	CR[a]/AVE[b] (MOOC)	CR[a]/AVE[b] (General)
Computer Self-Efficacy (CSE)	CSE 1	0.882	0.854	0.9521 76.96%	0.9321 69.71%
	CSE 2	0.972	0.856		
	CSE 3	0.970	0.927		
	CSE 4	0.830	0.852		
	CSE 5	0.740	0.750		
	CSE 6	0.847	0.757		
Perceived Convenience (PC)	PC 1	0.845	0.876	0.8424 72.77%	0.8286 70.77%
	PC 2	0.861	0.805		
Perceived Gains (PG)	PG 1	0.868	0.878	0.8148 68.80%	0.8454 73.24%
	PG 2	0.789	0.833		
Sense of Community (SC)	SC 1	0.838	0.900	0.8483 65.18%	0.9193 79.16%
	SC 2	0.847	0.879		
	SC 3	0.732	0.890		
Perceived Usefulness (PU)	PU1	0.826	0.872	0.9127 67.65%	0.9479 78.57%
	PU2	0.856	0.900		
	PU3	0.831	0.956		
	PU4	0.787	0.950		
	PU5	0.811	0.736		
Perceived Ease of Use (PEOU)	PEOU1	0.829	0.864	0.9332 77.78%	0.9356 78.45%
	PEOU2	0.873	0.873		
	PEOU3	0.919	0.946		
	PEOU4	0.904	0.857		
Attitude (AT)	AT1	0.927	0.906	0.8978 74.60%	0.9028 75.61%
	AT2	0.849	0.871		
	AT3	0.811	0.830		
Behavior Intention (BI)	BI1	0.897	0.853	0.9033 82.37%	0.7915 66.57%
	BI2	0.918	0.764		

[a]Composite reliability $= \dfrac{(\sum^{\text{standardized loading}})^2}{\left(\sum^{\text{standardized loading}}\right)^2} + \sum^{\varepsilon} j.$

[b]Average variance extracted (AVE)$= \dfrac{(\sum^{\text{standardized loadin}} g^2)}{\left[(\sum^{\text{standardized loadin}} g^2) + \sum^{\varepsilon} j\right]}.$

0.001, so that hypothesis H_4 is supported. From above results, the technology acceptance model proposed by Davis in 1989 is also certified in the research.

In the test results for users of MOOC platforms and traditional e-learning platform, the standardized path coefficients of perceived convenience with respect to perceived usefulness are 0.337,

Table 4. Correlation matrix among the variables (MOOC Platform).

	CSE	PC	CP	IA	PU	PEOU	AT	BI
CSE	0.877							
PC	0.302	0.853						
PG	0.189	0.468	0.829					
SC	0.184	0.523	0.429	0.807				
PU	0.153	0.610	0.566	0.627	0.822			
PEOU	0.400	0.551	0.549	0.489	0.613	0.882		
AT	0.221	0.526	0.548	0.433	0.641	0.528	0.864	
BI	0.164	0.577	0.614	0.432	0.658	0.595	0.713	0.908

Note: The numbers on the leading diagonal shows square root of AVE for each of the perspectives.

Table 5. Correlation matrix among the variables (traditional e-learning platform).

	CSE	PC	CP	IA	PU	PEOU	AT	BI
CSE	0.835							
PC	0.146	0.841						
PG	0.019	0.394	0.856					
SC	0.070	0.451	0.402	0.890				
PU	−0.041	0.453	0.561	0.607	0.886			
PEOU	0.049	0.387	0.582	0.184	0.303	0.886		
AT	0.049	0.556	0.604	0.636	0.660	0.596	0.870	
BI	−0.126	0.382	0.636	0.458	0.627	0.469	0.701	0.816

Note: The numbers on the leading diagonal shows square root of AVE for each of the perspectives.

Table 6. Measures of model fit for research model.

Indicator	Measurement Value (MOOC)	Measurement Value (General)	Recommended Value	Reference
Chi-Square (χ^2/df)	1.856	2.025	<3	Chau (1996), Segars and Grover (1993)
SRMR	0.031	0.039	<0.05	Hair, Anderson, Tatham, and Black (1998)
GFI	0.821	0.810	>0.8	Browne and Cudeck (1992), Doll, Hendrickson, and Deng (1998)
RMSEA	0.069	0.076	<0.08	Chau (1996), Segars and Grover (1993)
IFI	0.942	0.936	>0.9	Bagozzi and Yi (1988), Hair et al. (1998), Segars and Grover (1993)
CFI	0.941	0.935	>0.9	

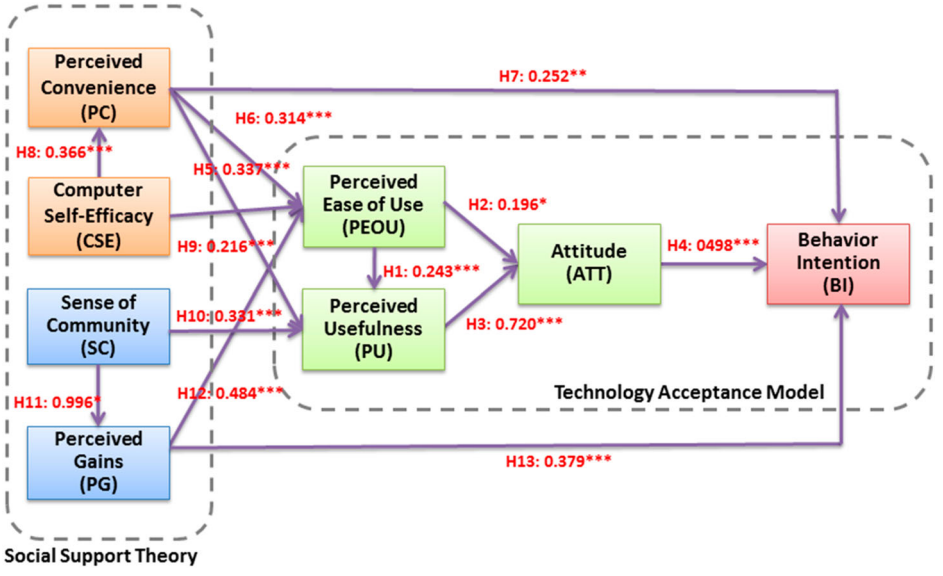

Figure 3. Model testing results for MOOCs platform (***$p < 0.001$,**$p < 0.01$,*$p < 0.05$).

0.197, respectively, so that hypothesis H_5 is supported. The standardized path coefficients of perceived convenience with respect to perceived ease of use are 0.314, 0.117, respectively, wherein the *p*-value of MOOC platform group reaches a significance level smaller than 0.001, so that hypothesis H_6 is supported; on the contrary, the traditional e-learning platform group does not reach significance level, so that hypothesis H_6 is not supported. Thereby, it indicates that the perceived convenience of the learners using MOOC platform will have positive effect on perceived ease of use. For traditional e-learning platform users, their perceived convenience has no significant

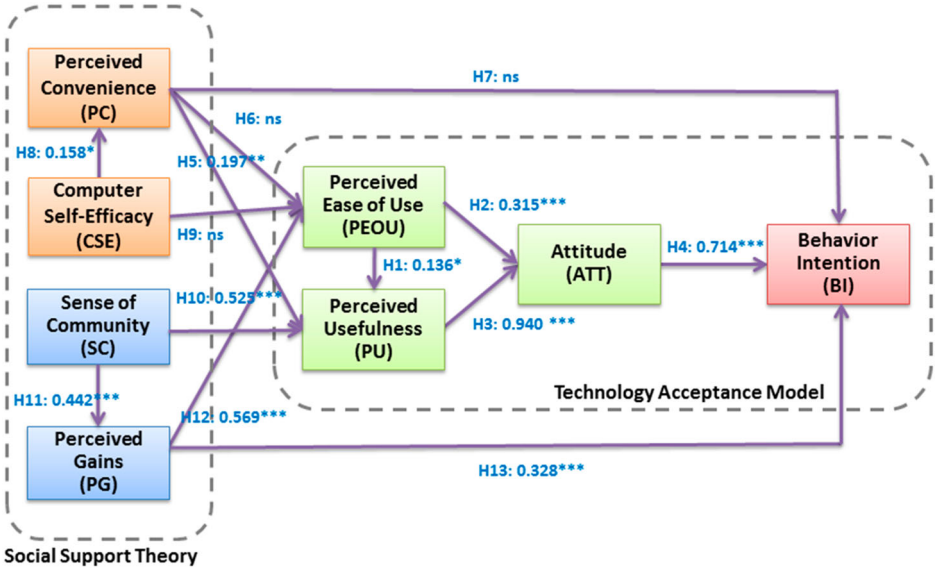

Figure 4. Model testing results for traditional e-Learning platform platform (***$p < 0.001$,**$p < 0.01$,*$p < 0.05$).

influence in comparison to perceived ease of use. The standardized path coefficients of perceived convenience with respect to behavior intention are 0.252, 0.125, respectively, wherein the *p*-value of MOOC platform group reaches a significance level smaller than 0.01, so that hypothesis H_7 is supported; on the contrary, the traditional e-learning group does not reach significance level, so that hypothesis H_7 is not supported. Thereby, it indicates that the perceived convenience of the learners using MOOC platform will have positive effect on behavior intention. For traditional e-learning users, their perceived convenience has no significant influence in comparison to behavior intention.

With respect to computer self-efficacy variable, the standardized path coefficients of computer self-efficacy with respect to perceived convenience are 0.366, 0.158, respectively. So that hypothesis H_8 is supported. The standardized path coefficients of computer self-efficacy with respect to perceived ease of use are 0.216, 0.023, respectively, so that hypothesis H_9 is supported; on the contrary, the traditional e-learning platform group does not reach significance level, so that hypothesis H_9 is not supported. Thereby, it indicates that the computer self-efficacy of the learners using MOOC platform will have positive effect on perceived ease of use. For traditional e-learning platform users, their computer self-efficacy has no significant influence in comparison to perceived ease of use for digital learning platforms.

For hypotheses related to sense of community and perceived gains, the standardized path coefficients of community with respect to perceived usefulness are 0.331, 0.525, respectively, so that hypothesis H_{10} is supported. The standardized path coefficients of sense of community with respect to perceived gains are 0.996, 0.442, respectively. Their *p*-values are smaller than 0.05 and 0.001, respectively, so that hypothesis H_{11} is supported. The standardized path coefficients of perceived gains with respect to perceived ease of use are 0.484, 0.569, respectively, so that hypothesis H_{12} is supported. The standardized path coefficients of perceived gains with respect to using attitude are 0.379, 0.328, respectively, so that hypothesis H_{13} is supported.

4.4. Discussion

With the aforementioned path analysis results, direct and indirect effect analyzes between variable are arranged for the research in order to understand explanatory ability between variables and

Table 7. Direct, indirect, and total effect on intention to use (MOOC Platform).

	Direct Influence			Indirect Influence			Total Influence		
	PEOU	PU	BI	PEOU	PU	BI	PEOU	PU	BI
CSE	0.216	–	–.	0.106	0.191	0.185	0.322	0.191	0.185
PC	0.314	0.337	0.252	–	0.076	0.179	0.314	0.413	0.431
PG	0.484	–	0.379	–	0.118	0.089	0.484	0.118	0.468
SC	–	0.331	–	0.482	0.117	0.208	0.482	0.448	0.208
PEOU	–	0.243	–	–	–	0.098	–	0.243	0.098
PU	–	–	–	–	–	0.359	–	–	0.359

Table 8. Direct, indirect, and total effect on intention to use (traditional e-learning platform).

	Direct Influence			Indirect Influence			Total Influence		
	PEOU	PU	BI	PEOU	PU	BI	PEOU	PU	BI
CSE	–	–	–	–	0.031	0.021	–	0.031	0.021
PC	0.197	–	–	–	–	0.132	0.197	–	0.132
PG	0.569	–	0.328	–	0.077	0.180	0.569	0.077	0.508
SC	–	0.525	–	0.251	0.034	0.432	0.251	0.559	0.432
PEOU	–	0.136	–	–	–	0.225	–	0.136	0.225
PU	–	–	–	–	–	0.671	–	–	0.671

the biggest influence factor that influences learners in using digital learning platforms. The effect analyzes are as listed in Tables 7 and 8.

From effect analyzes, it is known that the seven variables, perceived convenience, computer self-efficacy, sense of community, perceived gains, perceived ease of use, perceived usefulness and using attitude influence intention of learners for using digital learning platforms jointly. In spite of MOOC platform or traditional e-learning platform, using attitude is the biggest influence factor that influences behavior intention. Therefore, the research studied influence of other six variables on total effect of using digital learning platforms. In MOOC platform group, perceived gains (0.468) has the biggest influence, followed by perceived convenience (0.431); in traditional e-learning platform group, perceived usefulness (0.671) has the biggest influence, followed by perceived gains (0.508).

5. Conclusions

In this section, we discussed the empirical analysis results and presented the potential suggestions from academic and industry perspectives. Finally, the research limitations and future research were also figured out in Section 5.3.

5.1. Managerial implications

From empirical analysis results in the research, it may be discovered that the TAM proposed by Davis (1986) obtains positive and significant influence in either MOOCs group or traditional e-learning group. In an environment of using a certain digital learning platform, if the subjective perceived usefulness level of users for said platform is higher, then their positive perception for said platform is better to influence use intention of the users. In other words, when learners think MOOCs platform is helpful for their learning performance subjectively, it would facilitates users to induce positive using attitude for MOOCs platform, such that the intention of users to use learning platform is influenced. In addition, perceived ease of use tends to have positive and significant influence on perceived usefulness. That is, the level of ease to operate MOOCs platform would influence perceived usefulness of users positively. Therefore, our proposed model is in line with Davis (1986), Davis et al. (1989), Venkatesh and Morris (2000), Moon and Kim (2001), Chen et al. (2012), and Abdullah

and Ward (2016) who suggested the TAM has the robust and well explanation for behavior intention toward the information system.

Then, this study adopted the social support theory and proposed the hypotheses of perceived convenience, computer self-efficacy, sense of community, and perceived gains. With perceived convenience factor for MOOCs platform, it has significant influence on perceived usefulness, perceived ease-of-use, and behavior intention. However, it has not significant influence on perceived ease-of-use, and behavior intention for traditional e-learning platform. According to previous researches, Yoon and Kim (2007) also found that the perceived convenience of users does not have positive influence on their adoption of wireless network technology in the research of studying wireless network environment. Therefore, it may be inferred that the traditional e-learning mechanism is very popular and related educational environments are also well-established in the daily life. However, MOOCs platform resorts to "immediacy". Thousands, ten thousands of people from different cities, different countries learn together, so that when a learner encounters a question in learning, other learners all over the world might answer the question. As a result, MOOC platform allows time unlimited learning. Compared to MOOC platform, instructors on traditional e-learning platforms are mostly learners with the same background, and even more, may be learners in the same class, the same school. The advantage of immediate community response is unavailable because learners have considerable knowledge background and like life pattern.

With computer self-efficacy factor for MOOCs platform, it has significant influence on perceived ease-of-use and perceived convenience. Therefore, our proposed model is in line with Lee (2006), Gu et al. (2009), and Kilic (2014). However, it has no significant influence on perceived ease of use in traditional e-learning platform. It can be inferred probably due to complexity of traditional e-learning platform. Usually, it provides mainly download of material resources. The next is one-way teaching video. The design of digital learning platform tends to be simple and easy, such that low level computer users may learn how to use traditional e-learning platforms easily, so that there is no way to show significant influence of computer self-efficacy on perceived ease of use for digital learning platform. In addition, Yoon and Kim (2007) also found the self-efficacy of users does not have positive influence on perceived ease of use for their adoption of wireless network technology in the research of studying environment of wireless network. Therefore, the research infers that computer self-efficacy is not an important factor to influence perceived ease of use in traditional e-learning platforms.

With sense of community and perceived gains factors for both MOOCs and traditional e-learning platforms, the hypotheses were all supported and had significant influence on perceived ease-of-use, perceived usefulness, and behavior intention. Therefore, our proposed model is in line with Hackbarth et al. (2003), Pituch and Lee (2006), Chen and Chiou (2014), and Chen and Chen (2015) who suggested the sense of community and perceived gains have the positively related to TAM model. Finally, this study investigated the behavior intention for using different e-learning platform from social support perspective, as the empirically results, the tangible support (perceived convenience) and emotional support (computer self-efficacy) have no significant influence on behavior intention for traditional e-learning learners, but they pay more attention and care about belonging support (sense of community) and informational support (perceived gains) toward the e-learning system usage. On the contrary, the MOOCs leaners focus on tangible support (perceived convenience) and informational support (perceived gains), but still think emotional support (computer self-efficacy) and belonging support (sense of community) are important.

Therefore, we can assume that when novel e-learning approach starts, it should be needed and enhanced the informational support and let learners believe them can get the benefits. In the meantime, it is also important to provide the sufficient tangible support, especial for the educational materials or learning tools. The reason to offer better tangible support, can let learners have self-efficacy for computer operation ability indirectly. Finally, when the e-learning approach becomes more popular, then learners will transfer their attention to belonging support with the study community.

5.2. Practical implications

In the research, the factors that influence learners in MOOCs platform are studied by using statistical software according to the results of collected returned samples through questionnaire issued via network. Although there are years of implementation experiences for open digital learning platform abroad, it is still a new learning model with many spaces to be developed for instructors and learners in Taiwan. Moreover, there may be minor difference between styles of learners of different countries overall. If foreign operation model is simply emulated without change during development in Taiwan, the learning requirement of Taiwan learners cannot be satisfied exactly. Therefore, with the initial research results of the research for this issue, the following conclusion is used for reference in order for institutions and instructors who devote to open courses to start from the view of learners now or in the future, such that a learning mechanism that is closer to the requirement of learners is created.

First, the semi-supervised learning mechanism can be adopted for the education in Taiwan. Traditional cramming education model in Taiwan has been criticized by many scholars. It results in a unique innovation and independent consideration ability of students in Taiwan, together with excessive learning pressure, such that the learning attitude of students in Taiwan is passive, negative. Therefore, the learning styles of most learners in Taiwan result in passive group in comparison to the learners in Europe and America. For above phenomena, in addition to getting rid of traditional cramming education model, partial supervising learning mechanism till has to remain, such as regular homework assignment, quiz mechanisms when open digital learning platform is driven in Taiwan. By this way, learners are allowed to test learning effect real time. Further, instructors are allowed to handle learning progress of learners. At last, learners may be supervised indirectly to learn on schedule and continuously.

Second, the curriculum design should be convenient to use, easy to understand in MOOCs platform. According to the research results, the important factors that influence the use of MOOCs platform are primarily perceived gains, followed by perceived convenience. Accordingly, it may be deduced that learning method and learning mechanism should be similar to past learning styles of learners in curriculum design. In addition, platform course should focus on efficiency of real time feedback for learners to obtain answers about their questioning in the shortest time, such that learners will have higher use intention.

5.3. Research limitations and future works

In order for richness and completeness of subsequent related researches, difficulties and limitations encountered in the research are arranged and set forth as recommendations for research. First, the sample diversification can be extended. Although there were valid 357 samples questionnaires returned, the ages of the samples concentrate on 19–25 ages (72.5%), which are speculated as students of colleges and universities. Therefore, researchers in the future are recommended to pay more attention to age distribution to study if there is difference between different ages with respect to consideration factors for MOOCs platform. Second, the learning outcomes can be considered and evaluated by different educational platforms. In the study, only the factors of adoption intention of learners are discussed without studying whether learners improve their own knowledge ability exactly or not. Therefore, future researchers are recommended to analyze difference between before and after use of MOOCs platform for specific groups through experimental method. Finally, the course category or different learning styles of learners can be investigated, it is expected to study the issues for effectiveness of improving learning ability of learners with respect to MOOCs platform more perfectly.

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Appendix

A. Measures of constructs

Perceived Convenience

PC1 The traditional e-learning platform/MOOCs platform can make me easily carry out the online learning.
PC2 The traditional e-learning platform/MOOCs platform let me catch the learning information in real-time.

Computer Self-Efficacy

CSE1 For me the computer is easy to learn.
CSE2 For me the computer is easy to use.
CSE3 It is not difficult for me to operate a computer skillfully.
CSE4 It was easy for me to use a computer to do what I wanted to do.
CSE5 I have the confidence to learn a variety of computer skills.
CSE6 Learning computer for me is simple.

Sense of Community

SC1 The traditional e-learning platform/MOOCs platform can let me have willingness to share my learning experience in the discussion board.

SC2 The traditional e-learning platform/MOOCs platform can make me feel happy when my questions were be answered by others in the same study group.
SC3 To sum up, I am able to achieve full learning interactivity and feel myself belonging to the study group in the traditional e-learning platform/MOOCs platform.
Perceived Gains
PG1 The traditional e-learning platform/MOOCs platform can fit my learning style.
PG2 The traditional e-learning platform/MOOCs platform can satisfy my learning need.
Perceived Usefulness
PU1 The interface design of traditional e-learning platform/MOOCs platform in line with my need.
PU2 The learning mechanism of traditional e-learning platform/MOOCs platform in line with my need.
PU3 The learning operation of traditional e-learning platform/MOOCs platform in line with my need.
PU4 The content presentation of traditional e-learning platform/MOOCs platform in line with my need.
PU5 To sum up, I think the traditional e-learning platform/MOOCs platform is useful for me.
Perceived ease of Use
PEOU1 I think learning to use traditional e-learning platform/MOOCs platform is easy.
PEOU2 I think the interface that uses traditional e-learning platform/MOOCs platform is easy to understand to use.
PEOU3 I think the operation traditional e-learning platform/MOOCs platform process is not difficult for me.
PEOU4 Overall, I think it is easy to use traditional e-learning platform/MOOCs platform for learning.
Attitude
ATT1 I have a positive attitude towards traditional e-learning platform/MOOCs platform.
ATT2 I think it is a wise choice to carry out learning through the traditional e-learning platform/MOOCs platform.
ATT3 I think the use of traditional e-learning platform/MOOCs platform to meet my various learning needs.
Behavior Intention
BI1 I would recommend to use the traditional e-learning platform/MOOCs platform for my friends.
BI2 I will choose the traditional e-learning platform/MOOCs platform to learn in the future.