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Predicting the drivers of behavioral intention to use mobile learning: A hybrid SEM-Neural Networks approach

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ABSTRACT

This study empirically investigates on the elements that affect the user's intention to adopt mobile learning (m-learning) using a hybrid Structural Equation Modeling–Artificial Neural Networks (SEM–ANN) approach. A feed-forward-back-propagation multi-layer perceptron ANN with the significant determinants from SEM as the input units and the Root Mean Square of Errors (RMSE) indicated that the ANN achieved high prediction accuracy. All determinants are relevant and their normalized importance was examined through sensitivity analysis. The explanation on new computer technologies acceptance have been primarily based on the Technology Acceptance Model (TAM). Since TAM omits the psychological science constructs, the study address the weaknesses by incorporating two additional constructs, namely the personal innovativeness in information technology (PIIT) and social influences (SI). Out of the 400 survey distributed to mobile users, 216 usable questionnaires were returned. The results uncovered that the intention to adopt m-learning has significant relationship with TAM. The findings for PIIT, SI and the control variables of age, gender and academic qualifications however show mixed results. The results provide valuable information for mobile manufacturers, service providers, educational institutions and governments when strategizing their adoption strategies. Additionally, from the perspective of an emerging market, the study has successfully extended TAM with psychological constructs.

1. Introduction

Learning has always been restrained to brick and mortar classroom and traditional books, for decades. However, a new wave of learning has emerged with the increased capabilities of mobile devices (m-devices) and the wide availability of various network connectivity, e.g. UMTS (3G), HSPA (3G+), LTE (4G), WIMAX, and WAP (Hu, Lu, & Tzeng, 2014). Sharples (2007) defined mobile-learning (m-learning) as the learning between the learners via the technology of portability. Take for example, learning with the integration of Personal Digital Assistant (PDA), Smartphones, iPod, mobile telephones, laptops and tablet personal computer technologies (Berri, Benlamri, & Atif, 2006; Donnelly, 2009; Liu, 2009). Similarly, Sharma and Kitchens (2004) considers m-learning as the delivery of digitized e-contents through wireless phones hooked into PDAs. The development of m-learning has not only supports learning through a variety of settings, but also acts as an enabler to learning at different location and time (Gil & Pettersson, 2010). Based on a study by Ambient Insight (2010) in United States (U.S.), the m-learning's market in 2009 for products and services was at U.S. $632.2 million dollars but the figure was forecasted to reach U.S. $1.4 billion by 2014.

M-learning is distinctly different from electronic learning (e-learning) as the latter requires an Internet access as well as wired connection before any learning can take course. However, m-learning works on the wireless environment where m-devices are used. Therefore, learning is no longer restricted to only having attending classes. Mulliah (2006) commented that there are three advantages of m-learning in the likes of convenience, collaboration and fun as opposed to e-learning. In addition, m-learning devices are portable and small in size, thus it is easy to carry around at one's convenience (Schwiderski-Grosche & Knospe, 2002). As a result, acquiring knowledge is now at one's fingertips. According to Attewell (2005), there are several advantages of adopting m-learning. They include enhancing an individual's skills, providing them with opportunities to learn new things independently, the ability to determine weak or slow learners who require assistance, and

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encourage reluctant individuals to learn, resulting in improved learners' confidence. Thus, m-learning is a new education paradigm and is a preferred choice in higher education and life-long learning of every country (Liu, 2009). However, the factors influencing the adoption of m-learning are still unclear despite the rapid development of the current study as a new form of learning. Scholars like Pozzi (2007) stressed that m-learning is only adopted occasionally and in a supplemental manner. The sentiments were echoed by Herrington and Herrington (2007), who claimed that pedagogical use of m-devices is not widespread in higher educations. The statistic from the Malaysian Communications and Multimedia Commission (MCMC) confirmed that there are 29.6 millions mobile phone subscribers in Malaysia (Malaysian Communications and Multimedia Commission, 2010). In comparison with the numbers of subscribers, scholars like Wei, Marthandan, Chong, Ooi, and Arumugam (2009), stressed that the number of m-learning users in Malaysia still falls behind other developing countries. Further evidence from Wong and Hiew (2005) indicated that m-learning is still very much at an early stage in Malaysia. The availability of different m-devices according to Corbeil and Valdes-Corbeil (2007) does not indicate that students will adopt them for education purposes.

While the development of m-learning have been frequently discussed, most past studies were carried out in countries such as Taiwan (Hwang, Wu, Zhuang, Kuo, & Huang, 2010), New Zealand (Lu & Viehland, 2008), Macedonia (Fetaji & Fetaji, 2008), China (Liu, Li, & Carlsson, 2010) and Thailand (Poonsri, 2008). M-learning studies from a developing country perspective like Malaysia remains limited. Scholars studying m-learning primarily focused from the perspective of software/infrastructure for library services (Cummings, Merrill, & Borrelli, 2010; Hahn, 2008; Walsh, 2009), higher education (Cook, Bradley, Lance, Smith, & Haynes, 2007; Fetaji & Fetaji, 2008), museum (Hsu, Ke, & Yang, 2006) and further education (Savil-Smith, Attewell, & Stead, 2006). Interestingly, the driving factors on the intention to adopt m-learning have remained unexplored. Only through understanding why consumers lack of motivation to adopt a certain information technology (IT) can we make certain on the substantial return on investment (Magni, Taylor, & Venkatesh, 2010; Rogoski, 2005). The study therefore empirically creates a framework to explain on the factors that influence the intention to adopt m-learning through the extension of Technology Acceptance Model (TAM) with psychological science constructs. In addition, the study also incorporates gender, age and academic qualifications as control variables. The following is the structure of the paper. In the following section, we present on the overview of m-learning. Then, we present our research model, hypotheses development and methodology of our study. In the final section, the findings, conclusion, limitation and future research of m-learning adoption is discussed.

2. Literature review

2.1. An overview of mobile learning

Given that m-learning is a relatively new concept, it has been defined in various ways by earlier studies (Lu & Viehland, 2008). Attewell (2005) and Lu and Viehland (2008) defines m-learning as a learning which is similar to e-learning. M-learning uses wireless transmission and m-devices such as smartphones, tablets, multi-game devices and personal media players, instead of wired connections or traditional personal computers. Similarly, Lehner and Nosekabel (2002, p. 103) elaborated on m-learning definition as "any service or facility that supplies a learner with general electronic information and educational content that aids in acquisition of knowledge regardless of location and time". Therefore, individuals can learn independently of time and space (Amaral, 2006). Due to the numerous advantages, m-learning has gained popularity and many learning institutions are starting to adopt to this technology (Koike, Akama, Chiba, Ishikawa, & Miura, 2005). M-learning's popularity is largely due to its low cost, as well as allowing users to learn anytime and anywhere. In this study, m-learning refers to as the activities of learning with the usage of m-devices such as a mobile phone/smart phone through wireless communications among its users on a 365/24/7 basis.

2.2. Models of IT/IS adoption

Most models in predicting the acceptance of new technologies were derived from scholars with diverse backgrounds. IT scholars like Davis (1989) proposed the Technology Acceptance Model (TAM), while psychologists scholars like Fishbein and Ajzen (1975) and Ajzen (1991) concentrated on their research using Theory of Reason Action (TRA) and Theory of Planned Behavior (TPB). Rogers (1995) a marketing scholar on the other hand proposed the Diffusion of Innovation (DOI).

TPB is extended from TRA by adding an additional variable namely 'perceived behavior control' (Ajzen, 1991) to increase predictive power. TPB suggests that the new added variable with subjective norm and the individual's act of behavior can explained on the behavioral achievement of an individual. Attitude refers to as a person's favorable or unfavorable feelings about performing the behavior. On the other hand, subjective norms is defined as 'one's beliefs whether others approve or disapprove in engaging an activity (Fusilier & Durlabhji, 2005), while the perception on the individual's ability to perform a behavior explained on the concept on perceived behavioral control (Ajzen & Madden, 1986).

TAM focuses on perceived ease of use (PEOU) and perceived usefulness (PU) as the two prime purposes behind the intention to adopt information systems (IS) (Davis, 1989) and evolved using TRA. According to Agarwal and Karahanna (2000), O'Cass and Fenech (2003) and Lee (2006), TAM has been successfully carried out by IT scholars to forecast a wide variety of technology settings such as websites, internet shopping and e-learning. While TAM is useful in the explanation of users' intention, the external variables that impact the PU and PEOU were not completely discussed. Scholars therefore suggested for TAM to be extended to provide clearer understanding of users' decisions to adopt a certain technology (Chong, 2013a; Legris, Ingham, & Collerette, 2003). TAM2 for example was proposed as an extension of TAM (Venkatesh & Davis, 2000). In TAM2, however the attitude towards using was omitted as it shows a weak predictor of either actual system usage or behavioral intention (Venkatesh & Davis, 2000). DOI offers insights into how an innovation among users is diffused over time (Rogers, 1983). The model which is similar to TAM has been adopted by researchers to explain on the diffusion of IT adoption. Based on the relative time of adoption, the study lists five categories of adoption. They can be classified as late majority and laggards, innovators, early adopters early majority (Rogers, 1995). The innovators are risk takers and thus more likely accept new products and services. Gatignon and Robertson (1985) explained that the innovators are highly educated, have higher income, young, more socially mobile, have favorable attitudes towards risks and shows greater social participation. Studies by Serenko (2008) indicated that the user's readiness for innovation adoption is impacted by different personal traits. Individual with a higher degree of personal innovativeness for example are anticipated to be more confident on new technologies (Lewis, Agarwal, & Sambamurthy, 2003). Additionally, the theory consists of perceived characteristics of innovation which could be used to verify the adoption rate (Lu, Yao, & Yu, 2005). The elements are compatibility, relative advantage, trialability, complexity, and