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An Investigate of Influence Factor for Tertiary Students' M-learning effectiveness: Adjust Industry 4.0 & 12-Year Curriculum of Basic Education

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ABSTRACT

Mobile learning (M-learning) as a technology teaching has significant potential to improve student application and comprehension skills. The rapid development of the Internet and the resulting trends applying information available on the Internet have changed the nature of learning and learning behavior patterns of tertiary students. However, insufficient theoretical and empirical research on the effect of M-learning on learning attitude and M-learning effectiveness has been conducted for achieving any reliable understanding of the use of M-learning by tertiary students. This, study was therefore based on the theory of planned behavior, and combined the technology acceptance model and the structural equation model (SEM); it involved 892 tertiary student participants, and developed an empirical research model. The study found that in terms of M-learning acceptance, tertiary students have a positive evaluation and perception of using M-learning, with perceived enjoyment being the most significant factor. In addition, the impact of perceived innovation was significant in helping teachers understand students' learning outcomes. The teaching material of learning motivations was also significant, indicating that current tertiary students are more likely to value their friends as sources of information. External influences on self-efficacy were also significant, suggesting that teachers must consider the operability of M-learning technology, with particular attention paid to students' competency with the technology itself, as difficulty of use will reduce students' willingness to use M-learning.

Keywords: [1]
Technology acceptance model, M-learning, Tertiary students, Industry 4.0

1.Introduction

There has been growing interest recently in the application of mobile learning (M-learning) to create a unique educational environment (Chung, Hwang, & Lai, 2019). However, very little research to date has been conducted into such factors such as the advantages, limitations, effectiveness, challenges and characteristics of using M-learning in educational environments. The use of M-learning to promote the personalization of inclusive learning is also an area of increasing interest. According to Bacca et al.'s (2014) vocational educational training (VET) research, only 3.1% of studies in this area of interest were carried out employing a sample of students from vocational educational training institutions (VET) . From the point of view of this study, VET institutions are promising research partners not only for validation, but also for demonstrating the possibilities of M-learning scenarios in improving and acquiring professional competences. For example, M-learning could reduce the cost of carrying out some learning experiences

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where expensive learning material is necessary (Jeno, Vandvik, Eliassen, & Grytnes, 2019; Al-Emran, Mezhuyev, & Kamaludin, 2018a).

M-learning has, to date, primarily been used in education to explain a topic of interest and simultaneously provide additional information. M-learning educational games and M-learning for lab experiments are growing in popularity. The main advantage of M-learning is learning gains, while limitations primarily include difficulties in maintaining superimposed information, students paying too much attention to virtual information, and the consideration of AR as an intrusive technology(Al-Emran, Mezhuyev, & Kamaludin, 2018b; Bakhsh, Mahmood, & Sangi, 2017). M-learning has been effective in producing better learning performance, learning motivation, student engagement and positive attitudes. However, few learning systems have taken into account students' special needs when working with M-learning(Buabeng-Andoh, 2018; Hamidi & Chavoshi, 2017).

In response to the recent rapid development and innovation of intelligent networking (such as the Internet of Things), Taiwan encouraged the growth of IoT technology in colleges and universities by introducing vertical integration systems, rewarding innovators and cultivating future talents with core competence in technological innovation (Chung, Hwang, & Lai, 2019; Hamidi & Chavoshi, 2017). The implementation strategy promotes three key aspects (Hao, Dennen, & Mei, 2017; Harchay, Cheniti-belcadhi, & Braham, 2017):

(1) The horizontal layering technology taking root, vertically integrating system applications, and combining the assistance of cross-disciplinary teachers to enhance the cross-domain knowledge and technology depth of the teachers and students in the field of smart assets, with specific emphasis and enhancement of system design technology, such as wafers

(2) Implementing the teaching spirit and module curriculum development of problem-based learning (PBL), and making good use of resources such as open software and online learning to stimulate students' independent thinking and self-learning in the future in response to the multitude of IoT applications and the characteristics of rapid development

(3) Combining industrial resources, strengthening the practical experience of teachers and students in the field of electricity and capital, and introducing mature and promising industry platforms and solutions to facilitate the rapid development of smart IoT systems, while strengthening their industrial benefits [18] at the same time, with catering to the needs of the five major innovation industries promoted by the government, and cultivating new generations of ICT smart electronic cross-disciplinary industry talents with system innovation and integration capabilities.

Important science and technology development trends in education related to this study are as follows (Chung, Hwang, & Lai, 2019; Hamidi & Chavoshi, 2017):

(1) The teacher's website is currently the most widely used technology tool, allowing students and parents to access class notes, homework, teaching videos and grades.

(2) Less than half of students use social networking sites for educational purposes in schools.

(3) More than one-third of students use apps in schools, usually games.

(4) About half of the schools use laptops, while less than 30% use tablet computers or M-learning for learning purposes.

(5) A quarter of parents think M-learning is better than paper textbooks.

There is still a lot of room for growth in education, and although parents may have different concerns, technology can bring about many advantages, such as the flipped classroom education model, personalized learning environments, online learning, and digital access to the vast amount of available information, facilitating better understanding of the individual circumstances and needs of learners (Al-Emran, Mezhuyev, & Kamaludin, 2018a; Al-Emran, Elsherif, & Shaalan, 2016). Digital learning also offers flexible learning times, and reduces physical space constraints, allowing learning to take place anytime, anywhere, or learning and communicating with people on the other side of the world. As a result, it is easier for people to obtain higher education opportunities via the Internet (Briz-Ponce, Pereira, Carvalho, Juanes-Méndez, & García-Peñalvo, 2017; Harchay, Cheniti-belcadhi, & Braham, 2017).

The technology acceptance model was developed by Davis (1986), based on rational behavior theory. The purpose is to simplify the theory of rational behavior in order to propose a generalized theory with a rigorous and theoretical basis. This model is used to explain and predict the behavior of potential users upon interacting with information technology, and to analyze the factors that affect users' access to information technology. The technology acceptance model TAM considers beliefs: perceived usefulness (PU) and Perceived ease (PEOU) as factors that influence attitudes toward technology (Iqbal & Bhatti, 2017; Jeno, Vandvik, Eliassen, & Grytnes, 2019).

Similar to TRA, TAM assumes that computer use is determined by the M-learning effectiveness having a significant and positive impact on actual behavior. The technology acceptance model was developed to predict and explain the willingness of tertiary students to accept wireless networks. Studies on the adoption of broadband networks found that perceived usefulness significantly positively affected the attitude of using mobile wireless networks and is the determining factor of attitude (Jeno, Vandvik, Eliassen, & Grytnes, 2019; Joo, Kim, & Kim, 2016). When many scholars study information technology issues, they expand TAM and increase other possible influencing factors. Therefore, this study not only refers to the acceptance model of science and technology, but also introduces the theory of planned behavior, expecting to increase other factors that may affect tertiary students' acceptance of M-learning, in order to explore and explain the behavior of tertiary students accepting M-learning more broadly. The purpose of this study was to investigate the effects of tertiary students' M-learning acceptance, learning motivation, and self-efficacy on M-learning effectiveness.

2. Literature review

The development of wireless technology, action learning has gradually entered people's lives. Teaching within the academic system should use this new technology to assist in learning, expand learning content, and enhance learning efficiency (Tawfik, et al., 2018; Wai et. al., 2018).

M-learning can stimulate students' motivation and promote cooperation and discussion among students; teachers can also provide teaching feedback to students (Zhang, Yin, Luo, & Yan, 2017). Some scholars have suggested that meaningful knowledge has a lot to do with the situation. Can allow learners to be at the actual site (Hew, Qiao, & Tang, 2018; Wai et. al., 2018). The experience generated by the specific operations and exercises in the simulated situation is very important for the learner (Hew, Qiao, & Tang, 2018; Iqbal & Bhatti, 2017).

Past research has also found that actual on-site learning helps to enhance the knowledge and skills needed, and helps to adapt to future problems in similar situations. Therefore, having a good online teaching environment and providing students with real learning situations and effective learning strategies has become a very important research topic (Hamidi & Chavoshi, 2017; Hsu, 2016). Mobile learning focuses on the use of mobile vehicles and network technology to construct a ubiquitous learning environment, integrating traditional digital learning platform materials and activity design, and providing mobile vehicles and other mobile vehicles (Nicol, et. al., 2017; Siddiq, Scherer, & Tondeur, 2016; Shroff, Ting, & Lam, 2019).

Learners conduct individual and group activities for indoor and outdoor activities. It is important of m-learning acceptance in perceived usefulness, perceived ease of use, perceived innovation, and perceived enjoyment (Davenport, 2018; Day, 2018). The design of action learning can meet the learner's enthusiasm for actively acquiring knowledge, meeting situational learning needs, promoting learner's experience, reflecting learning, providing instant interactive learning, and achieving the integrity of teaching content (Chung, Hwang, & Lai, 2019; Hone, & El Said, 2016).

When teachers believe that the learning belief that action learning can enhance students' IT skills is higher. The learning benefit of the value-value students is better than that of the high-task students. When teachers believe that action learning can enhance students' self-efficacy in self- cognition and self-valuation. Students with high self-efficacy will have higher learning benefits when the learning beliefs of learning efficiency and IT skills are higher (Baydas, & Goktas, 2017; Chang, Liu, & Huang, 2017). A lot of evidence shows that task value and self-efficacy are the learning of students' action learning. The benefits have a significant impact (Chung, Hwang, & Lai, 2019; Hone, & El Said, 2016; Jeno, Vandvik, Eliassen, & Grytnes, 2019). As in the study, it can reflect the perceptual usefulness of task value constructs. The perceived usefulness variable has a positive correlation with the intention to use action learning(Baturay, Gökçearslan, & Ke, 2017). Some research found that the self-efficacy of student action learning has a positive impact on learning outcomes for students' learning motivation (Jeno, Vandvik, Eliassen, & Grytnes, 2019; Nikou & Economides, 2017a).

As mentioned above, the researchers assume that M-learning acceptance, learning motivation, and self-efficacy on M-learning effectiveness of the model perceived by tertiary students in Taiwan. The performance of learning benefits will be better. Computer self-efficacy affects the usefulness of perception and the usefulness of perception. Perceptual usefulness, perceived usefulness and perceived interest all influence the attitude of action learning. The attitude of action learning will positively influence the intention of use for tertiary students.

3. Methodology

3.1. Research subjects

This research took 702 tertiary students of 22 departments through a random sampling method. The respondents were students of 11 tertiary schools, which were stratified for region and educational networks. In this population, there were 6 public tertiary universities and 5 private tertiary universities.

3.2. Research design

This study employed structural equation modeling (SEM) to analyze the relationships among tertiary students' m-learning behavior uses information technology as a medium; therefore, using M-learning is an adoption of information technology, and M-learning behavior can be said to be "innovative" behavior.

This study uses the technology acceptance model to predict and explain a user's willingness to accept M-learning. At present, the use of M-learning is in an early stage of development, and a large number of technology pushes have yet to occur. The use of M-learning is not common, so the testing of M-learning effectiveness is more suitable as a dependent variable than the actual behavior. Therefore, this study does not discuss the actual behavioral facet, but the M-learning effectiveness as a predictor, and explains the user's willingness to accept M-learning.

Data were collected through a survey, which consisted of questions on demographics and multiple items for each construct in the study. Although none of the observation variables reached a normal distribution ($p<.05$), the multi-variance normal test was insignificant ($p>.05$), which demonstrated a normal distribution. According to the conditions of maximum likelihood (ML), within the most commonly used approach in SEM, one of the conditions should be a simple random sampling that meets a multi-variance normal distribution.

3.3. Research tools

The preliminary design of the questionnaire used in this study was developed based on the relevant literature and then revised according to the research topic. Scholars were then invited to help review and correct the questionnaire. The quantitative variables of this research questionnaire were taken by Likert's five point scale method: the unipolar 1 to 5 method was used for each question, respectively ranging from "strongly disagree" to "strongly agree". The "internal consistency reliability" of the test scale was tested using Cronbach's α value; a coefficient of 0.82 or more indicated the degree of credibility, and items of insignificant importance were removed. In addition to "M-learning acceptance" and "external influence", some test results had to be deleted to obtain a factor of 0.78 or more. The Cronbach's α value coefficients of the other facets were all greater than 0.81, indicating a certain degree of reliability.

4. Result

4.1. Verification of this research model

The sample of this study was mainly drawn from the network population, and the sampling time was one month; this study required participants to download the M-learning view first. Of the 923 questionnaires returned, 31 were invalid, resulting in an effective questionnaire rate of 96.64%. This study used SEM to analyze data to explore the causal relationships between study model variables. The most approximate likelihood estimation (MLE) was used to estimate the parameters, and the results were analyzed using LISREL software. Structural equation model evaluation should be based on basic fit, overall fit, and intrinsic fit.

1. Basic adaptation degree

This study first performs screening and correction mode correction of abnormal estimation values, and modifies or deletes each variable according to MOD's proposed modification indicators to improve the mode's Interpretation ability. By repeated inspection and mode adjustment, the correction results of each facet were obtained as follows: According to the SEM confirmatory factor analysis, the influence of the observed variables X6 and X7 on the "perceived ease of use" of M-learning acceptance was not significant. The effect of variable X16 on "Perceived enjoyment" was not significant, and the effect of X31 on "Self-evaluation" of the deconstructed surface of the control belief was not significant. These variables were deleted according to the suggestion of the revised index.

2. Overall fit

According to Hair et al. (1998), the overall model fit degree can be divided into three types: the measure of absolute fit, the incremental fit (incremental), and fit measures and parsimonious fit measures. The goodness of fit index (GFI) value obtained in this study was 0.88. Research indicates that the standard GFI value is greater than 0.9, and that the recommended GFI value should be greater than 0.8. The GFI value of this study was 0.84; although it does not meet the standard, it does meet the recommended values. The adjusted goodness of fit index (AGFI) should be greater than 0.9. The adjusted AGFI obtained in this study was 0.85, indicating that the AGFI value of this study did not meet the standard. The root mean square error of approximation (RMSEA) value is recommended to be less than 0.05. The RMSEA value of this study was 0.026, which is in line with this standard. The results of the absolute fit test indicate that the model constructed in this study is adapted to the observation data. The value-added fitness indices most commonly used to evaluate the overall mode adaptation degree are the normed fit index (NFI), the non-reference fit index (Non-Normed Fit Index, NNFI), and the comparative fit index (CFI). The NFI, NNFI and CFI values of this study were 0.98, 0.99 and 0.99, respectively, all reaching a standard greater than 0.9. This shows that the overall fit of the model constructed in this study and the observation data is ideal. Simple fitness is measured as PNFI (Reduced Baseline Fit Indicator): at least greater than 0.5, and PGFI (Reduced Suitability Indicator): at least greater than 0.5. According to Table 1, the PNFI and PGFI values for this study were 0.86 and 0.73, respectively, both greater than 0.5. The results of these studies show that the model constructed in this study should be a streamlined model.

Table 1. Overall goodness of fit test results

Type of fitness	Fit index	Evaluation standard	Analysis of results not researched	Goodness of fit
Absolute fitness volume	GFI	>0.9	0.966	Acceptable
	AGFI	<0.9	0.86	Poor
	RMSEA	<0.05	0.026	Acceptable
Incremental fitness	NFI	>0.8	0.98	Acceptable
	CFI	>0.9	0.99	Acceptable
	NNFI	>0.9	0.99	Acceptable
Parsimonious fitness	PNFI	>0.5	0.86	Acceptable
	PGFI	>0.5	0.74	Acceptable

3. Intrinsic fit

Hair et al. (1998) advocate evaluating the intrinsic fit of the model from the measurement model fit. Based on the recommendations of Bagozzi and Yi (1988), this study selected the most commonly used individual project indicators to evaluate the measurement mode, as described below:

(1) *Individual item reliability:* The reliability of each measurement index reflects the degree of consistency of the measurement tool used to measure the research facets. When using the LISREL mode analysis, the reliability index of each observation variable is the R-Square value, which is determined by the Squared Multiple Correlation (SMC). The higher the SMC, the higher the reliability; conversely, the lower the weight, the lower the reliability. The SMC values of the observed variables are lower than 0.5 in the observed variables X3, X4, X5, X17 and X30, but the SMC values of most of the observed variables are greater than 0.5, indicating that the reliability of the overall measurement of the study is good.

(2) *Composite reliability (CR):* The CR value of the potential variable refers to the reliability component of all the measured variables, indicating the internal consistency of the facet index. The higher the reliability, the higher the consistency. A consistency value of 0.7 is generally considered to be the lowest acceptable level. Table 2 shows that the CR values of all potential variables are above the 0.7 standard value, indicating good facet reliability.

(3) *Variance extracted (VE) of potential variables:* VE of potential variables is a measure of the variation of each variable in the construct extraction; it is the ability to evaluate the variation of each potential variable. It can be used to examine the convergence validity of potential variables. If the VE value is high, it indicates a higher reliability and convergence validity of the potential variable, where the recommended value is 0.5 or more. As shown in Table 2, the VE of each variable in this research mode is 0.5 or more, in accordance with the recommended value, indicating that the study has good convergence validity.

Table 2. Reliability analysis table for each variable of the research model

Item	Reliability	Extraction variation
Perceived usefulness	.882	.556
Perceived ease of use	.913	.773
Perceived enjoyment	.924	.766
Perceived innovation	.904	.689
Teaching material	.891	.654
External influence	.856	.676
Self- cognition	.887	.730
Self-valuation	.814	.538
M-learning acceptance	.920	.724
Learning motivation	.846	.667
Self-efficacy	.845	.688
M-learning effectiveness	.919	.734

4.2. Mode explanation

This study used LISERL software for the model validation and inspection of the sample selection estimation method. Table 3 shows the parameter values after the model estimation using the software. Before the model's goodness of fit evaluation, it first needed to be inspected to see if any violation of estimation existed or whether the estimated coefficient was beyond the defined scope. Based on the inspected violation of estimation, the estimated parameters in this study were all positive in the error variance, and no negative values existed. The standardized coefficients were all between 0.02 and 0.92. The estimated parameters of the data in this study did not have a violation of the estimation problem and were ready for the goodness of fit test. If a value was greater than the absolute value of 1.95, then it indicated that the estimated parameters had already reached a significance level of .05 (Hair, Anderson, Tatham, & Black, 1998). Table 3 shows that, apart from $\lambda 1$, the other estimated parameters in this study all reached a significant level.

Table 3. Tests of variables' means, standard deviations and normal distributions

Parameter	Standardized coefficient	Standard error	t value	Parameter	Standardized coefficient	Standard error	t value
λ1	0.571	0.201	4.768*	δ1	0.341	0.046	6.459*
λ2	0.304	0.202	4.644*	δ2	0.763	0.085	9.454*
λ3	0.568	0.115	5.102*	δ3	0.634	0.027	8.874*
λ4	0.582	0.124	7.324*	δ4	0.556	0.029	9.223*
λ5	0.641	0.121	9.025*	δ5	0.483	0.022	8.349*
λ6	0.896	—	—	δ6	0.177	0.015	3.560*
λ7	0.932	0.131	9.741*	ε1	0.145	0.020	4.676*
λ8	0.671	0.017	9.455*	ε2	0.523	0.027	8.911*

Note: Refer to indices in Table 1; * p <.05.

The normalization coefficient in the structural equation model is like the beta weight of the regression. The larger the coefficient, the greater the importance in the causal relationship. It can be seen that among the eleven hypotheses of the research model, the remaining eight hypotheses reach a significant level. In the structural mode of Figure 1, the direct effect between the variables is clearly presented.

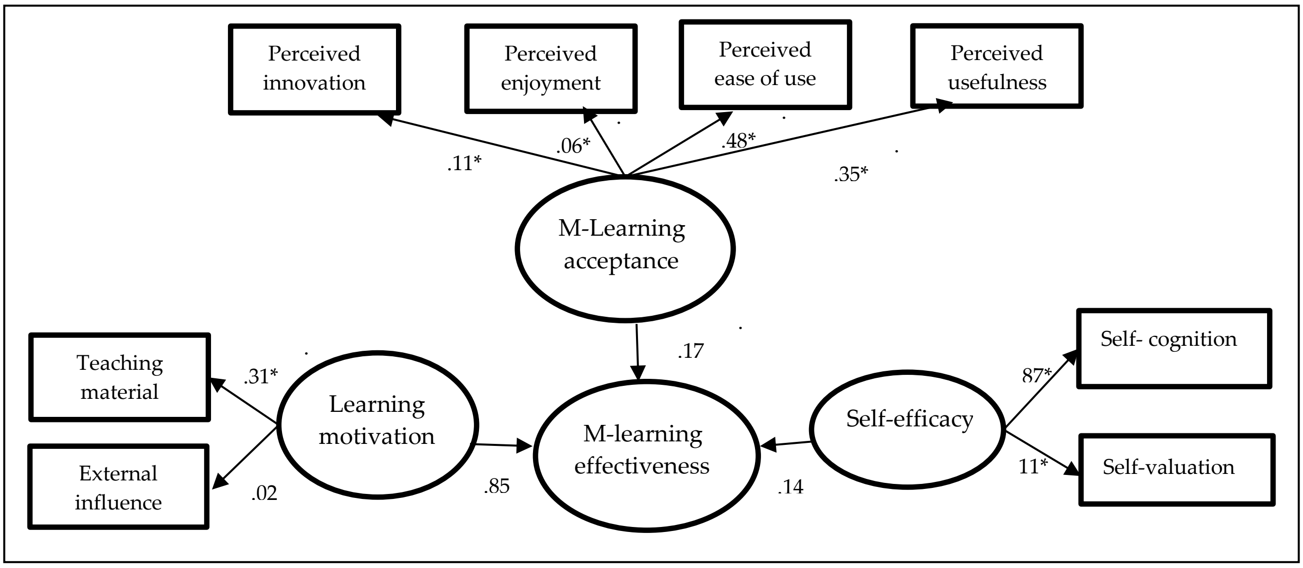

Fig1. Model of tertiary students' M-learning effectiveness

5. Conclusion

5.1. "M-learning acceptance" is the most important factor affecting "M-learning effectiveness", followed by "learning motivation" and finally "self-efficacy"

From the research results, among the factors affecting "M-learning effectiveness", the most important was "M-learning acceptance". In terms of whether M-learning can be used as the method adopted by tertiary students, the first consideration is the evaluation by, and feelings of, tertiary students about using M-learning, followed by the impact of the surrounding reference groups, and finally whether a learning infrastructure has the ability and resources to adopt M-learning. The "perceived enjoyment" assumption of "M-learning acceptance" is established; it has the most significant positive impact in fact. It can be seen that for tertiary students, the most important concern is whether the learning habits and needs of individuals are related to M-learning. The "perceived usefulness" hypothesis of "M-learning acceptance" is established, and has a positive influence. It can also be seen that the effect obtained by M-learning can be more or less similar to that obtained by ordinary early readers. The tertiary students gave a positive evaluation of M-learning. "Perceived innovation" is a hypothesis that "M-learning acceptance" is established and has a positive impact. This means that individuals who have a desire for new things or new technologies naturally have a positive perception of them, and are quick to adopt them (Chung, Hwang, & Lai, 2019;Jeno, Vandvik, Eliassen, & Grytnes, 2019). The situation of eagerness and sorrow may occur. "Perceived ease of use" does not support the assumption of "M-learning acceptance". The reason for this may be that the downloaded M-learning program required by the researcher is very simple, so it is not possible to say whether the impact is significant; users who use M-learning to generate good feelings are aware of the ease of use of M-learning, so this study cannot objectively claim that "perceived ease" significantly affects "M-learning acceptance".

5.2. "Teaching material " supports the hypothesis of "learning motivation" and verifies the theory of innovation diffusion.

Research indicates that the initial adoption of M-learning is still subject to many uncertainties. Potential users must be encouraged to seek the opinions of others to understand the adoption process of M-learning. Compared to external information, tertiary students place greater value in advice provided by their friends. Therefore, relevant industry develops promotion programs for this feature, and can launch an M-learning program offering access to friends of the tertiary students, so that M-learning can be broadcast to attract others to read and achieve the publicity effect (Al-Emran, Mezhuyev, , & Kamaludin, 2018b; Buabeng-Andoh, 2018).

5.3. The impact of “External influence” on “Learning motivation” is not significant

It can be seen that tertiary students trust information conveyed by people with whom they are familiar more than information conveyed by TV media and Internet word of mouth. "External influence" holds the assumption of "self-efficacy", which means that when students perceive their confidence and ability to adopt M-learning, the resources needed to adopt M-learning behavior are controlled (Al-Emran, Mezhuyev, & Kamaludin, 2018a; Hao, Dennen, & Mei, 2017).

5.4. “Self-evaluation” does not hold the assumption of “self-efficacy”

The reason for this may be that tertiary students cannot evaluate the resources required for M-learning, or the current resources required for M-learning, such as the Internet, pose no barrier to access to the students; that is, the students do not feel that they have a higher M-learning simply because they have the resources to use M-learning. The control of learning makes this hypothesis impossible (Harchay, Cheniti-belcadhi, & Braham, 2017; Jeno, Vandvik, Eliassen, & Grytnes, 2019).

6. Application

To date, discussion on the acceptance of new information technology has mostly adopted the Technology Acceptance Model. This study uses the technology acceptance model theory to explore the factors of users' adoption of M-learning from the new information technology perspective, and also has a good explanatory power (R2 = 79%). In this study, taking into account all the influencing factors, the authors hoped to offer a complete discussion on the factors influencing users' adoption of new information technology behaviors. In addition, the research found that five factors: "perceived usefulness", "perceived enjoyment", "perceived innovation", "teaching material " and "external influence" cannot be ignored in the study of M-learning. Effective control of the factors that significntly affect the use of M-learning by tertiary students is therefore necessary. On the above factors, this study verifies that "perceived innovation" has a significant effect on "M-learning acceptance", indicating that users who like to experience new technology or new types of things are less likely to reject M-learning.

7. Future research recommendations

Many different education systems are available in today’s market. M-learning, and the factors influencing tertiary students’ acceptance of M-learning will also vary according to the type and system, which can be further explored by follow-up research. In addition, because there are few tertiary students who have real experience in M-learning, this study does not explore the actual behavior of tertiary students. However, the M-learning method will inevitably become a trend in the future, and follow-up research may employ more research samples. A group discussion with tertiary students who have studied M-learning and tertiary students who have not studied M-learning, or the involvement of tertiary students in the M-learning topic including future research variables will make the research related to M-learning behavior more complete.

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