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Learner Behaviour in a MOOC Practice-oriented Course: In Empirical Study Integrating TAM and TPB

 

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Abstract

Few practice-oriented courses are currently integrated into online learning platforms, such as OpenCourseWare, Khan Academy, and Massive Open Online Courses (MOOCs). It is worthwhile to explore how learners respond to information technology and new teaching methods when practice-oriented course are placed online. Therefore, this study probes learner willingness to participate in a practice-oriented course distributed through a MOOC platform, investigating relationships among perceptions, behavioural intentions, and actual behaviour. The current research framework integrates the Technology Acceptance Model and the Theory of Planned Behavior as its core theoretical basis. Empirical data were collected through a cross-section survey. All participants were students of 2D Animation Production, with a total of 272 respondents. The questionnaire data used Partial Least Squares Structural Equation Modeling (PLS-SEM) analysis. Results show: (a) attitude exerted the greatest influence on learners' behavioural intention; (b) learners' perceived behaviour control, subjective norm, and attitude, which directly and positively influence their behavioural intention; (c) behavioural intention exhibited dual mediation effects; (d) behavioural intention positively influenced actual behaviour in the C-TAM-TPB model, with a high level of overall model fit.

Keywords: MOOCs, practice-oriented course, technology acceptance model, theory of planned behavior, C-TAM-TPB, 2D animation

Introduction

As of December 2016, Coursera, a well-known MOOCs platform, had more than 1,700 running courses. Of those, over 700 new coursers were added in 2016 alone (Shah, 2016). The annual growth rate of Coursera is substantially greater than OpenCourseWare, from MIT. However, the proportion of the practice-oriented courses opened on all the leading MOOCs has never exceeded 5%. This low proportion indicates the difficulty to teach, learn, and operate practice-oriented courses within the MOOCs context.

As MOOCs diffuse through education and society, the following issues may need to be addressed: Is peer assessment fair? Should there be course design standards and/or standardization? How to implement checks when learners are trusted to complete assignments themselves? What video production methods are maximal? Is a low rate of course completion important? These issues, as they relate to MOOCs, have been fully discussed and studied by numerous researchers (Lowenthal & Hodges, 2015; Rodriguez, 2012; Margaryan, Bianco, & Littlejohn, 2015; Jordan, 2015). Clearly, we are still early in the research that truly understands learner perception and attitude within the MOOC environment. Shih, Feng, and Tsai (2008) pointed out that E-learning was a trending subject in studies of learner perception and attitude. The specific situation for practice-oriented course material, delivered through a MOOC, is even less understood and requires investigation into learner adaptability and behaviour participating in a MOOC that includes a practice-oriented focus.

TAM and TPB

The Theory of Planned Behavior (TPB) and the Technology Adoption Model (TAM) are the two most important theories used in studies of individual behaviour when using information technology products (Davis, Bagozzi, & Warshaw, 1989; Ajzen, 1985). Many empirical studies have found support for these two theories. Both of these theories have been found to apply to an individual's behaviour within the context of information technology use (Taylor & Todd, 1995b; Venkatesh & Davis, 2000; Adams, Nelson, & Todd, 1992; Davis, 1989; Van der Heijden, Verhagen, & Creemers, 2003; Armitage & Conner, 2001; Moon & Kim, 2001). Delivery of MOOCs entails information technology and information systems that TAM and TPB are well suited to describe. A single theory or model may not sufficiently describe complex research topics. The current study combines TAM and TPB (C-TAM-TPB; Taylor & Todd, 1995a) to overcome the limitations of a single theory and generate synergies from combinations of these theories, thereby improving explanatory power and model fit. According to Armitage and Conner (2001), few reliable inferences can be drawn from measurements of behavioural intention to actual behaviour, even though most studies limit their data collection to behavioural intention. Learners may express behavioural intention to learn online, but their actual behaviour may not occur. In addition, Hung, Liang, and Chang (2005) examined 58 well-known aspects of TAM-related literature and pointed out that the effect size between behavioural intention (BI) and actual behaviour (B) was not robust. Thus, the first focus of this study is to enhance the explanatory power between these two variables; that is, behavioural intention and actual behaviour within a MOOC practice-oriented course setting. The second focus of this paper is to describe the factors that influence MOOC learners' application of information technology to new modes of learning. The current study includes empirical results of a practice-oriented course on MOOCs, and results provide reference for MOOC platforms' efforts to include practice-oriented courses.

Research Questions

Currently, very few studies have delved into the behaviour and mental mechanisms of learners who were willing to take online practice-oriented courses. Therefore, this study intends to identify the factors that influence learners through an online practice-oriented course teaching 2D Animation Production. The aims of this study include

- exploring learners' behavioural intentions compared to actual behaviours while using a MOOC to learn a practice-oriented 2D design course while also collecting data on direct and indirect influential factors; and
- an investigation, through C-TAM-TPB, of the MOOC learners' willingness to enroll in the practice-oriented 2D design course, and thereby explain and predict willingness to continue studies when a practice-oriented design course is delivered via MOOC.

Conceptual Background and Research Hypotheses

Many previous studies have probed the factors influencing e-learning intention. Those results often draw on various theories and research models, including the Theory of Reasoned Action (Fishbein & Ajzen, 1975), the Theory of Planned Behavior (Ajzen, 1991), and the Technology Acceptance Model (Davis, 1989), all of which could predict information technology acceptance behaviour (Cheon, Lee, Crooks, & Song, 2012; Chang, Liang, Shu, & Chiu, 2015). One of the most used and influential models is TPB, which explores human behaviour while integrating volitional and non-volitional viewpoints and explaining behavioural intention through individuals, organizations, and society (Ajzen, 1991; Han & Yoon, 2015; Wu, Li, & Fu, 2011). This theory, however, lacks a clear description of acceptance of new information technologies and systems (Han & Yoon, 2015). Hence, the current study uses two types of internal focus of control, as suggested by TAM: perceived ease of use (PEOU) and perceived usefulness (PU). These two variables do not change with environment or across situations, making them important predisposing factors that influence attitude (ATT), as described in TPB (Taylor & Todd, 1995a; 1995b). C-TAM-TPB can explain behavioural intention from volitional and non-volitional perspectives while observing measures of perceived ease of use and perceived usefulness.

The following discussion of existing literature is organized as follows: Section 1 covers MOOCs, while Section 2 focuses on TAM, and then Section 3 explores TPB.

MOOCs (Massive Open Online Courses)

Open online courses are widely available to the general public through the Internet (Peter & Deimann, 2013). Common characteristics of MOOCs include videos delivering core instructional content (often ranging from 5 to 15 minutes per video). Such content can be viewed once or repeatedly, at any time and from any place, at low, normal, or high speed of playback. In most such courses, student scores are earned through assignments, online discussions, and evaluation instruments like tests and quizzes. High enrollment rates often accompany the opening of the typical MOOC course, but this tends to be followed by a low course completion rate (Pretz, 2014; Jordan, 2015). With no barriers to enrollment, many learners register just with the goal of obtaining some amount of course content, without considering actually completing the course requirements (Stack, 2015). Unlike students within a traditional school setting, online learners are more easily distracted while participating in an online course, making it difficult for teachers to monitor, supervise, and encourage learners (Li, Tseng, & Kang, 2017; Khorsandi, Kobra, Ghobadzadeh, Kalantari, & Seifei, 2012; Cragg, Dunning, & Ellis, 2008). Teachers also face the downside of large amounts of assignments to review for little to no extra remuneration. One common approach to overcome these issues is the mechanism of peer assessment (Kulkarni et al., 2013; Suen, 2014). Peer assessment is nothing new, but executing it within cyberspace is and requires technological tools. In fact, from course preparation, marketing/messaging, and enrollment to delivery, feedback/interaction, and assessment, technology plays a central role in making the MOOC possible. If the technology, or the comfort level of using it, is not smooth, success will be impossible. Thus, models of technology acceptance can be helpful in understanding the situation.

TAM (Technology Acceptance Model)

Davis (1989) derived the Technology Acceptance Model (TAM) from the Theory of Reasoned Action, as proposed by Fishbein and Ajzen (1975), and the Theory of Planned Behavior. This model suggests that behavioural intention positively influences performance. This approach effectively predicts perceived ease of use and perceived usefulness, which influences how individuals will use information technology that is new to them. This model applies the belief-attitude-intention-behaviour relationship in order to model user acceptance of information technology or information systems (Davis et al., 1989; Bernadette, 1996; Giesbers, Rienties, Tempelaar, & Gijselaers, 2013). Researchers have found TAM to be widely applicable and, in general, a parsimonious theoretical construct (Venkatesh & Davis, 2000; King & He, 2006). Empirically supported across many studies, TAM has also been positively used within the e-learning context (Juan, Chiu, & Francisco, 2006; Shin & Kang, 2015; Giesbers et al., 2013).

Selim (2003), and Sun, Tsai, Finger, Chen, and Yeh (2008) found that perceived usefulness and perceived ease of use are important indicators of online course acceptance. According to Davis (1989), applying TAM, perceived ease of use influences perceived usefulness, and both constructs together influence user attitude toward information technology use. Perceived usefulness refers to an individual's belief that using a particular information technology will improve his or her work efficiency. A positive perception of usefulness leads to a more positive attitude toward adoption. Perceived ease of use increases when a learner believes it is easy to learn a particular system, which also leads to increased likelihood of continuous use of the system (Davis et al., 1989; Taylor & Todd, 1995a). Ong, Lai, and Wang (2004) and Liaw (2008) pointed out that perceived ease of use influences the learner's behavioural intention to use an online learning system.

Li, Qi, and Shu (2008) found perceived ease of use significantly predicted perceived usefulness and behavioural intention. According to Schillewaert, Ahearne, Frambach, and Moenaert (2005), and Wu and Chen (2017), perceived usefulness is a significant mediator of the effects of perceived ease of use influence on behavioural intention. Importantly, behavioural intention has a mediating effect on an actual system (Luarn & Lin, 2005). Thus, this study proposes the following four hypotheses:

H1. A learner's perceived ease of use of a MOOC positively influences behavioural intention.

H2. A learner's perceived ease of use of a MOOC positively influences attitude.

H3. A learner's perceived usefulness of a MOOC positively influences attitude.

H4. A learner's perceived ease of use of MOOC positively influences perceived usefulness.

Attitude formation is based on experiences during an action, as well as previous related experiences, which may have deferred actions due to difficulties. This amounts to preferences of the individual (Fishbein & Ajzen, 1975). According to Bamberg, Ajzen, and Schmidt (2003); Davis et al. (1989); and Taylor and Todd (1995a); attitude has a positive and significant influence on behavioural intention. Therefore, this study proposes the following hypothesis:

H5. A learner's attitude towards using a MOOC positively influences behavioural intention.

TPB (Theory of Planned Behavior)

The Theory of Planned Behavior (TPB) was proposed by Ajzen (1985; 1991) by extending the Theory of Reasoned Action, and was mainly used to explain that an individual could decide whether or not to perform a certain behaviour according to his or her own free will (Fishbein & Ajzen, 1975). Namely, an individual's behavioural intention is the best predictor of behaviour. Ajzen (1985) added the constructs of perceived behaviour control (PBC), attitude toward behaviour and subjective norm (SN) to the Theory of Reasoned Action. Several researchers have empirically supported TPB in their studies of e-learning (Cheon et al., 2012; Chu, & Chen, 2016; White et al., 2012; AI-Harbi, 2011).

Behavioural intention refers to the subjective probability of an individual to perform a certain behaviour. The stronger the behavioural intention of an individual, the smaller the expected hindrance, indicating they are more likely to perform the behaviour, while also indicating the perceived behaviour control is stronger (Fishbein & Ajzen, 1975). This is one of the reasons that Ajzen (1985) used the constructs of behavioural intention and perceived behaviour control to reflect motivation and ability. Perceived behaviour control refers to whether an individual has ample resources and opportunities to perform a specific behaviour, and to what degree that behaviour can be controlled. When an individual is more able, or has more related resources, to use a particular system, they have a stronger behavioural intention to use this system, resulting in frequent or positive experiences or both (Taylor & Todd, 1995a). In short, when learners are involved in a MOOC practice-oriented course, the perceived behaviour control refers to the degree of ease or difficulty the learner perceives.

A subjective norm can be regarded as an influential social factor. While making a decision, the individual will incorporate others' expectations, resulting in normative pressure (Ajzen, 1991; Rivis & Sheeran, 2003). The current study predicts that learners would be more likely to continuously learn through a MOOC if they perceived support or encouragement from their important relationships (such as supervisors, friends, and peers) (Taylor & Todd, 1995a). Bamberg et al. (2003), and Venkatesh and Davis (2000) found that the construct of subjective norm positively and significantly influenced behavioural intention. Thus, subjective norm influences an individual's intention to perform a certain behaviour. Results may vary according to time, place, system, and cultural background, all of which are potential persuasive factors (Abbad, Morris, & De Nahlik, 2009). Based on this research thread, the current study proposes the following hypotheses:

H6. A learner's subjective norm about using a MOOC positively influences behavioural intention.

H7. A learner's perceived behaviour control over using a MOOC positively influences behavioural intention.

H8. A learner's perceived behaviour control over using a MOOC positively influences actual behaviour.

H9. A learner's subjective norm about using a MOOC positively influences actual behaviour.

From the perspectives of TPB and TAM, behavioural intention and actual behaviour are highly correlated (Venkatesh & Davis, 2000; Venkatesh, Morris, & Ackerman, 2000; Moon & Kim, 2001; Featherman & Pavlou, 2003). When an individual has stronger behavioural intention to use a particular information system, they would tend to actually use such a system more frequently. As pointed out by both Armitage and Conner (2001), and Hung et al. (2005), the path from behavioural intention to actual behaviour deserves further study. Thus, this study proposes the following hypothesis:

H10. A learner's behavioural intention of using a MOOC positively influences actual behaviour.

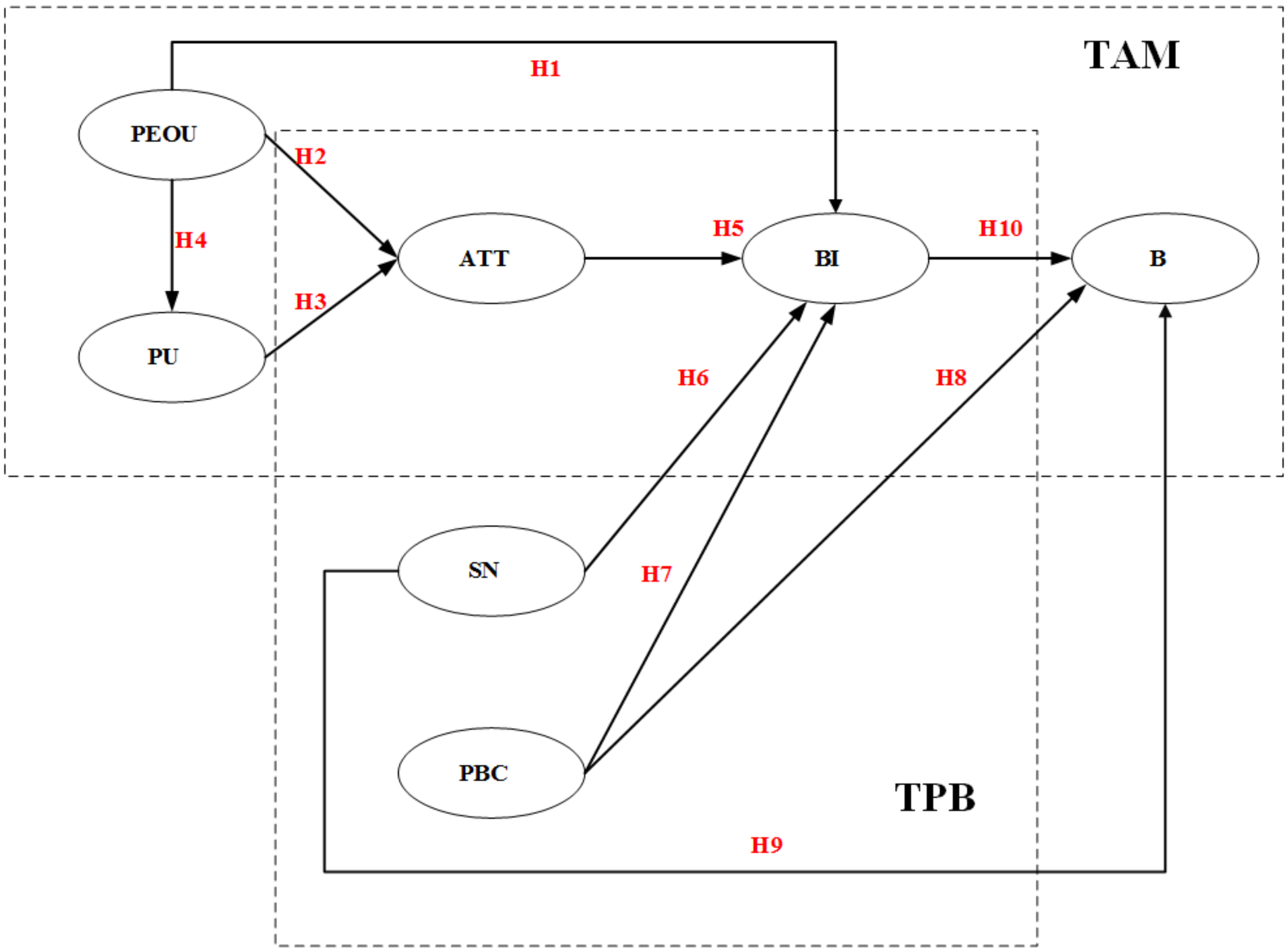

Figure 1. Hypothesized model.

Methodology

Participants and Procedures

The sample frame of this study was a course on 2D Animation Production, available on Sharecourse, one of Taiwan's MOOCs platforms. The course duration was 10 weeks, with 22 hours in total. The course was entirely free of charge, and a course completion certificate was issued to learners reaching a minimum final score of 60. Participants included: (a) learners enrolled for 2D Animation Production and (b) learners who had viewed the instructional videos related to 2D Animation Production. As the course proceeded to the fourth week, a notice was posted on the platform bulletin board requiring participants to answer the questionnaire on the network platform. The questionnaire was open for two weeks. A total of 272 valid questionnaires were collected. Respondents' average age was 23.71; 89.8% were aged between 16 and 35; 69.8% were female and 30.2% were male. The largest education group was College/University at 69.8%, while Senior/Vocational High School and Postgraduate accounted for 14.3% and 14.0%, respectively. Of the respondents, 68.4% were students; 6.6% and 6.2% were designers and teachers, respectively.

Measures

The current study's structural model includes seven constructs and the questionnaire. The perceptual scales measured and measurement items are shown in Appendix A. The questionnaire consisted of three sections: section one collected demographic data, while sections two and three employed a nominal seven-point Likert scale (ranging from 1 strongly disagree to 7 strongly agree). Participants answered the survey questions according to their self-perception. The survey's second section included four constructs from TAM: PEOU, PU, BI, and ATT; while the third section included constructs from TPB: PNC, SN, and B.

Analysis Method

The current study employed PLS-SEM (Partial Least Squares Structural Equation Modeling) to verify the relationships among the research variables. SmartPLS 2.0 is used for data analysis, mainly because PLS could overcome the collinear problems caused by limited observed values, missing values, and overly high correlations among the predictive variables. Principal component analysis and path analysis are also employed to determine best regression coefficient combinations of X and Y (Ringle, 2004).

Empirical Analysis and Results

PLS-SEM analysis and estimation were conducted in three stages, as suggested by Chin (1998), and Fornell, Johnson, Anderson, Cha, and Bryant (1996). The first stage analyzed model reliability and validity. The second stage tested the model path coefficients, while the third stage examined the mediation effect. Details of the analysis is given in the following sections.

Reliability and Validity of the Instrument

Construct validity was examined in accordance with the three principles of convergent validity, as suggested by Fornell and Larcker (1981). Convergent validity of all construct measurement items should meet the following three conditions: (a) the factor loading (λ) should be significant and higher than 0.5; (b) the composite reliability (CR) should be larger than 0.6; and (c) average variance extracted (AVE) should be higher than 0.5 (Chin, 1998). Table 1 shows results for reliability and validity of all constructs. The significance level of factor loading was $p<0.001$ for all constructs. The factor loadings of all items was higher than 0.5. All the values of CR exceed 0.8, and range between 0.89 and 0.91. All the values of AVE were higher than 0.5, and range between 0.65 and 0.68. Thus, the three required conditions were met. Factor loadings of all items ranged between 0.80 and 0.82, and obtained the required significance level ($p<0.05$). In addition, the Cronbach's α of all items were higher than 0.7, indicating a high confidence level. Thus, all the items exhibited convergent validity (Chin, 1998).

Discriminant validity was tested in two ways (Henseler, Ringle, & Sinkovics, 2009). First, the cross-loading matrix, and second, using Fornell-Lacker's criterion adopted in this study, comparing the correlation coefficients among all latent constructs with the square roots of AVE. When the AVE value is higher than the diagonal value of the row and column in the latent construct correlation coefficient matrix, it denotes significant discriminant validity among the construct measurements. According to data analysis, the square roots of all variables' AVE ranged between 0.81 and 0.83. As shown on the right of Table 1, the AVE values of all variables were higher than the correlation coefficients among all latent constructs. Additionally, all the cross-loadings of individual items under each variable were higher than their factor loadings under other variables (Fornell & Larcker, 1981), as shown in Table 2. Therefore, this questionnaire exhibited adequate discriminant validity.

Table 1

Reliability and Validity Analysis Results

Construct	**Mean**	**STD**	**Factor Loading**	**CR**	**Cronbach's α**	**AVE**	**ATT**	**B**	**BI**	**PBC**	**PEOU**	**PU**	**SN**
ATT	5.45	1.12	0.82	0.91	0.88	0.68	**(0.83)**						
B	6.21	1.36	0.80	0.88	0.82	0.65	0.66	**(0.81)**					
BI	5.51	1.18	0.81	0.89	0.84	0.68	0.80	0.70	**(0.82)**				
PBC	5.51	1.35	0.82	0.89	0.84	0.68	0.71	0.59	0.67	**(0.82)**			
PEOU	5.12	1.38	0.82	0.89	0.84	0.68	0.69	0.59	0.64	0.64	**(0.82)**		
PU	4.65	1.22	0.81	0.91	0.87	0.66	0.73	0.55	0.69	0.64	0.75	**(0.81)**	
SN	5.38	1.31	0.81	0.90	0.87	0.65	0.66	0.58	0.66	0.52	0.57	0.61	**(0.81)**

Table 2

Loading and Cross-Loading

Construct	**Items**	**ATT**	**B**	**BI**	**PBC**	**PEOU**	**PU**	**SN**	**VIF**
ATT	**ATT_1**	**0.81**	0.60	0.67	0.57	0.61	0.59	0.56	1.87
	ATT_2	**0.81**	0.55	0.62	0.65	0.54	0.53	0.47	
	ATT_3	**0.86**	0.64	0.68	0.59	0.62	0.61	0.58	
	ATT_4	**0.84**	0.60	0.68	0.59	0.61	0.67	0.60	
	ATT_5	**0.79**	0.54	0.69	0.54	0.56	0.58	0.49	
BI	**BI_1**	0.70	0.55	**0.79**	0.55	0.66	0.62	0.59	2.32
	BI_2	0.69	0.60	**0.85**	0.59	0.52	0.59	0.59	
	BI_3	0.69	0.61	**0.85**	0.57	0.52	0.58	0.54	
	BI_5	0.55	0.70	**0.74**	0.48	0.46	0.50	0.44	
B	**B_2**	0.49	**0.77**	0.61	0.46	0.42	0.44	0.43	1.98
	B_3	0.50	**0.80**	0.53	0.48	0.43	0.40	0.47	
	B_4	0.54	**0.79**	0.62	0.44	0.50	0.46	0.50	
	B_5	0.61	**0.79**	0.65	0.51	0.50	0.49	0.48	
	PEOU_1	0.50	0.49	0.49	0.54	**0.83**	0.54	0.41	

PEOU	PEOU_2	0.60	0.48	0.55	0.46	**0.77**	0.61	0.46	1.27
	PEOU_3	0.59	0.60	0.53	0.59	**0.83**	0.66	0.51	
	PEOU_4	0.58	0.52	0.56	0.52	**0.82**	0.64	0.48	
PBC	PBC_1	0.55	0.45	0.49	**0.80**	0.43	0.47	0.38	1.56
	PBC_2	0.58	0.56	0.54	**0.81**	0.57	0.52	0.41	
	PBC_3	0.56	0.47	0.55	**0.80**	0.48	0.53	0.44	
	PBC_4	0.66	0.58	0.60	**0.88**	0.63	0.59	0.47	
SN	SN_1	0.49	0.43	0.47	0.44	0.45	0.52	**0.77**	1.12
	SN_2	0.48	0.51	0.50	0.42	0.47	0.47	**0.78**	
	SN_3	0.50	0.56	0.54	0.41	0.45	0.47	**0.84**	
	SN_4	0.60	0.55	0.62	0.44	0.54	0.51	**0.84**	
	SN_5	0.58	0.49	0.57	0.39	0.46	0.51	**0.81**	
PU	PU_1	0.65	0.56	0.63	0.58	0.70	**0.82**	0.53	1.09
	PU_2	0.54	0.45	0.53	0.46	0.60	**0.84**	0.50	
	PU_3	0.68	0.53	0.61	0.51	0.70	**0.84**	0.47	
	PU_4	0.56	0.54	0.57	0.57	0.55	**0.80**	0.51	
	PU_5	0.49	0.45	0.46	0.48	0.52	**0.76**	0.49	

The Test of Structural Model Path Coefficients

This study used PLS-SEM for structural model analysis, exploring the intensity and direction of the relationships among variables. The PLS-SEM estimation was conducted mainly according to the six steps proposed by related scholars: (1) check for multicollinearity problems; (2) check the significance of the standardized path coefficient (β); (3) test the size of the R^2 value and the path coefficients; (4) estimate the f^2 effect size; (5) evaluate the predictive relevance (Q^2); (6) examine the indicator of Goodness of Fit (Rigdon, 2012; Hair, Ringle, & Sarstedt, 2011). Collinearity could be evaluated by using the variance inflation factor (VIF) to investigate if a collinearity problem exists. As shown in Table 2, the minimum and maximum VIFs of all variables were 1.09 and 2.32, within the values (0.2<VIF<5) suggested by Hair et al. (2011). Thus, this model does not exhibit any multicollinearity problem.

The structural model is next analyzed using PLS-SEM in order to obtain the explained variance (R^2), standardized path coefficient (β), and t-value; where R^2 and the β are the main indicators to judge whether or not a model is good (Chin, 1998). Structural model analysis results are shown in Figure 2. According to the overall structural model analysis, the path coefficient of learners' perceived ease of use of a MOOC to behavioural intention is 0.104 (t=1.712), reaching the significant level, thus, H1 is supported: perceived ease of use positively influences behavioural intention. The path coefficient from perceived ease of use to attitude is 0.334 (t=4.308), reaching the significant level, thus, H2 is supported: greater perceived ease of use improves the learner attitude. The path coefficient from perceived usefulness to attitude is 0.477 (t=6.495), surpassing the significant level, thus, H3 is supported: greater perceived usefulness improves attitude. The path coefficient from perceived ease of use to perceived usefulness is 0.748 (t=25.162), reaching the significant level, thus, H4 is supported: the greater the learners' perceived ease of use, the greater their perceived usefulness. The path coefficient from attitude to behavioural intention is 0.496 (t=6.000), reaching the significant level, thus, H5 is supported: the better the learners' attitude, the stronger their behavioural intention. The path coefficient from subjective norm to behavioural intention is 0.202 (t=2.464), reaching the significant level, thus, H6 is supported: the higher the subjective norm, the stronger the learners' behavioural intention to use a MOOC. The path coefficient from perceived behaviour control to behavioural intention is 0.151 (t=2.490), reaching the significant level, thus, H7 is supported: the better the learners' perceived behaviour control, the stronger their behavioural intention to learn through a MOOC. The path coefficient from perceived behaviour control to actual behaviour is 0.185 (t=2.835), reaching the significant level, thus, H8 is supported: the better the learners' perceived behaviour control, the better their actual behaviour to learn through a MOOC. The path coefficient from subjective norm to actual behaviour is 0.189 (t=3.151), reaching the significant level, thus, H9 is supported: the higher the learners' subjective norm, the better their actual behaviour to learn through a MOOC. Finally, the path coefficient from behavioural intention to actual behaviour is 0.455 (t=6.644), reaching the significant level, thus, H10 is supported: the stronger the MOOC learners' behavioural intention, the stronger the actual behaviour. In summary, all the hypotheses of the model are supported.

The PLS-SEM approach evaluates the R^2 value of endogenous constructs in the structural model, providing a reference for overall assessment of fit (Hulland, 1999). As seen in Figure 2, the R^2 values of the four endogenous constructs were 0.560 (perceived usefulness), 0.578 (attitude), 0.687 (behavioural intention), and 0.538 (actual behaviour). The R^2 values of behavioural intention and actual behaviour were quite high, indicating that actual behaviour and the six preceding factors explain 53.8% of the variance; this result demonstrated a good fit between actual behaviour and its preceding factors. To sum up, these four endogenous constructs explained over 50% of the variance, which proves that this structural model had quite good explanatory power, and meets the standards of Cohen (1988).

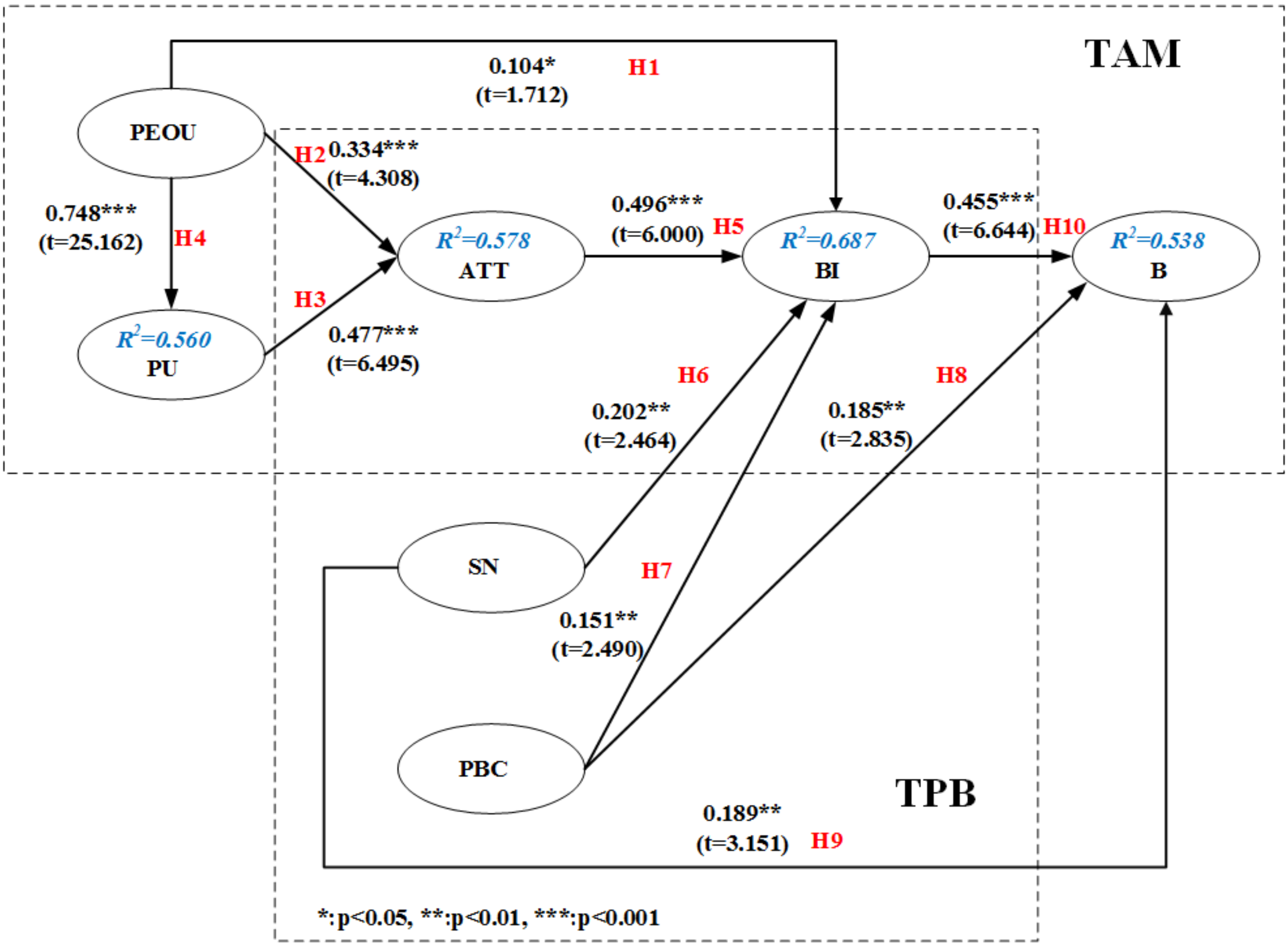

Figure 2. Structural model PLS results.

In addition to the model's predictive power, f^2 effect size is an important indicator. Besides assessing the R^2 of all the endogenous constructs, the specific exogenous variables that cause changes toR^2 were removed in order to evaluate whether the removed variables had any significant effect on the endogenous variables; this measurement is called the f^2effect size, and the computation formula is provided in Appendix B. According to the general principle of f^2 assessment, 0.02, 0.15, and 0.35 denote the weak, medium, and strong effects of exogenous latent variables, respectively (Cohen, 1988). As shown by Table 3, the average f^2 effect size was larger than 0.15, showing a medium and above effect. Of special note was the f^2 effect size of actual behaviour, which was 0.38, higher than 0.35 (strong effect). The observed R^2 could be used to evaluate and predict accuracy; additionally, researchers should examine the Q^2 value of Stone-Geisser, which has been considered an indicator of predictive relevance (Geisser, 1974; Stone, 1974). As shown in Table 3, the Q^2 value of the endogenous latent variable was larger than zero, denoting that the path model, which has predictive relevance. Meanwhile, Tenenhaus, Vinzi, Chatelin, and Lauro (2005, p. 173) determined the PLS Goodness-of-Fit index (GoF) can be a "as it may be meant as an index for validating the PLS model globally." Wetzels, Odekerken-Schroder, and van Oppen (2009) suggested using the communality of 0.50 and the R^2 (Cohen, 1988) to measure the GoF: GoF_{small}=0.10, GoF_{medium}=0.25, and GoF_{large}=0.36. As seen in Table 3, the GoF of this study was 0.63, higher than 0.36, indicating a very satisfactory goodness of fit.

Table 3

Regression Analysis of Mediation Effect

Total effect	ATT	B	BI	PBC	PEOU	PU	SN	VAF	R^2	f^2	Q^2	GoF†
ATT		0.226	0.496					64%	0.578	0.18	0.21	
B									0.538	0.38	0.43	
BI		0.455						38%(PBC□BI□B) 45% (SN□BI□B)	0.678	0.21	0.25	**0.63**
PBC		0.258	0.151									
PEOU	0.691	0.203	0.447			0.748						
PU	0.477	0.108	0.237					46%	0.56		0.21	
SN		0.281	0.202									

† $\text{GoF} = \sqrt{\overline{communality} \times \overline{R}^2}$

Finally, this study now summarizes the model predictive power indicators and goodness-of-fit, as proposed by related scholars. Results can provide a reference for future researchers (as shown in Table 4), including the indicators of the assessment of the structural model, the explanatory power of the assessment of measurement model as well as the mediation effect test.

Table 4

The Model Predictive Power Indicators and GoF Indices

Goodness-of-Fit Measures for Measurement Model				
Criterion	**Value criterion**	**Value**	**Result**	**Literature**
Cronbach's alpha (CA)	CA > .800 or .900 (0.700). Values must not be lower than .600	CA >0.85	Yes	Cronbach (1951), Nunnally and Bernstein (1994)
Composite reliability (CR)	CR > .800 or .900 (0.700). Values must not be lower than .600	CR >0.90	Yes	Nunnally and Bernstein (1994)
Indicator loadings	Values should be significant at the .050 level and higher than .70	0.80	Yes	Chin (1998)
AVE	AVE > 0.500	0.67	Yes	Fornell and Larcker (1981)
Cross-loadings	Factor Loading should higher than Cross Loading	higher	Yes	Chin (1998)
Fornell-Larcker criterion	the square root of the AVE of each construct should be higher than the construct's highest correlation	higher	Yes	Fornell and Larcker (1981)
Goodness-of-Fit Measures for Structural Model				
VIF	0.2<VIF<5	1.60	Yes	Hair, Ringle, and Sarstedt (2011)

R^2	0.670 (High), 0 .333(medium), 0.190(weak).	0.59	medium	Chin (1998), Ringle (2004)
Path coefficients	p<0.05	<0.05	Yes	Huber, Herrmann, Meyer, Vogel, and Vollhardt (2007)
f^2	0.02~0.15 (weak), 0.15~0.35 (medium),> 0.35(strong)	0.38	large	Cohen (1988), Chin (1998), and Ringle (2004)
Q^2	Values of 0 and below indicate a lack of predictive relevance.	>0.21	relevance	Stone (1974), Geisser (1974)
GoF	0.1(small), 0.25(medium), 0.36(large)	0.63	large	Tenenhaus et al. (2005)
Test of the Mediating Effects				
VAF	VAF>80%*(complete mediation), 20%≤VAF≤80%*(partial mediation), VAF<20%*(no mediation effect)	46%, 64%, 38%, and 46%	Partial mediation	Hair, Hult, Ringle, and Sarstedt (2016)

Analysis of the Mediation Effect Test

The mediation effect test is important to PLS, and three elements should be included to meet the mediation effect conditions: (a) the independent variable can significantly explain the hypothetical mediating variable; (b) the hypothetical mediating variable can significantly explain the dependent variable; and (c) after adding the mediating control path, the original value of the relationship between the independent variable and dependent variable change significantly (Baron & Kenny, 1986). Therefore, the following tests involving the three mediating variables were conducted on the current model: (a) the mediation effect of perceived usefulness on perceived ease of use and attitude should be tested (H4→H3); (b) the mediation effect of attitude on perceived usefulness and behavioural intention should be tested (H2→H5); (c) the mediation effect of behavioural intention on perceived behaviour control and actual behaviour should be tested (H7→H10); and (d) the mediation effect of behavioural intention on subjective norm and actual behaviour should be tested (H6→H10). After the mediating variables are added, all paths of indirect effect (H4→H3; H2→H5; H7→H10; H6→H10) must reach the significance level. In other words, after adding the mediating variables, the values of the direct effects will decrease and the partial effect values will be absorbed by the mediating variables. While the Sobel test (Helm, Eggert, & Garnefeld, 2010) is usually adopted to test for a mediation effect, it requires unstandardized scores for calculation. The current study, however, includes a small sample, lowering test power. To overcome this, the current study applied the bootstrapping method of Preacher and Hayes (2008) to find indirect-effect sample allocation, which is mainly used to measure the proportion of variance accounted for (VAF). When VAF is larger than 80%, complete mediation is indicated. In the case of 20%≤VAF≤80, only partial mediation is indicated. When VAF is less than 20% no mediation effect is present. As seen in Table 3, of the mediation effect test analysis, the VAFs of perceived usefulness, attitude, and behavioural intention are 46%, 64%, 38% (PBC→BI→B), and 45% (SN→BI→B), respectively, showing partial mediation.

Discussion and Conclusions

Key Findings

Two important predisposing factors of TAM, perceived ease of use and perceived usefulness, are themselves fundamental and practical benefits, as learners expect a practice-oriented MOOC course to be simple and easy to learn, improving self-efficacy or work performance or both; in this specific case, by learning 2D Animation Production. As described in the current study, perceived ease of use and perceived usefulness positively influence a learner's attitude. When this is true, learners find it easy to use a MOOC platform. This result is identical to that of Iqbal and Bhatti (2015). Especially, PU, as compared with PEOU, is a strong predictor of attitude, a finding also supported by Okazaki and dos Santos (2012). Moreover, this study added mediating variables to measure the relationships among the variables in a more holistic manner (Bagozzi, 2007). Perceived usefulness has a partial mediation effect on perceived ease of use and attitude. A VAF of 46% shows that perceived usefulness influences the overall model as a mediating variable. This result is in accord with the findings of Fishbein and Ajzen (1975); Adams, Nelson, and Todd (1992); Davis (1989); and Van der Heijden et al. (2003). Current results also show that perceived ease of use can enhance attitude through perceived usefulness. In other words, perceived ease of use is a relatively effective factor in influencing attitude and behaviour. This result implies that perceived ease of use is an especially important predictive variable for learners with a less positive attitude.

According to Hung et al. (2005), a range of studies have found the explanatory power of perceived ease of use in predicting attitude and behavioural intention was not strong, with small effect sizes. However, within the C-TAM-TPB framework generated in the current study, the R^2 values of attitude and behavioural intention among the four endogenous constructs were 0.578 and 0.687, respectively. Such high R^2 values indicate the high explanatory power of the independent or mediating variables that influence these two endogenous constructs within the C-TAM-TPB framework.

Current results demonstrate that learner behavioural intention is positively influenced by perceived ease of use, attitude, subjective norm, and perceived behaviour control. Thus, when learners perceive greater ease of use, hold a more positive attitude, and have a more stable subjective norm and perceived behaviour control, they will have stronger behavioural intention to become involved, and this stronger behavioural intention will then influence the intensity of resulting actual behaviour. Nevertheless, among these constructs, attitude exerts the greatest influence, meaning that a more positive and better attitude results in stronger behavioural intention. Thus, attitude is the principal factor to influence a MOOC learner's behavioural intention regarding a practice-oriented course. Attitude is the principal factor that can motivate learners to continue with a practice-oriented course. If a learner can properly adjust his or her attitude, they will continue learning through a MOOC delivery without difficulty. These results align with the findings of Park (2009). Subjective norm is also discussed in this study. This variable was derived to compensate for the insufficient consideration of social norms in TPB. The current study achieved the expected result: subjective norm positively influences both behavioural intention and actual behaviour. Namely, when an individual observes their friends, classmates, peers, or family members learning through a MOOC, they will have a stronger behavioural intention to act like those other people.

Considering the relationship between behavioural intention and actual behaviour, this study finds it is possible that online learning may improve behavioural intention and actual behaviour through subjective norm and perceived behaviour control. When executed properly, the result can be improved performance of actual behaviour through the mediation effect. In this C-TAM-TPB framework, behavioural intention has a partial mediating effect on subjective norm and actual behaviour. Behavioural intention also has a partial mediating effect on perceived behaviour control and actual behaviour. The VAFs were 45% and 38% respectively, so behavioural intention has dual mediating effects. Figure 2 shows that the learners' behavioural intentions significantly and positively influence actual behaviour. This aligns with the results of Luis and Franz (2004); Taylor and Todd (1995a, 1995b); Yu, Ha, Choi, and Rho (2005); and Okazaki and dos Santos (2012). The path coefficient was 0.455 and reached the significance level and the f^2 effect size of actual behaviour was 0.38, evidence of a strong effect. As seen from Table 3, the GoF index of the C-TAM-TPB was as high as 0.63 and 53.8% of variance could be explained between actual behaviour and the six preceding factors. All these factors together reflect a high-level of overall fit.

Academic Implications

This study integrated previous related literature of TAM & TPB in order to investigate learners' actual behaviours in a MOOC practice-oriented course, presenting innovative implications for research regarding attitudes, behavioural intentions, and willingness to actually enroll in the practice-oriented course. This study makes the following academic contributions.

First, for MOOC learners, TAM shows that perceived ease of use and perceived usefulness are related to information technology and can actually impact an individual's behavioural intention. Therefore, given the robust nature of the TAM theory (Venkatesh & Davis, 2000; King & He, 2006) and considerable empirical support within the in e-learning domain (Juan et al., 2006; Shin & Kang, 2015; Giesbers et al., 2013), researchers should seriously consider learner intention to accept a MOOC when designing such courses. In the current study, the MOOC practiced-oriented course required practical exercises that resulted in utility for learners. Consequently, perceived usefulness directly influenced attitude, which added value to the existing MOOC learning approach.

Second, respondents' behavioural intentions to learn through a MOOC were explored from the perspective of TPB. In addition to positive attitude towards using a MOOC, the influence of behavioural intention was considered. While most previous literature on MOOC learning directly examines factors of learning effects, they have seldom investigated the influence of learners' subjective norm on their behavioural intention to learn through a MOOC, nor have they examined the mediating role played by behavioural intention. Nevertheless, behavioural intention is an important factor that determines whether or not the learner actually adopts a MOOC. In other words, learners will not use a MOOC just because the MOOC system is very easy to use or their subjective norm is strong. Rather, learners will first assess their behavioural intention to use a MOOC, and then generate the willingness to use it continuously.

Third, in addition to attitude and subjective norms, according to TPB, perceived behaviour control will influence willingness and the decision for actual behaviour and behavioural intention. Namely, when an individual is more able or has more relevant resources to use such a system, he or she will have a stronger behavioural intention to use the system, and their actual behaviour will become more frequent or more positive (Taylor & Todd, 1995a). Past literature has mostly explored the direct influence of attitude towards usage of behavioural intention, while the current study adopted perceived behaviour control in order to investigate how behavioural intention impacted the mediating variables of actual behaviour. This approach has described learners' personal influence on actual continuation of use in a more holistic manner. As shown by mediation analysis, behavioural intention had a mediating effect, directly impacting actual behaviour. This result is in accord with those of Moon and Kim (2001), and Featherman and Pavlou (2003), showing that stronger behavioural intention to use an information system leads to more usage time and higher frequency of actual system use, which coincides with the results of Armitage and Conner (2001). The current study is based on literature related to TAM & TPB, employing behavioural intention as a mediating factor while exploring learners' actual behaviour using a MOOC in order to extend studies regarding attitudes, behavioural intention, and actual behaviour.

Practical Implications

In light of the empirical results, this study presents the following three practical implications as strategic references for designers and teachers of MOOC practice-oriented courses.

- Attitude and subjective norms influence behavioural intention: According to the research findings, learners' behavioural intentions are influenced by attitude and subjective norms. However, for such intention to materialize into actual behaviour, learners must ensure that they are not disturbed by external factors. Specifically speaking, the first step is to help learners have a positive attitude towards the practice-oriented course. A promotional video of two to three minutes should be presented before the MOOC course is opened. This promotion video plays a crucial role by emphasizing the required effort so that learners will feel the goal is obtainable. Utility value is also considered as a substantial factor influencing learner intention. Next, in addition to the presentation of practical work, related industries should be introduced during the first class in order to enhance the connection between practice-oriented courses and industry, and strengthen motivation and willingness to learn. Meanwhile, people who are important to learners (e.g., peers) should be encouraged to participate to facilitate the development of the subjective norm. The purpose of such mutual participation is particularly helpful as online courses rely on self-regulation. Participation along with peers can promote positive behavioural intentions and actual behaviours. Additionally, it is very important for teachers and teaching assistants to encourage learners in discussion areas, as learners tend to give up when they encounter difficulties. In this case, if teachers can encourage and inspire the learners in person, the learners will feel positive influence. Lastly, learners should be assisted in a timely manner; for instance, videos explaining assignments and demonstrating practical techniques should be added to the discussion area to help learners quickly see the efforts of teachers and teaching assistants.

- Perceived usefulness and perceived ease of use are important to behavioural intention. Within the C-TAM-TPB context, learners' perceptions of information technology and information systems can be observed and learners' feelings about course content can be immediately reflected in their behavioural intention. Margaryan et al. (2015) reflect the current study's findings when emphasizing three MOOC course design elements: (a) Curriculum Media. Teachers should be able to master the teaching content. However, the content must be specially designed in order to meet online teaching standards while teaching videos must be recorded and professionally produced, avoiding recordings of ordinary off-line teaching sessions. On-line teaching places teachers in multiple roles. They simultaneously act as director, screenwriter, and performer, while also retaining the traditional teacher role as articulate and able to attract and retain the attention of students. The teaching methods differ from traditional classes, including describing, having conversations, story-telling, operating, and using animations or illustrations. Teachers can choose the tools that best match their own teaching requirements; (b) Content Visualization. After recording, video editing specialists are required. The production theme, titles, and the lecturer's key points, though graphics, should be inserted where appropriate. High quality titles improve video presentation, which helps retain viewer interest. Captions, special effects, and animations can also be applied in order to increase the learner interest during viewing; and (c) Digitization Management. Once recorded, the courses must be uploaded to the MOOC platform. In addition to the functions of video and reading instructional material, the learning platform should equipped with an online synchronous discussion room, peer assessment, automatic evaluation, learning experience feedback recording and idea bank for teachers, online tests or quizzes, and assignment submission. Various operations, such as course information release, feedback in the discussion area, evaluation design, and copyright authorization require a complete and integrated learning platform. These issues require the appropriate personnel and participants in order to generate a quality result.

- Perceived behaviour control is important to behavioural intention and actual behaviour: The discussion area and assignment sharing are also important elements for such courses, as the discussion area can promote interaction. Though online learning has poor interaction (Caulfield, Collier, & Halawa, 2013; Rubin, 2013), the most basic rule is to reply to questions posted in the discussion area within 48 hours. This way, learners can experience the instantaneity of interaction, as well as involvement in the discussion area, which reflects the learners' attitude and behavioural intention. Teachers must occasionally create topics of discussion for learners in order to initiate participation. Moreover, through assignment sharing, some learners can feel a sense of achievement and receive feedback, which further strengthens confidence and improves self-efficacy. The discussion area should also offer extracurricular resources that are easily accessible to learners. Learners will be motivated to continue learning by communicating with and encouraging each other in the discussion area. A well-managed discussion area can change learners' perceived behaviour control, thereby positively influencing behavioural intention and even actual behaviour.

Limitations and Future Research

All the research subjects of this study were learners in a MOOC. However, as the teachers and teaching assistants were not strongly bound to the learners, it was rather difficult to control the number and quality of the self-selected participants. Additionally, the sample frame focused on a 2D Animation Production MOOC course from among a wide variety of practice-oriented courses. This may limit generalized validity. Therefore, the characteristics of different practice-oriented courses should be further investigated and analyzed. For instance, cooking courses entail tastes and flavours, which differ from practice-oriented design courses that involve visual appreciation.

In the future, researchers can further delve into how MOOC learners are influenced by curriculum design, assignment types, and different interactions. In addition, with the exception of the mediation effect, this study did not touch upon the regulating effect of related constructs, which are worthy of in-depth exploration. For example, if the target course is a mandatory elective practice-oriented college course, the relationship between the learners' attitude and behavioural intention may be affected by whether it is used voluntarily (Fishbein & Ajzen, 1975). Furthermore, this study only investigated learner behavioural intention and actual behaviour via the C-TAM-TPB framework. Future researchers can incorporate other aspects or external variables, such as Task-Technology Fit, ISS model, course quality, course interaction, learning platform functions, and learning motivation, in order to explore which construct, among various learning behaviours, can exert the greatest influence on a learner's behavioural intention and actual behaviour.

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Appendix A

Measurement Items

Construct	Measures	Items	Source
Perceived Ease of Use	PEOU1	It is simple to learn the animation course through the Internet.	Davis (1989); Sun et al. (2008); Ngai, Poon & Chan (2007); Lee (2010)
	PEOU2	It is convenient to learn the animation course through the Internet.	
	PEOU3	It is easy to learn related design skills in the animation course on the web.	
	PEOU4	The E-learning interaction of the animation course helps me learn effectively.	
Perceived Usefulness	PU1	Learning through the Internet helps me acquire knowledge about animation production more easily.	Davis (1989); Venkatesh & Davis (2000); Sun et al. (2008); Ngai, Poon, & Chan (2007); Bhattacherjee (2001)
	PU2	Learning the animation course through the Internet can improve my personal competitive advantages.	
	PU3	I think learning the animation course through the Internet can increase my specialized knowledge about animation production.	
	PU4	Learning the animation course by Internet can help me with the difficulties in work or classwork.	
	PU5	Learning animation production skills helps me to achieve a higher-level or higher grade in school or get a job.	
Perceived Behaviour Control	PBC1	I can arrange time on my own to learn animation through the Internet.	Chau & Hu (2001); Taylor & Todd (1995b)
	PBC2	I can obtain sound information equipment by myself to learn animation through the Internet.	
	PBC3	Learning the animation course through the Internet causes little disturbance to my life (work or studies).	
	PBC4	I can master everything that appears during the E-learning of animation.	
Attitudes	ATT1	It is a very good method to learn animation through the Internet.	Taylor & Todd (1995a); Perugini & Bagozzi (2001)
	ATT2	I am active in learning animation through the Internet.	
	ATT3	I feel joyful to learn animation through the Internet.	
	ATT4	Learning the animation course through the Internet can upgrade my professionalism in animation.	
	ATT5	Learning the animation course through the Internet can satisfy my personal interest in animation.	
Behaviour Intention	BI1	I am willing to recommend others to learn animation production through online courses.	Bhattacherjee (2001)
	BI2	I pay close attention to information related to online animation courses.	
	BI3	I will be enthusiastic about participating in online animation teaching activities.	
	BI5	I often search for animation-related knowledge or information on the Internet.	
Actual Behaviour	B2	I often watch animation teaching films on the Internet.	Van der Heijden, Verhagen, & Creemers (2003); Ngai, Poon, &
	B3	I often use the Internet to learn and take courses that I am interested in.	

	B4	I am willing to learn an animation course through the Internet, rather than other learning channels.	Chan (2007); Juan, Chiu & Francisco, (2006)
	B5	I feel time flies when I learn animation production on the Internet.	
Subjective Norm	SN1	I will learn the animation course through the Internet if recommended by teachers or elders (supervisors).	Taylor & Todd (1995b); Chau & Hu (2001); Venkatesh & Davis (2000)
	SN2	I will learn the animation course through the Internet if recommended by friends (classmates).	
	SN3	Now it is very popular to learn through the Internet, so I will learn the animation course on the Internet.	
	SN4	The way this course is promoted motivates me to take the animation E-learning course.	
	SN5	The current animation films on the market are quite wonderful, so I would like to learn about animation production.	

Appendix B

The formula of f^2 effect size

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$