Applying TAM to the Adoption of E-learning Platform

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ABSTRACT

This paper explores the factors influencing the use of E-learning platform in the academic context. A quantitative study was conducted through a questionnaire directed to Chinese university students, obtaining 327 valid answers. The results of this study identify that all factors of perceived usefulness (PU), perceived ease of use (PEU), and satisfaction (SAT) have significant influences on continuance intention (CI), with PU having the most substantial impact on learners' intention to use the E-learning platform. This study could contribute to understanding users' cognition and behavior in the mobile digital environments and has particular guiding significance for users' E-learning activities.

Keywords: *TAM, E-learning Platform.*

1. INTRODUCTION

Nowadays, Information Technology (IT), with its predominant advantages, has profoundly changed every industry, including education. By the end of December 2020, 1,454 colleges and universities in China offered online education, with 1.03 million lecturers offering 1.07 million courses online and 17.75 million college students studying through the E-Learning platform (Su, 2020)[1]. For the E-Learning process to be successful and efficient, educators should identify the factors affecting users' intention to adopt the online platform. Technology Acceptance Model (TAM)[2] is considered one of the most powerful research models for analyzing users' perceptions and behavior regarding the use of specific learning methods. This investigation aims to explore the following questions:

1. Which factors have the most substantial impact on E-Learning platform adoption?

2. How can educators and designers improve the quality of the platform?

2. LITERATURE REVIEW

2.1. E-learning Platform

E-learning is a mode of education and learning activities in the network environment. Various resources can be integrated into the platform. For example, MOOCs, which stands for Massive Open Online Courses, are delivered online using an E-Learning platform (Alraimi et al., 2015)[3]. Likewise, FCL (Flipped Class Model), which was first put forward in 2016(Bergmann & Sams, 2016)[4], needs to use a platform to conduct different activities between lecturers and students.

2.2. TAM

Technology Acceptance Model (TAM) represents the most powerful theoretical emphasis to innovation adaptation literature, also being extensively utilized by scholars to explore a variety of technological innovations adoption (Hameed et al., 2012)[5]. Since the TAM model was proposed in 1989 (Davis, 1989)[2], many scholars have taken this model as the research object to verify the relationship between perceived usefulness, perceived ease of use, perceived evaluation, and willingness to continue using. According to Venkatesh and Davis (2000)[6], the social influence and cognitive instrumental processes were considered new crucial variables deciding perceived usefulness. Venkatesh & Bala (2008) [7]developed a comprehensive, integrated model of the determinants regarding the adoption of IT at the individual level. The TAM has become a theoretical framework with a clear and stable structure, used in many research fields such as sociology, psychology, and information technology. The TAM model has been applied and extended in different areas such as E-banking and E-commerce in recent years. Its validity and reliability have been strongly proved (Luo & Zhu, 2015)[8]. As a new learning method triggered by new technology, mobile learning based on MOOC courses is an innovation compared with the previous learning methods, which can also be tested by the TAM model (Alraimi et al., 2015)[3].

3. RESEARCH FRAMEWORK AND HYPOTHESES

PEU stands for perceived ease of use. TAM has been examined as a way to predict students' intentions in the E-learning context relating to the ease of using these online learning platforms (Selim 2003, 2007)[9][10]. According to Pituch and Lee (2006)[11], results suggest that the complexity of Learning Management Systems (LMS)may be an important factor in students' intention to use E-learning platforms. Yuen and Ma (2008)[12] shared similar results. Hence, the following research hypotheses are proposed:

H1: Perceived ease of use (PEU) positively affects perceived usefulness (PU) while using an E-learning platform.

H2: Perceived ease of use (PEU) positively affects users' satisfaction (SAT).

PU is short for perceived usefulness, representing how college students can feel helpful after using the online learning platform. Perceived usefulness has a positive and significant influence on students' intention to use online learning platforms for study. It affects learners' satisfaction and willingness to continue using them (Sayaf et al., 2022)[13]. Results also suggest that it can be positively related to behavioral attitudes toward E-learning (Pinho et al., 2020)[14]. Hence, we propose:

H3: Perceived usefulness (PU) positively impacts continuance intention (CI) to use the E-learning platform.

SAT stands for satisfaction. Satisfaction has the most substantial effect compared with other factors ' influences on continuance intention (Lee, 2010)[15].

CI stands for continuance intention. It represents the willingness of the users to continue to use the E-learning platform according to the usefulness, ease of use, and satisfaction they experienced. (Bhattacherjee, 2001a)[16]. Hence, we propose:

H4: Perceived usefulness (PU) positively impacts users' satisfaction (SAT).

H5: Users' satisfaction (SAT) positively affects continuance intention (CI).

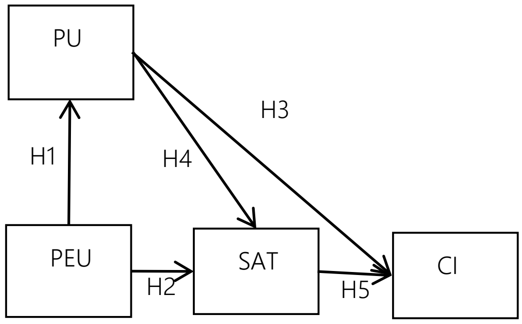


Figure 1 Research Model and Hypotheses

4. RESEARCH METHODOLOGY

A survey was developed predominantly from previous research. The items were using a five-point Likert scale anchored on "1" representing "strongly disagree" and "5" representing "strongly agree. "The research model consisted of four constructs which were measured using multiple-item scales. The six items for perceived usefulness and perceived ease of use were adapted from Davis (1989)[2]. The satisfaction and continuance intention constructs were adapted by Bhattacherjee (2001a, 2001b)[16][17].

The target respondents for this study were college students. The questionnaire was distributed through the Internet, and incomplete answers were eliminated. Finally, a total of 327 valid responses were received. The respondents correspond to 196 females and 131 males. Concerning education, 13.1% of respondents were first-year students; 75% of respondents were sophomores; 52.2% of respondents were juniors or seniors, and 5.5% of respondents were postgraduate or Ph.D. students. As for the frequency of using the E-learning platform, 30.3% of respondents choose "1-3 times weekly"; 38.5% of respondents choose "4-7 times weekly"; 15.6% of respondents choose "more than 8 times weekly," while the rest of respondents selected "never."

5. RESULTS AND ANALYSIS

5.1. Measurement Model Analysis

5.1.1. Reliability and Convergent Validity

The factor loading for constructs is above the cut-off values of 0.650, while the values of Cronbach's Alpha range between 0.789 and 0.816, exceeding the cut-off value of 0.70 (Fornell, C., & Larcker. D.F., 1981)[18]. As for Composite Reliability, all the results are above threshold values of 0.70 (Hair, Black, Babin, & Anderson, 2010)[19]. The AVE values are also above 0.50. See Table 1.

Table 1. Reliability and Convergent Validity

Construct	Items	Loading	Cronbach's α	CR	AVE
PU	PU1	0.679			
	PU2	0.807	0.789	0.786	0.552
	PU3	0.739			
	PEU1	0.819			
PEU	PEU2	0.714	0.792	0.741	0.590
	PEU3	0.715			
	SAT1	0.754			
	SAT2	0.763			
SAT	SAT3	0.690	0.816	0.817	0.529
	SAT4	0.698			
	BI1	0.783			
	BI2	0.711			
CI	BI3	0.677	0.804	0.807	0.521
	BI4	0.684			

5.1.2. Discriminant Validity

As shown in Table 2, the correlation results for any pair are lower than the square root of AVE, which confirms that the scale has good discriminant validity.

Table 2. Discriminant Validity

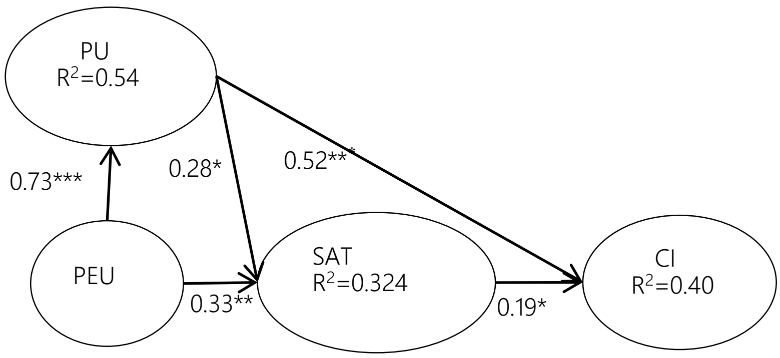
	PU	PEU	SAT	BI
PU	0.743			
PEU	0.732	0.768		
SAT	0.519	0.535	0.728	
CI	0.616	0.479	0.455	0.722

5.2. Goodness-of-Fit Analysis

The Goodness-of-Fit indices for the model are: χ2/df=2.402<3 (Schumacker & Lomax, 2004) [20]; GFI=0.929>0.9; AGFI=0.896>0.8 (Marsh, H.W., Balla, J.R., & McDonald, R.P. 1988; Bollen, 1990)[21][22]; RMSEA=0.066<0.08(Hu, L., & Bentler, P.M., 1999)[23];CFI=0.945>0.9(Fan, X., Thompson,B., & Wang, L., 1999)[24]; TLI=0.930>0.9(Bentler, P.M., & Bonett, D.G., 1980)[25]. All of the indices are at excellent or acceptable levels.

5.3. Structural Model Analysis and Hypotheses Testing

The results regarding R^2 and path coefficient are presented in Figure 2. Table 3 illustrates more details about different indicators and hypotheses testing results.



Note: *p-value<0.05, **P<0.01, ***P<0.001

Figure2 Results for the Research Mode

PEU accounted for approximately 54% of the variance in PU ($R^2 = 0.54$), while PU and PEU managed to explain 32.4 % of the variance in SAT ($R^2 = 0.324$). The whole model, including PU, PEU, and SAT constructs, explained 40% of CI variance ($R^2 = 0.40$). All of the hypotheses gained empirical support. H1 shows the most vital relationship; Perceived ease of use significantly affects the perceived usefulness of the E-learning platform (β=0.732; t=8.795; P<0.001). H2 was supported; Perceived ease of use substantially affects satisfaction (β=0.334; t=3.023; P<0.01). H3 was supported; Perceived usefulness significantly affects the users' intention (β=0.520; t=6.027; P<0.001). H4 was supported; Perceived usefulness significantly affects satisfaction (β=0.275; t=2.505; P<0.05). H5 was also supported; Satisfaction has a significant effect on continuance intention. The summary of the results is presented in Table 3.

Table 3. Reliability and Convergent Validity

Hypotheses	β	T-value.	Results
H1 PEU→PU	0.732***	8.795	Support
H2 PEU→SAT	0.334**	3.023	Support
H3 PU→CI	0.520***	6.027	Support
H4 PU→SAT	0.275*	2.505	Support
H5 SAT→CI	0.185*	2.475	Support

Note: *p-value<0.05, **P<0.01, ***P<0.001

6. DISCUSSION

The previous analysis shows that PU and PEU from the TAM significantly determine the continuance intention of the E-learning platform through user satisfaction.

PEU has the most significant influence coefficient on PU, probably because the survey was mainly conducted among college students in a population group between 18-28 years old. This young generation prefers to choose valuable and friendly operating systems when they accept a brand-new technology.

Users pay more attention to PEU than SAT, and the better quality and design of the platform can make learners more willing to continue using online learning websites. The better the experience of an online learning platform is, the more valuable it will be to users, and the stronger the corresponding satisfaction and willingness to use it continuously. Thus, a high-quality E-learning platform should have rich content and a friendly interface to meet the needs of learners with different educational backgrounds and learning purposes.

7. CONCLUSION AND LIMITATIONS

7.1. Conclusion

The model was developed based on an intensive literature review regarding TAM and E-learning. The model showed a moderate predictive power among perceived usefulness and satisfaction， explained 40% of the variation of e-learning continuance intention, and moderately explained the variance of perceived usefulness and satisfaction with 54% and 32.4%, respectively. In addition, the findings suggest increasing awareness among college students about the usefulness and benefits of the e-learning system to improve its usability and popularity. Moreover, they pay much attention to the perceived usefulness of the platform, which can be seen as an important way to improve their grades and supplement their knowledge. Perceived usefulness has the most significant impact on users' continuance intention to use the E-learning platform.

7.2. Limitations

A future study should expand the number of survey respondents. The questions under each construct need to be more specific and targeted so that the scale and model can obtain better reliability and validity. The proposed model has explained 40%, 54%, and 32.4% of perceived usefulness, satisfaction, and continuance intention respectively of the E-Learning platform; however, it does not fully capture the determinants of these factors. In other words, other variables affecting the E-learning platform have not been examined in the model. There is still room to investigate more quality factors in the future.

AUTHORS' CONTRIBUTIONS

Jiyun Chen is a senior lecturer, Department of Tourism Management, Faculty of Humanities, Jinling Institute of Technology, Nanjing Jiangsu Province, P.R.China. She obtained a Master of Business in International Tourism and Hospitality Management from Griffith University in 2006, Australia.

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