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# The Impact of Personality Traits towards the Intention to Adopt Mobile Learning

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**Abstract.** Mobile devices have become increasingly more common in the digitally connected world. 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 proposes the use of an extended technology acceptance model (TAM) theory that includes variables 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 experiences in 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. Personality traits such as perceived enjoyment and self-efficacy have impact on behavior intention to adopt mobile learning.

**Keywords:** Mobile learning, adoption, personality traits, e-learning, perceived enjoyment, self-efficacy

## 1 Introduction

Mobile devices have spread at an unprecedented rate in the past decade and 95% of the global population live in an area covered by a mobile-cellular network [1]. Mobile learning (m-learning) can be used to support students' learning in higher education settings [2], particularly significant in cases such as the COVID-19 pandemic. 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]. M-learning as a dynamic learning environment makes use of the wireless mobile devices such as mobile phones, personal digital assistants (PDAs), iPads, and smart phones [5]. M-learning allows students to access course materials as well as learning activities at any location and in real time and to share ideas with others, and participate actively in a collaborative environment [6], thus overcoming the deficiencies of e-learning such as lack of human interaction and enthusiasm [7].

In order to engage digital generation in the learning process, interactive learning as part of m-learning is recommended in the higher education classroom [8]. However, the success or failure of m-learning implementation depends on learners' readiness to embrace technology in their education [9]. To enrich studies on the m-learning discipline, the objective of this study is to identify the highest influential extrinsic factor that influence the m-learning adoption.

According to the Ambient Insight Comprehensive Report (2015), in Asia, Malaysia is ranked fifth highest for predicted m-learning growth rates for 2014 to 2019. In spite of this, m-learning in Malaysia is still in an emerging stage [10]. Most projects or studies continue to emphasize the notion of establishing foundational understanding of m-learning, and activities sustained by mobile technology [11, 12].

This study identifies factors that influence m-learning adoption based on technology acceptance model. An individual's intention to adopt m-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. Technology Acceptance Model (TAM) is one of the most widely used theories in studying the adoption of IT innovation 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 phenomena like m-learning. Moreover, we determine the impact of personality traits such as self-efficacy on the intention to adopt m-learning. Specifically, the present study poses a research question: *What is the effect of personality traits on adoption of m-learning?*

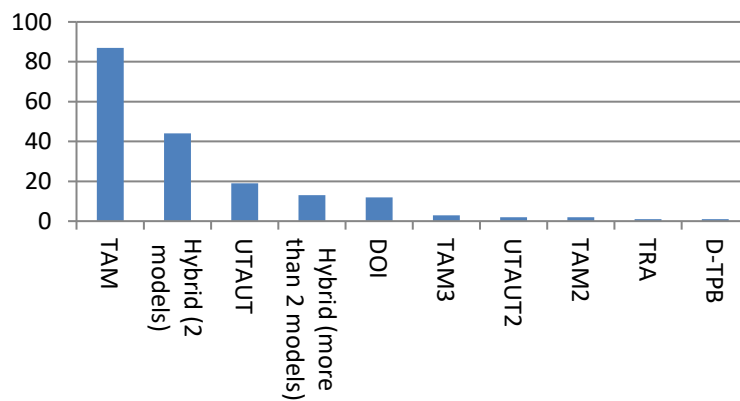
## **2 Literature review**

### **2.1 Technology Acceptance Model (TAM)**

Users' acceptance and adoption of technology has captured the attention of various scholars and became a principal 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. A number of theories have been used in existing literature, and "adoption" is one of the more popular research areas in the Information Systems discipline [15]. Dominant theories in the technology adoption literature are Theory of Reasoned Action (TRA), Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Unified Theory of Acceptance and Use of Technology (UTAUT). Several studies have attempted to add more constructs to better explain adoption behavior over the years.

The findings from various research areas such as mobile commerce studies show that usage of TAM and UTAUT is the first priority of researchers to research on the understanding of user intentions [16]. Moreover, the associations between certain constructs such as ease of use, usefulness, attitude, and intention were found as the strongest determinants to identify user intentions. Likewise, the UTAUT 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. Therefore, personality traits can provide critical factors to explain the process of adoption. Figure 1 describes the utilization of technology adoption theories in the m-commerce literature. TAM has been used in the majority of studies (n=87) in comparison with hybrid models or other theories in the literature [16].



**Fig. 1.** Dominant theories in mobile commerce adoption [16]

The TAM explains how users come to accept and use technology. Noticeably the TAM has been adopted and expanded by including many factors of mobile internet or similar mobile systems (i.e. mobile commerce, mobile payment, mobile shopping). For example, in mobile payments, the service adoption, perceived usefulness, social influence, mobility and reachability are the key factors that affect adoption. TAM was adopted to analyze user satisfaction and intention to continually use m-wallets [17]. According to data collected from young users in India, perceived usefulness and perceived ease of use significantly affect user satisfaction [18]. Likewise, in order to validate the customers' adoption of mobile payments services in India [15], expanded TAM includes other external factors: perceived usefulness, trust, cost, and social-influence are used. Their statistical results largely approved the role of both perceived usefulness and ease of use in predicting customers' intention to adopt mobile internet commerce.

Another review study conducted on mobile commerce suggested TAM as the most popular technology acceptance frameworks used in research. This study reviewed 201 articles and adopted a systematic literature review to analyze and highlight the usage of technology adoption theories in mobile commerce [19].

The constructs of TAM: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU) of the technology, are the two major outcomes of TAM. TAM with these variables can realize the benefits of positive adoption of the technology 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. The true behavioral intention to use findings affect real usage. Moreover, other constructs like perceived risk, perceived enjoyment, personal innovativeness, self-efficacy, trust, security, and perceived cost have been increasingly investigated. Hence this research has adopted the TAM model as one of the most widely used theories in studying the adoption of IT innovations.

Customers' personality characteristics attracted some attention from mobile internet studies as well. For example, self-efficacy as a personal trait was mentioned by a number of studies as a key predictor of the customer's perception and intention towards use of different kinds of mobile technology [13, 20].

**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. This factor has been widely used as an antecedent of user acceptance in various technology acceptance theories [3]. Extant studies on m-learning, like e-learning [21], and social networking sites [22] 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 [23]. 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 [3].

**2.1.3 Perceived ease of use.** The extent to which students perceive using a new system as being simple and not requiring too much effort usually shapes their willingness to adopt such a system [24]. Indeed, mobile internet could be considered as a new low-cost 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 [25].

## **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". Prior studies have proposed that intrinsic motivators, such as perceived enjoyment [23]; 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 [26]. Self-efficacy as an index may measure an individual's self-confidence in utilizing innovation, and it is an important factor that affects high technology adoption [27]. Self-efficacy in a learning environment may positively affect learner's motivation, concentration, and learning effectiveness. Students with a higher level of self-efficacy tend to have more confidence in learning situations [20]. 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 that uses technology [20].

## 3 Hypotheses Development

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

Self-efficacy is the thought 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 [13].

*H1: Self-efficacy has a positive effect on Perceived Ease of Use.*

Extrinsic motivation is an example of Perceived Usefulness in the TAM model [28] One of the effective factors of usage behavior and intention in the TAM model is Perceived Usefulness.

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

M-learning systems are useful because of context-aware support that provides useful data to users all the time and from anywhere. Furthermore, these tools can 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 [29]. 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 to use.*

## 4 Research methodology

### 4.1 Measurement

A survey questionnaire was designed as part of the quantitative research methodology. 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 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 of two faculties in University Technology Malaysia that used e-learning previously. Data were collected through structured questionnaires. According to Krejcie and Morgan [30] list method, 351 questionnaires were disseminated to the respondents.

We used 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 relevant 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 [31]. The general agreed-upon lower limit for Cronbach's  $\alpha$  is 0.70 [32]. Table 2 shows the correlations between total scores.

**Table 2.** Correlations between total scores

Scale Items	No. 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

Factor	Scale item	Item loading	% of Variance Explained	Cumulative Percentages
Perceived Enjoyment	PE1	0.854	57.048	57.048
	PE2	0.884		
	PE3	0.862		
Perceived Ease of use	PEU1	0.902	16.114	73.162
	PEU2	0.90		
	PEU3	0.856		
	PEU4	0.625		
Perceived Usefulness	PU1	0.769	12.016	85.178
	PU2	0.765		
	PU3	0.834		
	PU4	0.796		
Self-Efficacy	SE1	0.904	8.666	93.844
	SE2	0.929		
	SE3	0.915		
	SE4	0.903		
Behavior Intention	BI1	0.879	6.156	100.0
	BI2	0.891		
	BI3	0.890		
	BI4	0.889		



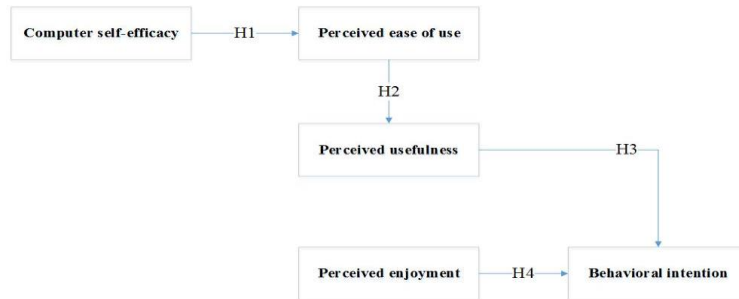
## 5.2 Regression analysis

Linear regression was applied to calculate the values of the relationships between two variables. The linear regression matrix has built four parameters and  $R^2$  as the coefficient of the correlation. The significance 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 the Beta ( $\beta$ ) value. Table 4 shows the regression results of the hypotheses.

**Table 4.** Regression results of hypotheses

Construct	$\beta$	t	$p$	$R^2$	Result
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

From Table 4, we can determine that Perceived Ease of Use impacts Perceived Usefulness towards m-learning adoption. The highest value of  $R^2$  shows that the relationship is strong. We found the Perceived Usefulness is the most influential factor, towards Behavior Intention to use m-learning. The hypothesis 2 (H2) was accepted because the relation between the variables are strongly sufficient. In this case hypothesis 3 (H3) was accepted because  $P=0.000$  and  $R^2=0.365$  and  $\beta$  has a positive value (0.404) showing that the relationship is positive as it describes the direction. As can be seen that Self-Efficacy and Perceived Ease of Use are positively related. Hypothesis (H4) is accepted because the result shows a strong relationship between Perceived Enjoyment and Behavior Intention. Consequently, it can be resulted that Perceived Enjoyment is related to Behavior Intention in the m-learning adoption. Based on the accepted hypotheses, the research model has been presented in Figure 2.



**Fig. 2.** Research Model

## 6 Discussion and implications

We empirically analyzed the effectiveness of personality traits factors in m-learning adoption in an educational context. M-learning adoption aims to help students to access course materials at any location and any time, which is highly relevant in the digital world, especially as the world is forced to undertake most tasks online during the Covid-19 pandemic. Secondly, we propose an extended TAM, which considers the inclusion of relevant additional variables from personality traits such as perceived enjoyment and self-efficacy. The results supporting the TAM [23] in the context of adoption, reinforce the critical role that perceived ease of use and usefulness have in creating students' acceptance of m-learning as a new technology [33]. Therefore, when the purpose of m-learning adoption is beyond the intrinsic motivation of simply "having fun", it appears that the impact of easiness and usefulness in users' attitudes should be considered. Although the literature recognizes that personality attracted some attention from mobile studies [13], to our knowledge, there is no research that simultaneously considers the personality trait variables of self-efficacy and perceived enjoyment, to better understand the individuals' level of adoption of m-learning. Third, the study suggests that the students' self-efficacy and perception of enjoyment revealed a strong positive influence on perceived ease of use on students' adoption of internet-based learning systems such as m-learning.

The empirical results provide noteworthy evidence for teachers wishing to adopt m-learning in their classrooms. The results of the study demonstrate how enjoyment, perceived ease of use and usefulness positively influence students' intention towards m-learning. Besides, the results indicate that the more exciting the m-learning can be for the students; the more likely it is that they will use it for effective learning. Although it is generally accepted that in mixed utilitarian-hedonic systems "time flies when you are having fun", instructors should be aware that students' time could also be spent significantly as they experience states of anxiety [30]. Therefore, enjoyment should be considered to include a level of learning challenge that is appropriate, i.e. the learning activities are not discouragingly hard or boringly easy. This is important since the student population of digital natives may be more heterogeneous than expected. Students may have different ability and capabilities to use computer and mobile for learning.

The obtained results suggest that the design of the m-learning platforms should consider not only the students' learning outcomes, but also the enjoyment component and self-efficacy that refer their ability must have a primordial role in these pedagogical endeavors for learning.

Our results also indicate that Self-Efficacy refers to the judgment of individuals about their capabilities to use information systems in diverse situations [33]. The result of analysis in this research shows a relationship between ability of students and Perceived Ease of Use. In addition, according to [34], Self-Efficacy revealed a strong positive influence on Perceived Ease of Use. On the other hand, most of the new University students (Gen Z students) have capability of using information technology so they will not be afraid easily and they show enormous persistence in the use of their mobile devices for majority of activities. In this regard, transition of learning on their

mobile devices is expected to be more natural to new students rather than a transition from face-to-face learning.

Finally, it should be highlighted that instructors should pay attention to the students' personality in their education. Specifically, the results show that personality traits have impact on behavior intention. Two variables, perceived enjoyment and self-efficacy are extrinsic motivations that have an impact on behavior intention. In other words, through improving hedonic elements of the system, teachers can make significant impact on adoption m-learning. In addition, m-learning is found useful in the learning mode for individuals due to its learning flexibility. These findings support that perceptions of the usefulness of m-learning and that the perceived usefulness as an extrinsic factor has the highest influence on students' intention to adopt mobile. These results provide valuable insights for educators to formulate and design interesting interface and enjoyable content for m-learning environments. We conclude with a note that the design of future m-learning should encompass features which can deliver higher levels of satisfaction to the learners, as affirmed by the results of this research.

## **7 Limitations and Conclusion**

This research is prone to several limitations. First, the actual use of m-learning was not incorporated in the proposed research model. 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 m-learning. Lastly, since the sampling locations were confined to two faculties of one university only, the findings could not be generalized across all University students and around the world. There could be situational factors such as education policies, learning culture and specific university procedures that may impact the adoption of m-learning. Nevertheless, we argue that there will be some impact of student personality traits on the adoption of m-learning, albeit the degree of impact may vary across different geographical areas.

Apart from considering behavioral intention, future scholars are encouraged to integrate the 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 m-learning is recommended to be tracked and recorded to deliver insightful information on students' m-learning progress. Further studies are encouraged to broaden the sample size and involve an extensive range of public and private tertiary education institutions across the world.

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