The Impact of Personality Trait towards the Intention to Adopt Mobile Learning

Abstract

Mobile devices have spread at an unprecedented rate in the past decade and 95% of the global populations live in an area covered by a mobile-cellular network [1] .Mobile learning can be used to support students' learning in higher education settings [2], particularly more in the current COVID-19 situation. Mobile Learning as a model of e-learning refers to the acquisition of knowledge & skills utilizing mobile technologies. The aim of this study is to identify the extrinsic influential factors for the adoption of mobile learning. This study propose the use of an extended technology acceptance model (TAM) theory that includes variable of personality traits such as perceived enjoyment and Computer self-efficiency. The participants of this study were 351 students at University Technology Malaysia who had past experience on E-learning. The study found that perceived usefulness as an extrinsic factor has the highest influence on students' intention to adopt mobile learning through an investigation of technology acceptance toward mobile learning and personality traits such as perceived enjoyment and self- efficacy impact on behavior intention to adopt mobile learning.

Key words: Mobile learning, adoption, personality traits

Introduction

The integration of mobile technology into higher education has gained considerable attention [3]. Mobile devices, especially smart phones, are the most frequently used technological devices for daily routines. Reflecting this, they are being integrated into teaching [4]. [5] Define mobile learning as a dynamic learning environment using wireless mobile devices such as mobile phones, personal digital assistants (PDAs), iPads, and smart phones. Mobile learning allows students to access course materials as well as learning activities at any location and in real time [6] and to share ideas with others, and participate actively in a collaborative environment [7] thus overcoming the deficiencies of e-learning such as lack of human interaction and enthusiasm [8].

In order to engage the digital generation in the learning process, interactive learning such as mobile learning is recommended in the higher education classroom [9-10]. However, the success or failure of mobile learning implementation depends on learners' readiness to embrace technology for their education [11]. To enrich the studies on mobile learning field, the objective of this study is to identify the highest influential extrinsic factor to influence the adoption of mobile learning.

This study identifies factors that influence to adopt mobile learning based on technology acceptance model. An individual's intention to adopt mobile learning may vary according to the perceived benefits and costs, but the factors that affect this adoption may also vary according to the usage behavior of technologies. TAM has been used and modified to explore the adoption a range of educational technologies [12]. TAM is one of the most widely used theories in studying the adoption of IT innovations and new information systems [13] thereby identifying extrinsic and intrinsic motivations on the individual's acceptance of different information technologies. Perceived enjoyment as an external variable can affect the adoption of a new technology like M-learning. Moreover, we determine the impact of personality traits such as self-efficacy on the intention to adopt mobile learning. Specifically, the present study poses a research questions: What is the effect of personality trait on adoption of mobile learning?

2. Literature review

2.1 TAM (technology acceptance model)

Users' acceptance and adoption of technology has captured the attention of various scholars and become a principle field of study over the past few decades [14]. The need to explain the usage behavior of technologies and their determinants has prompted the development of a number of theoretical frameworks [15]. These include the theory of reasoned action (TRA) [16], the theory of planned behavior (TPB) [17], the technology acceptance model (TAM) [18], and the diffusion of innovation model (DOI) [19], While personality is one of the antecedents of individual factors, the Theory of Planned Behavior (TPB) does not include the individual factors. Likewise, the UTAT model includes the individual dimension but it investigates the individual in term of experience, age, and gender. Personalities of students and lecturers are very different and there are many indicators for these behaviors. A critical matter, which can enable the process of adoption, is determining these indicators. Hence TAM is applied since it is one of the most widely used theories in studying the adoption of IT innovations and new information systems.

Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of the innovation are two major goals of TAM. TAM with these variables can realize the possible adoption of the innovation. The degree to which a user thinks a new technology improves their performance called Perceived Usefulness. The degree to which a user thinks selecting a technology is simple and user-friendly is Perceived Ease of Use. True behavioral intention to use findings affects real usage.

2.1.1 Behavioral intention

Behavioral Intention evaluates the strength of a user's commitment to perform a specific behavior and shows the intensity of an individual's intention to adopt a specific behavior [18]. [20] Posited this factor is reflected as a signal of actual behavior and predicts actual usage [21]. This factor has been widely used as an antecedent of user acceptance in various technology acceptance theories [22]. Extant studies on mobile learning [23], virtual reality in learning [24] e-learning [25], and social networking sites [21] have integrated this factor to evaluate adoption and implementation of technology. Thus, this factor is regarded as a prime determinant in this research.

2.1.2 Perceived usefulness

Perceived usefulness could be addressed as the functional and extrinsic benefits that are realized by using technologies [18]. Extrinsic motivation refers to the performance of an activity because it is perceived to be instrumental in achieving valued outcomes that are distinct from the activity itself. Benefits could be related to the extent to which student perceive using mobile internet as being a more productive way of doing things, saving their time and effort in using services rather than employing traditional tools to access the same kind of services [26-27].

2.1.3 Perceived ease of use

The extent to which student perceive using a new system as being simple and not requiring too much effort usually shapes their willingness to adopt such a system [18].

Indeed, mobile internet could be considered as a new technology that will require that student have a certain level of experience and knowledge to use it both safely and efficiently. In the prior literature of mobile technology, there are a good number of studies that have approved the impact of the role of perceived ease of use on the student intention to adopt such technology [28].

2.2 Perceived enjoyment

Perceived enjoyment is defined as the “degree to which the activity of using technology is perceived to be enjoyable in its own right apart from any performance consequences that may be anticipated” [29]. Prior studies have proposed that intrinsic motivators, such as perceived enjoyment [18]; can explain the Behavioral Intention to use information systems. The Perceived Usefulness has a significant effect on the intention for technology adoption and its influence was complemented by enjoyment. Therefore, Enjoyment as an external variable can affect the adoption of a new technology as in M-learning.

2.3 Self-efficacy

Self-efficacy is an individual’s belief in their ability to successfully perform the behaviors required to produce certain outcomes [30]. Self-efficacy as an index may measure an individual’s self-confidence in utilizing innovation [31], and it is an important factor that affects high technology adoption [32]. Self-efficacy in a learning environment may positively affect a learner’s motivation, concentration, and learning effectiveness. Students with a higher level of self-efficacy tend to have more confidence in learning situations [33]. Moreover, self-efficacy has been found to have a positive effect on the intention to use web-based learning, and instructors with a high level of self-efficacy related to technology tend to prefer teaching using technology [33].

3. Hypotheses Development

This study focuses on the relationship between TAM and two external factors. Therefore, we posit the following hypotheses:

Self-efficacy is the thoughts of a human being around their capacity for using and managing several actions that require designed types of performance. In this condition, the users that show higher intention to use mobile tools in educational processes are the users that have previously used mobile devices and have good experience about that [34].

H1: self-efficacy has positive effect on Perceived Ease of Use.

Extrinsic motivation is an example of Perceived Usefulness in TAM model [35] one of the effective factors of usage behavior and intention in TAM model is Perceived Usefulness.

H2: Perceived Ease of Use of m-learning has a significant positive effect on Perceived Usefulness

M-learning systems are useful because of context-aware support and that provides useful data to users all the time and from anywhere. Furthermore, these tools are able to develop and foster the relationship among students and lecturers.

H3: Perceived Usefulness of M-learning has a positive impact on behavioral intention to use

Perceived enjoyment based on the prior researches has a significant influence on Behavioral Intention to use computer systems [36-37]. It is predictable that Perceived Enjoyment can have a salient effect on Behavioral Intention. Personality traits might have a significant influence on perceived enjoyment and behavioral intentions.

H4: Perceived enjoyment is positively related to Behavioral Intention.

4. Research methodology

4.1 Measurement

The survey questionnaire was designed based on quantitative data analysis method. The questions were designed on a five-point Likert scale to evaluate the explanation coverage of each item. The scale included 1 to 5, where 1=strongly disagree, 2=disagree, 3=neutral, 4=agree and 5=strongly agree. A major consideration in the current survey tool design was to maintain its brevity with a focus on obtaining a sufficient response rate.

4.2 Data collection and sample characteristics

This study collected data from undergraduate and postgraduate students that used E-learning previously. Data were collected through structured questionnaires. The questionnaires were disseminated through personal delivery and collection. The target population of this study was accounting students of two faculties in University Technology Malaysia. According to Krejeie and Morgan [38] list method 351 questionnaires were disseminated to the respondents.

We used a descriptive statistics for assessing the demographic data of the respondents. Table **1** shows the general characteristics of the sample.

Table 1: general characteristics of the sample

Measure	Items (coding)	Ratio %
Gender	Male (1)	39%
	Female (2)	61%
Age	>25	28%
	25-34	57%
	<35	15%
Education level	Undergraduate	49%
	Postgraduate	51%

Faculty	Faculty of Health Science	68%
	Faculty of Biomedical engineering	32%
Type of devices		
	Smart phone	89%
	Tablet	11%

4.3 Data analysis

The collected data were entered in SPSS V21 for data analysis. Different analyses were done in SPSS, such as descriptive analysis to demonstrate the respondents' attributes and properties, and regression analysis to obtain the relationship between two variables.

5. Results

5.1 Reliability and validity

The reliability coefficient demonstrated whether the test designer was correct in expecting a certain collection of items to yield interpretable statements about individual differences (Klopfer and Kelley 1942) The general agreed-upon lower limit for Cronbach's α is 0.70 [39] Table 2 shows the Correlations between total scores.

Table 2: Correlations between total scores

Scale Items	Number of Items	Corrected Item-Total Correlation
Perceived Ease Of Use	4	0.636

Perceived Usefulness	4	0.699
Behavior Intention	4	0.522
Perceived Enjoyment	3	0.521
Computer Self-Efficacy	4	0.673

For analyzing the basic structure for questions on the research survey and separately categorizing them into their respective scales, a principal component analysis with a varimax rotation method was performed. Table **3** shows Factor loading for the rotated adoption factors.

Table 3: Factor loading for the rotated adoption factors

Scale Items	1*	2*	3*	4*	5*
PE1	0.854				
PE2	0.884				
PE3	0.862				
PEU1		0.902			
PEU2		0.90			
PEU3		0.856			
PEU4		0.625			
PU1			0.769		
PU2			0.765		
PU3			0.834		
PU4			0.796		
SE1				0.904	
SE2				0.929	
SE3				0.915	
SE4				0.903	
BI1					0.879
B I2					0.891

B I3					0.890
B I4					0.889
% Of Variance Explained	57.048	16.114	12.016	8.666	6.156
Cumulative Percentages	57.048	73.162	85.178	3.844	100.0

5.2 Regression analysis

Regression analysis was done to attain high-accuracy results. Linear regression was applied to calculate the values of the relationships between two variables. The linear regression matrix has built four parameters, R^2 as the coefficient of the correlation or the relation shows the strength and direction of the relationship. The significant of the relationship was shown by the P values, which should be equal or less than 0.05 for a significant relationship. The slope and the direction of the relationship are shown by Beta (β). Based on 351 completed questionnaires collected, Table 4 shows Regression results of Hypotheses.

Table 4: Regression results of Hypotheses

Constructs	*β*	*t*	*P*	R^2	*Hypothesis testing results*
PEU→ PU	0.330	7.049	0.00	0.353	*H2* is supported
PU→BI	0.636	12.373	0.00	0.553	*H3* is supported
CS→PEU	0.414	12.373	0.00	0.365	*H1* is supported
PE→ BI	0.402	6.739	0.00	0.340	*H4* is supported

The positive value of β (0.330) indicates the direction of the relationship. From the table above, we determine that Perceived Ease of Use impacts Perceived Usefulness in mobile learning adoption. The coefficient of the regression determines if the relationship is accepted or rejected. In this part the value of R^2 is high and the higher value of R^2 shows that the relationship is strong. R^2 scored greater number, which is 0.553 while the significance indicator (P) is equal to 0.000 and Beta (β) recorded positive value with 0.636. It suggests that Behavior Intention is positively related to Perceived Usefulness. We found the Perceived Usefulness is the most influential factor, towards Behavior Intention to use mobile learning. The hypothesis 2 (H2) was accepted because the relation between the variables are strongly sufficient. According to this finding, their capacity and the amount of ease of using the mobile learning have a strong and positive relationship. In this case hypothesis 3 (H3) was accepted because P=0.000 and R^2 =0.365 and β has a positive value (0.404) showing that the relationship is positive as it describes the direction. As can be seen from the table Computer Self-Efficacy and Perceived Ease of Use are positively related. The Perceived Enjoyment has a significant effect on Behavior Intention to use. P is less than 0.05 and the value of β (0.402) shows a strong relationship between Perceived Enjoyment and Behavior Intention, so the hypothesis (H4) is accepted. Consequently, it can be resulted that Perceived Enjoyment is related to Behavior Intention in M-learning adoption.

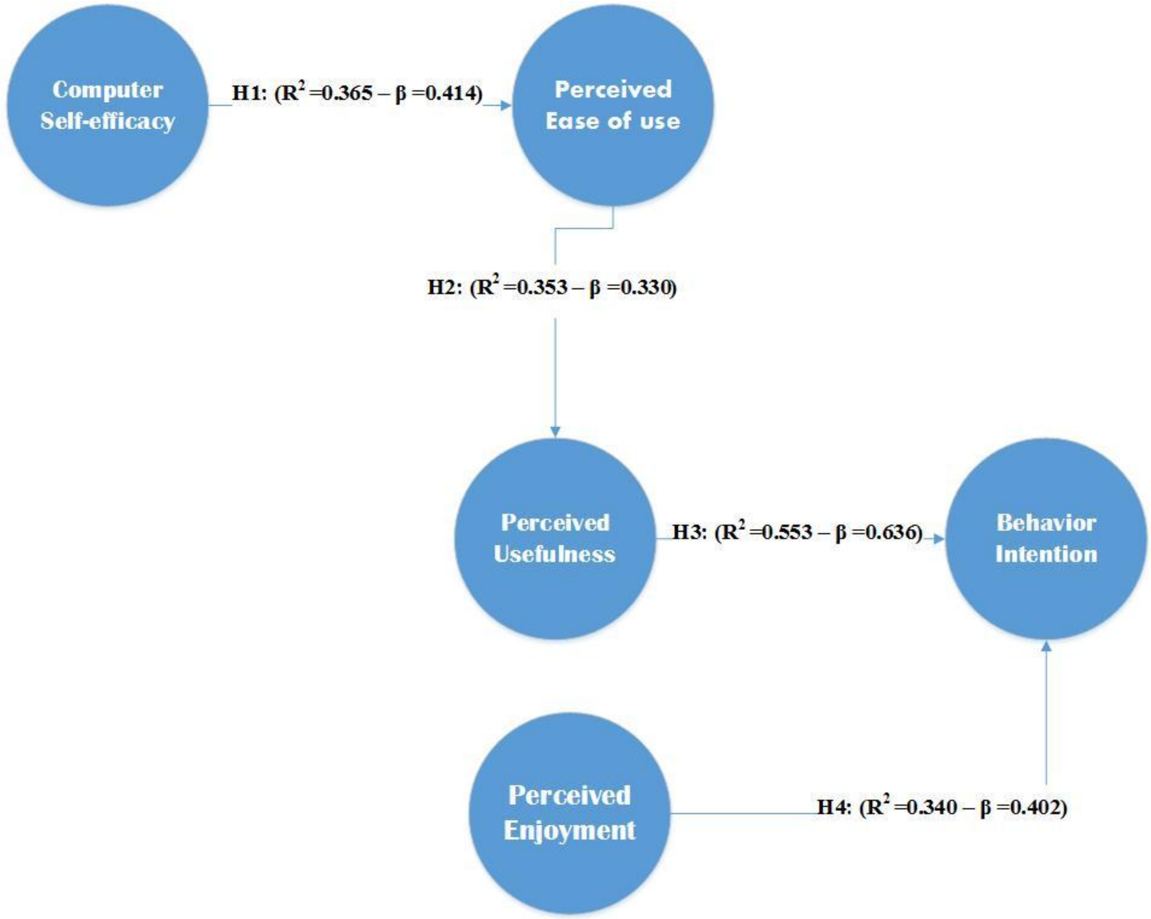

Figure 1: proposed model

5.2.1 The most influential Factor leads to Adoption of M-learning

The result of the regression presented the most influential factor that leads to adoption mobile learning. Perceived Usefulness is the most significant factor that influences adoption of mobile learning. In the table 4, R^2 which measures the level of relationship between variables, scored the greater number which is 0.553 while the indicator of the significant (P) is equal to 0.000 and this is considered significant at alpha level 0.05. Beta (β) is another parameter shows the direction of the relationship, it recorded positive value in 0.636. This depicts Perceived Usefulness is positively related to Behavior Intention. R^2 which is the most important parameter scored the highest number with 0.553 compared to the all regression analysis. From this it can be drawn that the Perceived Usefulness is the most influential factor that leads to adoption of M-learning.

6. Discussion

According to the result of analysis, this research identified a significant relationship between Perceived Ease of Use and Perceived Usefulness. Previous researchers found out the significant influence of Perceived Ease of Use on students' intention and Perceived Usefulness simultaneously based on [40]. Perceived Ease of Use on students' intention is indirectly related through Perceived Usefulness [41]. Pursuant to previous researches and the current study, findings can prove a significant relationship between Perceived Ease of Use and Perceived Usefulness on intention of students.

According to hypothesis 2, Perceived Usefulness has the most significant effect on Intention of students. It is an extrinsic motivation, which plays an important role in acceptance of a new technology [18] M-learning introduces many advantages such as collaborating and sharing knowledge. Also M-learning found useful in learning mode for individuals due to its learning flexibility. This findings support that perceptions of the usefulness of M-learning; M-learning usefulness and students' intention to adopt new technology are related. This hypothesis in this research was the most effective, which means that students perception about usefulness of M-learning is high and the reason for this perception can be related to students' background about usefulness of a new technology like M-learning because the respondents of this study used E-learning already.

Computer Self-Efficacy refers to the judgment of individuals about their capabilities to use computers in diverse situations [42]. According to the result of analysis, this research finds a relationship between ability of students and Perceived Ease of Use. In addition, Computer Self-Efficacy revealed a strong positive influence on Perceived Ease of Use about internet-based learning systems [43]. On the other hand, most of the respondents have capability of using information technology so they will not be afraid easily and they persist their efforts. As a result, it is possible for these individuals to overcome whatever obstacles they confront [42].

According to the result of analysis, Perceived Enjoyment found to be a significant determinant of the intention for using M-learning. In addition, Perceived Enjoyment is an extrinsic motivation like Perceived Usefulness that can have influence on intention of students. Prior studies found a significant relationship between Perceived Enjoyment and Behavioral Intention to use M-learning and this outcome support them [44-45] .Based on the results, the individual's intention for using M-learning in education could increase through promoting their Perceived Enjoyment of M-learning and through improving hedonic elements of the system, the Perceived Enjoyment of a system can be easily elevated and influence the intention of students to adopt M-learning.

Contribution

This research probed into the dynamics of technology acceptance in the domain of mobile learning, with specific emphasis on the moderating effects of personality traits. Differing from what was hypothesized in this study; personality traits have impact on BI. This study found that Perceived Enjoyment and self- efficacy are extrinsic motivation which can have impact on behavior intention of students. Also perceived usefulness as an extrinsic factor has the highest influence on students' intention to adopt mobile. This result provides valuable insight for educators to formulate and design interesting interface and enjoyable contents of mobile learning system. The design of mobile learning should encompass features which can deliver greater satisfaction.

Limitations and recommendations

Certain limitations were revealed in the current research. First, the actual use of mobile learning was not incorporated in the proposed conceptual framework. Second, the causality among the constructs may not be readily inferred owing to the study's cross-sectional nature. Third, the investigation was based on the respondents' self-reported intention to use mobile learning, lastly, since the sampling locations were confined to two faculties of university only, the findings could not be generalised across all students of university.

Apart from considering BI, future scholars are encouraged to integrate actual use of technology in the proposed model and adopt a longitudinal study to validate the cause-effect relationships. Furthermore, instead of relying on self-reported intention to use, actual usage of mobile learning is recommended to be tracked and recorded to deliver insightful information on students' mobile learning progress. Further studies are encouraged to broaden the sample size and involve an extensive range of public and private tertiary education institutions.

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