The effects of convenience and speed in m-payment

Aik-Chuan Teo and Garry Wei-Han Tan
Faculty of Business and Finance, Universiti Tunku Abdul Rahman, Kampar, Malaysia
Keng-Boon Ooi
Faculty of Business, Management and Accountancy, Linton University College, Mantin, Malaysia
Teck-Soon Hew
Faculty of Business and Accountancy, University of Malaya, Kuala Lumpur, Malaysia, and
King-Tak Yew
Faculty of Business and Finance, Universiti Tunku Abdul Rahman, Kampar, Malaysia

Received 1 August 2014
Revised 24 December 2014
Accepted 27 December 2014

Abstract

Purpose – The purpose of this paper is to uncover the effects of perceived transaction convenience (PTC) and perceived transaction speed (PTS) on unified theory of acceptance and use of technology (UTAUT) in the context of m-payment.

Design/methodology/approach – A predictive analysis approach was used to examine the PTC and PTS using a two-stage partial least square (PLS) and neural network (NN) analyses.

Findings – The findings reveal that only effort expectancy (EE) and facilitating conditions (FC) were discovered to significantly influence BI. More importantly, PTC was found to have positive significant relationship with EE and performance expectancy (PE). Moreover, PTS also supported the positive relationship with BI and EE.

Practical implications – The findings of the study provided further insights to mobile payment service providers, online banking industry players, and all decision makers and stakeholders involved.

Originality/value – Despite of many attempts devoted to understand m-payment adoption, the effects of PTC and PTS on m-payment are not well understood.

Keywords Behavioral intention (BI), Mobile payment, Neutral network (NN),
Partial least square-structural equation modeling (PLS-SEM),
Unified theory of acceptance and use technology (UTAUT)

Paper type Research paper

1. Introduction

Mobile payment (m-payment) refers to individual or business activities that utilizes mobile internet enabled electronic device to perform any economic transactions (Liébana-Cabanillas *et al.*, 2014). Unlike the temporal and spatial constraints in both online and offline payments (Zhou, 2013a), m-payment enables users to complete their payments in a safer, faster, and more convenience transactions at anytime and anywhere (Liébana-Cabanillas *et al.*, 2014; Zhou, 2013a; Ondrus and Pigneur, 2009). Acknowledging its benefits, a recent report reveals that the global m-payment transaction is expected to jump to $1.3 trillion in 2017. The high growth of m-payment services is evidence by both remote payment and NFC transactions when purchasing physical products (Holden, 2012). The industrial experts have also anticipated that the

Industrial Management & Data Systems
Vol. 115 No. 2, 2015
pp. 311-331

0263-5577
DOI 10.1108/IMDS-08-2014-0231

m-payment will be one of the future "killer" applications in mobile communications (Ghezzi *et al.*, 2010; Ondrus and Pigneur, 2009).

Even though, m-payment has been on the agenda for years, unfortunately only a small number of mobile handset-based or contactless card-based payment solutions have successfully reached mass market (Gonggrijp *et al.*, 2013; Ghezzi *et al.*, 2010). Gonggrijp *et al.* (2013) explained that the markets are one-sided in nature whereby suppliers create and market the product to create customer values. To ensure success in the payment market, the authors further stated that the system needs to reach critical mass for both users and merchants. Regrettably, Schierz *et al.* (2010) commented that the reality is different from what is expected which consequently a disappointment for m-payment service providers.

As the adoption decision lies on the consumers' hand, Schierz *et al.* (2010) emphasized on the needs to comprehend the determinants of consumers' adoption. Little attention has been given in understanding m-payment adoption from the unified theory of acceptance and use of technology (UTAUT) perspective (Yu, 2012). The adoption of UTAUT has been widely applied in mobile commerce (Chong, 2013b), and mobile banking (Yu, 2012), but little attention is given on m-payment. As the purpose of UTAUT was initially developed to understand the adoption of IT among organizational based, Stofega and Llamas (2009) stressed the importance to extend the model in consumer technologies. Chong (2013b) indicated that the extension of the model is therefore needed from the consumer-based perspectives due to the different usage and costs.

From the review of literatures, several common factors such as perceived financial cost, trust (Zhou, 2013b), etc. were used to extend the UTAUT model; however, little attention has been paid to the constructs like perceived transactional convenience (PTC) and perceived transaction speed (PTS). Despite the convenience construct was widely used in the field of marketing and consumer behavior, there is still short of empirical validation within the context of mobile commerce (Jih, 2007). If given any, many argued that the constructs of convenience and perceived ease of use are too similar (Yoon and Kim, 2007). Applying the concept of intrinsic and extrinsic of IT by Gefen and Straub (2000) in the context of m-payment, if mobile phone is used to make payment, ease of use would not affect the adoption because the ease of use is not an inherent quality of the entire payment experience. On the other hand, when the mobile phone is used to inquire for payment, PEOU should affect its adoption as the required information is embedded in the system which its quality is associates with the ease of use. As such, we concluded that perceived convenience is enveloped in a broader sense as comparison to ease of use. Similarly, Chen (2008) also supported that transaction speed is one of the critical requirements in the payment industry. Unlike the developed countries (i.e. Japan and South Korea) that have grown-up land line internet infrastructures (Lu *et al.*, 2011), the examination of the two key benefits of m-payment, namely PTC and PTS in developing country such as Malaysia remains interesting. In fact, the extensions with PTC and PTS to UTAUT may make an important theoretical contribution and strategic formulation for both academicians and practitioners respectively.

The flow of the paper is outlined as follows. First, the paper commence with the conceptual background of the study. This is followed by an overview of m-payment and the theoretical background. Thereafter, we review the related literatures on m-payment and subsequently formulate the research hypothesis. The paper continues with the research methodology. Lastly, the paper ends with discussions of the key findings, implications, limitations, and future research directions.

2. Theoretical background

2.1 Factors influencing m-payment adoption

Theory of Reasoned Actions (TRA) was coined Fishbein and Ajzen (1975). Based on TRA, the intent to perform a behavior is driven by actual behavior. Behavioral intention (BI) is driven by individual's attitude towards a behavior and social norms. TRA has served as a theoretical baseline of Theory of Planned Behavior (TPB) (Ajzen, 1985) and technology acceptance model (TAM) (Davis, 1989). Among different IS theories, TAM is one of the most influential research models to elucidate user's adoption to adopt IT (Davis, 1989). TAM has been applied in a wide range of research (Sipior *et al.*, 2011; Chong, 2013a; Leong *et al.*, 2013a; Teo *et al.*, 2012). Yet, several researchers commented that TAM still has its limitations. The model not only being viewed as simple and over studied (Barki, 2007) but also its ability to describe only 40 percent of variance in BI. To increase the predictive power, many studies extended TAM model with different constructs such as Tan *et al.* (2014a), Chong (2013a), and Leong *et al.* (2013a). As such, researchers have difficulties to compare the research findings. Recognizing the needs of the unified model, Venkatesh *et al.* (2003) developed UTAUT. Unifying from the eight prominent IS adoption model, the authors posits the four core constructs which consists of effort expectancy (EE), performance expectancy (PE), facilitating condition (FC), and social influence (SI). Since the unified model explain 70 percent variance in BI of technology, many current research have adopted the model in mobile commerce (Chong, 2013b), mobile entertainment (Leong *et al.*, 2013b), and mobile banking (Zhou *et al.*, 2010).

2.2 Extending UTAUT model

The main thrust of our theory is to extend and advance the existing UTAUT model from the context of m-payment. UTAUT (Venkatesh *et al.*, 2003) is consolidated from eight IS models namely TRA, TAM, MM, TPB, C-TAM-TPB, MPCU, IDT, and SCT. As suggested by Venkatesh *et al.* (2003), further researches should examine the UTAUT model using alternative measures of intention and behavior in revalidating and extending the model to other contexts. The primary constructs of PE, EE, SI, and FC were validated for IS applications such as web-enabled video/audio conferences, database application, portfolio analyzer, and proprietary accounting systems (Venkatesh *et al.*, 2003, p. 438). These constructs may be universal for most of the IS applications but it may not provide adequate predictive power since m-payment possesses special characteristics such as convenience usage and fast transaction speed that are significantly different from these applications. Therefore PTC and PTS constructs were derived from the Theory of Convenience and Prospect Theory, respectively. These m-payment-related constructs may further advance the existing UTAUT model and provide deeper understanding of the previous IS theories and contribute toward the existing UTAUT theory.

Drawing from the marketing and consumer behavior literatures, this paper extended UTAUT model by adding PTC and PTS. The notion of convenience first appeared in the marketing literatures on product categories (Copeland, 1923). Since then, several researchers have proposed different conceptual frameworks to examine on the convenience of services such as Yale and Venkatesh (1986), Brown (1990), and Berry *et al.* (2002). The classification of convenience according to Yale and Venkatesh (1986) for example, can be classified into six categories which consists of time utilization, appropriateness, handiness, accessibility, portability, and avoidance of unpleasantness. Regardless of the different models, one of the well-known models

of service convenience was developed by Berry *et al.* (2002). The authors proposed five types of convenience which consists of decision, access, transaction, benefit, and post-benefit. Acknowledging that the users' choice of mobile-commerce has often linked with the convenience it offers (Kim *et al.*, 2010; Luarn and Lin, 2005), Jih (2007) found that the users' intention to shop was positively affected by the perception of transaction convenience. A recent report by Smith (2014) found that the shopping cart abandonment is increasing in Malaysia. This may due to the inconvenience in transactions such as providing billing and shipping details via the limited display screen on a mobile phone. The impact of transaction inconvenience is congregated of monetary and non-monetary cost (effort and time) (Berry *et al.*, 2002).

Based on the use of Prospect Theory (Kahneman and Tversky, 1979) across the diverse areas of research, it is possible to explicate users' perceived values of time during a transaction (Lin and Bei, 2008). The consumers' perception of time can be applied using Prospect Theory in three different aspects. First, during a transaction, when the actual time utilized to a lesser extend is less than the expected time, consumers will feel happy and vice versa. Second, when the quantity of time difference increases, marginal perceived value of saving time decreases while quality of the time differences increases as the marginal perceived loss of waiting decreases. Third, over the similar duration of time, the perception of a negative value (i.e. long waiting time) is larger than the positive value (i.e. short waiting time). Hence, when consumers need to wait for the m-payment transaction to be completed, we may postulate that transaction speed is an imperative factor. A recent report indicated that a second hold-up in loading a page leads to a 3.5 percents drop in conversions (O'donoghue, 2014). Besides, Hsieh (2007) denoted that the limited network bandwidth is one of the obstacles of m-commerce. Unlike advanced countries like South Korea, Japan, and Hong Kong, Malaysia was ranked among the slowest countries for both desktop and mobile internet speeds based on Google's study (Kharif, 2012). As the higher bandwidth permits users access to voice, video, and data services simultaneously, hence, it will be interesting to examine PTC as an imperative factor as users need to wait for the m-payment transaction to be completed.

3. Hypotheses development

3.1 SI

SI takes place when an individual's behavior is affected by others. Chong (2013b) indicated that the influence from peers, family, and media affects individual in making m-commerce adoption decision. SI not only serves as the critical construct in understanding adoption behavior (Karahanna *et al.*, 1999) but the empirical findings also revealed the significant relationship between SI and BI of m-payment (Yu, 2012). As Malaysia is a collective society (geert-hofstede.com, n.d.), the influence of SI might be greater due to the close and long-term commitment in social group. Backed with the rise of the social media, users tend to seek opinions from their friends and families related to the m-payment experiences. Therefore, we put forward the following hypothesis:

H1. SI is positively related with BI of m-payment.

3.2 PE

PE refers to the extent which an individual anticipates that employing the system will eventually help to enhance their job performance (Venkatesh *et al.*, 2003). PE reflects the user perception of performance enhancement when using the system. Hayashi

(2012) explained that m-payment offers user with greater accessibility to monitor finances closely and helps control spending as compared to traditional payment alternatives. The effect of PE is also captured in both UTAUT- and TAM-based studies. Adopting UTAUT-based studies, Lu *et al.* (2009) through 1,432 respondents in China found that PE significantly influenced individuals to use mobile services. Similarly, Kim *et al.* (2010) also discovered that PU was one of the most significant factors towards BI of m-payment. Regardless on the findings, the development of m-payment solutions may be different from one country to another due to the infrastructures. After Maxis Malaysia has launched its Fast Tap NFC, for example, several banks and retail (i.e. Starbucks Malaysia) have released different m-payment solutions which led to the following hypothesis:

H2. PE is positively related with BI of m-payment.

3.3 EE

EE refers to the extent of ease when individual use the system (Venkatesh *et al.*, 2003). Unlike traditional payment alternatives, users required more time and effort to download, key-in multiple accounts, and learn how to use the m-payment application (Hayashi, 2012). Empirical findings from Wong *et al.* (2014), Chong (2013b), and Kim *et al.* (2010) have confirmed the significant impact of EE in technology adoption studies. Contrary, Yu (2012) found that EE is not a significant driver in affecting BI. These inconsistent results have motivates us to further validate the relationship between EE and BI. Hence, we suggested the following hypothesis:

H3. EE is positively related with BI of m-payment.

3.4 FC

In the mobile context, FC characterized users with equipped skills for instance configuring and operating mobile phones to access to wireless internet. The construct basically mean that users who possesses the operational skills in configuring and operating m-devices will eventually leads to BI. Chen and Chang (2013) via 189 respondents found that FC is positively associated with the BI of NFC mobile phone applications. Hence, the following hypothesis is presented:

H4. FC is positively related with BI of m-payment.

3.5 EE and PE

According to UTAUT, EE has positive impacts on PE (Venkatesh *et al.*, 2003). As the concept is parallel with the relationship between PEOU and PU, several TAM-based studies further supported the positive relationship between PEOU and PU (Teo *et al.*, 2012; Leong *et al.*, 2013a; Sim *et al.*, 2011). The perception of an effortless system such as m-payment will lead to a high expectation towards PE. Hence, we proposed the hypothesis as mentioned below:

H5. EE is positively related with PE of m-payment.

3.6 Perceived transaction convenience (PTC)

Transaction convenience is defined as "consumers' perceived expenditures of time and effort to affect transaction" (Berry *et al.*, 2002, p. 7). In the m-payment context, Hayashi (2012) elaborated that m-devices will eradicate the inconvenience of bringing multiple plastic cards by permitting users to connect m-payment to the card accounts. Chen (2008) further supported that the convenience of having a single payment device to substitute multiple payment alternatives contributes to the benefits of m-payment.

Thus, it is not surprisingly that many studies supported the positive relationship between PTC and innovation adoption. Eastin (2002) found that the perceived convenience has positive relationship with e-commerce activities. Similarly, Yoon and Kim (2007) also reported that PTC is a determinant of user's adoption and use of information technology (IT). In the context of e-retail banking, Liao and Cheung (2002) found that the construct of convenience is one of the most critical quality traits in the perceived usefulness. Chen (2008) through the survey using 299 prospects of m-payment users found that PTC is positively related to perceived usefulness. In the relationship between TC and EE, Hayashi (2012) discovered that the overall convenience and ease of use are the main motivation of using a particular payment instrument. Hence, we postulated the following hypotheses:

H6. PTC is positively related with BI of m-payment.

H7. PTC is positively related with PE of m-payment.

H8. PTC is positively related with EE of m-payment.

3.7 PTS

To yield higher adoption of m-payment, Chen (2008) urged that service to have differentiation advantage over the conventional payment methods, particularly in the area of transaction speed. Yang (2009) further asserted that the rapid transaction reply speed will encourage the use of mobile banking. Carlsson *et al.* (2006) indicated that both data transfer speed and connection speed also served in encouraging and discouraging the use of 3G+ services. Recognizing this importance, Pagani (2004) have listed the speed of use as the most critical determinant of mobile multimedia services adoption. The relationship between PTS and PE has been further confirmed in several studies. For example, Liao and Cheung (2002) provide evidence that the transaction speed have significant influence on the PU on internet-based e-banking. Besides, Chen (2008) also empirically found that PTS has positively relationship with PU from the perspective of m-payment adoption. The impact of PTS on EE is also important in technology adoption intention. Lin and Lu (2001) found that the low response time (i.e. heavy traffic loads and poor website designs) is one of the reasons that inhibit the use of internet. In the m-payment context, NFC technology allows users to wave-and-go at the point of sales terminals, which ultimately makes the completion of the transaction easier (Tan *et al.*, 2014a). Thus, we postulated the following hypotheses:

H9. PTS is positively related with BI of m-payment.

H10. PTS is positively related with PE of m-payment.

H11. PTS is positively related with EE of m-payment.

4. Methodology

Despite the market potentials of m-payment, Lu *et al.* (2011) indicated that the payment habit does not change from traditional to electronic and mobile commerce. This has led us to understand the respondents that have no experience in using m-payment; having a bank account; and owned an internet-based enabled mobile phone. Prior to the survey, a pre-test is conducted on 30 randomly selected university students to examine the clarity of the statements and items in the questionnaires. Open-ended questions were also included to gather the respondent's feedback of the questionnaires. Drawing from the feedbacks, only minor changes were made due to spelling error. The responses

from the pre-test that met the target selection criteria were included in our studies. The non-probability convenience sample was used in this study. There are several advantages of employing convenience sampling in data collection. First, the study adopted university students as younger age users are open minded and more willing to adopt new innovations (Yang, 2005; Lightner *et al.*, 2002; Pijpers *et al.*, 2001). Second, the adoption of university students as samples is also consistent with many mobile studies in Malaysia such as Wong *et al.* (2014), Sim *et al.* (2014), and Tan *et al.* (2014b). Thus the findings can be generalize to represent the population in Malaysia as the respondents come from all over 14 states which comprises of different background and religion in Malaysia (Leong *et al.*, 2013a). In addition convenience sampling was adopted as the group have higher tendency to adopt m-payment in future in view of their higher academic qualifications and income potential (Yang, 2005). The approach is also comparable with Leong *et al.*'s (2013a) study on m-payment in Malaysia. A total of 400 university students from one of the largest universities in Malaysia participated in the survey with the approval from the participating university and we managed to collect a total of 194 usable questionnaires with a response rate of 48.5 percent.

4.1 Instrument development

The first section of the questionnaire survey is pertaining to demographic profiles of target respondents, whereas the second section comprise 23 items to measure the adoption constructs of m-payment and the BI to use m-payment in the model (i.e. SI, PE, EE, FC, PTC, PTS, and BI). All of the items were adopted from previous literatures and Table I displays the respective sources. All the constructs were measured by seven-point Likert scale, from 1 = "Strongly Disagree" to 7 = "Strongly Agree". The Table II shows the demographic profiles of the respondents.

4.2 Statistical analysis

A partial least square-neural network (PLS-NN) predictive-analytic approach was engaged whereby the structural equation modeling (SEM) was deployed in testing the hypotheses, validity and reliability of the measures via Smart PLS 2.0 M3 software. We then used the neural network (NN) analysis to further verified and predict the antecedents of the significant predictors obtained from the partial least square-structural equation modeling (PLS-SEM) analysis (Scott and Walczak, 2009). Since PLS-SEM is a variance or component-based linear model which does not require data normality (Kankanhalli *et al.*, 2003; Ranganathan *et al.*, 2011; Sheng and Teo, 2012), it may not be able to capture non-linear decision-making process (Leong *et al.*, 2013a). On the other hand, NN is able to detect both linear and non-linear relationships and has even out-performed the traditional regression analyses such as MRA, SEM, etc. but has the

Constructs	Number of items	Sources
Social influence (SI)	3	Venkatesh *et al.* (2012)
Performance expectancy (PE)	4	Venkatesh *et al.* (2003)
Effort expectancy (EE)	4	Venkatesh *et al.* (2012)
Facilitating conditions (FC)	3	Venkatesh *et al.* (2012)
Perceived transaction convenience (PTC)	3	Chen (2008)
Perceived transaction speed (PTS)	3	Chen (2008)
Behavioral intention (BI)	3	Venkatesh *et al.* (2012)

Table I. Sources of questionnaire and number of items

	Frequency	Percent
Gender		
Female	123	63.4
Male	71	36.6
Age		
Below 20 years old	121	62.4
21-25 years old	70	36.1
26-30 years old	1	0.5
31-35 years old	2	1.0
Academic qualification		
No college degree	72	37.1
Diploma/advanced diploma	15	7.7
Bachelor degree/professional qualification	105	54.1
Master degree	1	0.5
PhD degree	1	0.5
Specialization		
Business	156	80.4
Science	33	17.0
Arts	5	2.6
Type of mobile phone		
Basic phone	31	16.0
PDA	2	1.0
3G mobile phone	11	5.7
Smartphone	150	77.3
Data plan		
Yes	41	21.1
No	153	78.9

Table II.
Demographic profiles of the respondents

weakness of a "black box" operation algorithm and thus not suitable for hypothesis testing (Sim *et al.*, 2014). Therefore, in order to complement each other, a PLS-SEM analysis is used to obtain the significant determinants of m-payment adoption and then these determinants will be taken as the input neurons of the NN models. Although response surface methodology (RSM) with polynomial regression (Brown *et al.*, 2008, 2012; Venkatesh and Goyal, 2010) is able to detect non-linear relationships, however, due to the complexity and time consuming process in determining the second-order model either quadratic or cubic model and based on the simplicity and better predictive performance of the NN approach as shown in numerous studies, we have decided to use NN instead of the RSM approach in this study. In fact NN has several advantages over RSM which include:

- The ability of NN to achieve modeling and optimizing processes in a single analysis (Farooq Anjum *et al.*, 1997).
- No need of the trial and error time consuming process used in the RSM approach in determining the model as the process is almost entirely data driven (Farooq Anjum *et al.*, 1997).
- The NN has out-performed the RSM approach. This can be seen from the NN predictive power which is much better with very low error than the RSM approach in predicting the dependent variable (Baş and Boyacı, 2007; Betiku and Ajala, 2014; Bingöl *et al.*, 2012; Pilkington *et al.*, 2014; Witek-Krowiak *et al.*, 2014).

In this study, we first evaluated the measurement model to test the reliability, convergent validity, and discriminant validity before examining the structural model.

4.3 Testing of common method bias (CMB)

Common bias may arise in this survey as the information for predictor and response variables are gathered from the same respondents. According to Tan *et al.* (2014a, p. 298), CMB can be defined as "the overlapping between two variables due to high correlations between the underlying constructs". For this reason, Harmon's single factor test was carried out and the common variance is less than 50 percent (Lee *et al.*, 2013). Hence, it is proved that CMB is not a problem in this study.

4.4 Non-response bias

In order to test the non-response bias, we have conducted a chi-square test of independence on the demographic variables (Armstrong and Overton, 1977 as cited in Doong and Wang, 2011) and found no significant difference between the early and late respondents. Besides that we have also examined the differences across all research constructs using *t*-test (Ranganathan *et al.*, 2011) and found no significant differences. Therefore, we have ruled out the issue of non-response bias in our study.

4.5 Evaluation of measurement model

The convergent and discriminant validity tests were conducted in order to examine the measurement model (Teo and Bhattacherjee, 2014; Krishnan *et al.*, 2013). Convergent validity, according to Leong *et al.* (2013a, p. 5611), can be defined as "the ability of a construct to produce the same outcomes even though various approaches are utilized". Convergent validity was examined for the measurement model according to the following three main criteria (Fornell and Larcker, 1981 as cited in Leong *et al.*, 2013a, p. 5611; Leong *et al.*, 2012):

(1) factor loadings for all items should be > 0.50;

(2) the values of composite reliability (CR) for all constructs should be > 0.70; and

(3) the average variance extracted (AVE) values should be > 0.50.

As presented in Table III, the CR for all constructs were greater than 0.70. In addition, the factor loadings for all items were also larger than the acceptable threshold of 0.50 and the AVE values were well above 0.50 and thus we can conclude that the convergent validity has been established.

Deng *et al.* (2014) suggest that the discriminant validity test can be examined by comparing the square root of AVEs and correlation values among the latent variables. In Table IV the result indicates that the values of square root of AVEs are larger than the correlations values and hence we can conclude that the discriminant validity has well established.

4.6 Evaluation of structural model

Figure 1 shows the structural model used for this study whereas Table V shows the findings obtained from hypotheses testing.

As reported in Table V the results showed that the constructs of EE, FC, PE, PTC, PTS, and SI explained 45.98 percent of the m-payment BI adoption, hence proving the UTAUT model applicable in the m-payment context. In addition, the extended UTAUT

Constructs	Items	Loadings	AVE	CR
BI	BI1	0.8937	0.7752	0.9117
	BI2	0.9103		
	BI3	0.8898		
EE	EE1	0.7981	0.7227	0.9124
	EE2	0.8483		
	EE3	0.8831		
	EE4	0.8704		
FC	FC1	0.8578	0.7284	0.8894
	FC2	0.8796		
	FC3	0.8221		
PE	PE1	0.8679	0.7916	0.9382
	PE2	0.8840		
	PE3	0.9139		
	PE4	0.8924		
SI	SI1	0.9123	0.8501	0.9445
	SI2	0.9373		
	SI3	0.9163		
PTC	PTC1	0.8936	0.7878	0.9176
	PTC2	0.9031		
	PTC3	0.8655		
PTS	PTS1	0.8727	0.8115	0.9281
	PTS2	0.9233		
	PTS3	0.9058		

Table III.
Factor loadings, average variance extracted and composite reliability

Notes: PE, performance expectancy; EE, effort expectancy; FC, facilitating conditions; PTS, perceived transaction speed; PTC, perceived transaction cost; SI, social influence; BI, behavioral intention; AVE, average variance extracted; CR, composite reliability

	BI	EE	FC	PE	SI	PTC	PTS
BI	*0.8805*						
EE	0.4322	*0.8501*					
FC	0.5282	0.4936	*0.8535*				
PE	0.3321	0.5541	0.3666	*0.8897*			
SI	0.4292	0.3587	0.6068	0.3906	*0.9220*		
PTC	0.5415	0.3844	0.5221	0.4406	0.4469	*0.8876*	
PTS	0.5799	0.3666	0.4660	0.3385	0.3377	0.6452	*0.9008*

Table IV.
Discriminant validity test

Notes: PE, performance expectancy; EE, effort expectancy; FC, facilitating conditions; PTS, perceived transaction speed; PTC, perceived transaction cost; SI, social influence; BI, behavioral intention, Square root of AVE is shown on the major diagonal (italics)

model was also proven in the research result in predicting consumer's m-payment BI adoption (Yu, 2012).

The PLS-SEM results as reported in Table V showed that the BI to adopt m-payment was significantly influenced by EE ($\beta = 0.1506$, $p < 0.05$), FC ($\beta = 0.1711$, $p < 0.05$), and PTS ($\beta = 0.3204$, $p < 0.01$), with PTS showing the strongest influence on BI to adopt m-payment. With this, *H3*, *H4*, and *H9* were supported. On the contrary, it was also evident that the constructs of PE ($\beta = -0.0321$, $p > 0.05$), PTC ($\beta = 0.1540$, $p > 0.05$), and SI ($\beta = 0.1068$, $p > 0.05$) was not significant in influencing the BI to adopt m-payment. Therefore, *H1*, *H2*, and *H6* were not supported.

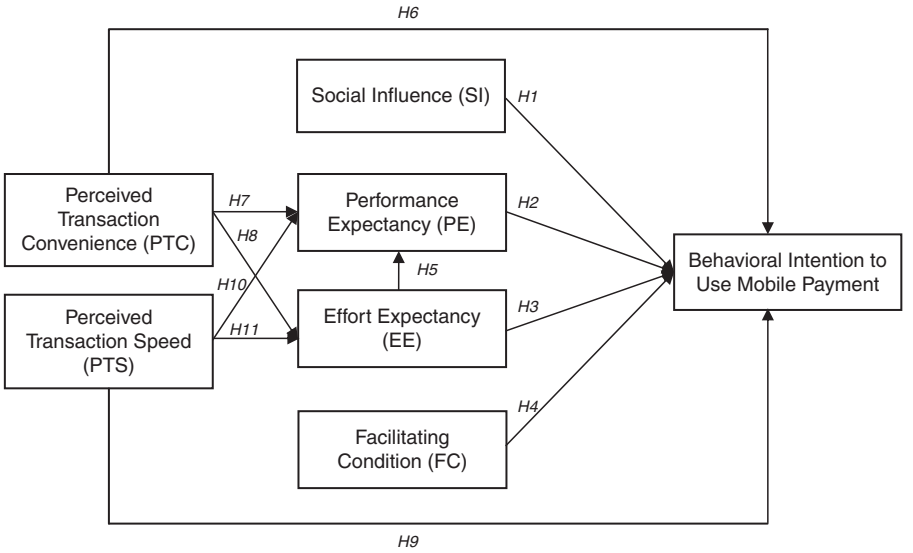

Figure 1.
Research framework

Hypothesis	Path	β	Remarks
H1	SI→BI	0.1068	Not supported
H2	PE→BI	−0.0321	Not supported
H3	*EE→BI*	*0.1506**	*Supported*
H4	*FC→BI*	*0.1711**	*Supported*
H5	*EE→PE*	*0.4513***	*Supported*
H6	PTC→BI	0.1540	Not supported
H7	*PTC→PE*	*0.2663***	*Supported*
H8	*PTC→EE*	*0.2534***	*Supported*
H9	*PTS→BI*	*0.3204***	*Supported*
H10	PTS→PE	0.0012	Not supported
H11	*PTS→EE*	*0.2031**	*Supported*

Notes: BI (R^2) = 0.4598; EE (R^2) = 0.1719; PE (R^2) = 0.3678. PE, performance expectancy; EE, effort expectancy; FC, facilitating conditions; PTS, perceived transaction speed; PTC, perceived transaction cost; SI, social influence; BI, behavioral intention. **$p < 0.01$; *$p < 0.05$

Table V.
PLS-SEM results for hypotheses testing

Besides that, PTS ($\beta = 0.2031$, $p < 0.05$) and PTC ($\beta = 0.2534$, $p < 0.01$) are also significant and impact EE in a positive manner; it also indicated that PTS and PTC were significant determinant of EE ($R^2 = 17.19$ percent). Hence, *H8* and *H11* were supported. However, the result also showed that PTS ($\beta = 0.0012$, $p > 0.05$) has insignificant influence on PE. Therefore, *H10* was not supported.

Furthermore, the results also revealed that both EE ($\beta = 0.4513$, $p < 0.01$) and PTC ($\beta = 0.2663$, $p < 0.01$) are significantly influencing PE, and that the factors of EE and PTC explained 36.78 percent of the variance in PE. Thus, *H5* and *H7* were supported.

4.7 NN approach

A NN is "a machine that is invented to model the manner in which human brain performs a specific task or function" (Haykin, 2007, p. 24). A NN is defined as

"a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

(1) Knowledge is acquired by the network from its environment through a learning process.

(2) Interneuron connection strengths known as synaptic weights are used to store the acquired knowledge" (Haykin, 2007, p. 24).

NN has several advantages over other conventional linear methods. The non-linearity allows the investigation of non-linear relationships such as investigation of non-compensatory decision processes (Svozil *et al.*, 1997). NN analysis also does not require distribution assumptions such as normality of sample (Moosmayer *et al.*, 2012). In fact NN has higher prediction rates compared to the conventional regression methods (Chiang *et al.*, 2006).

In order to examine the relative importance of these predictors, a multilayer perceptron training algorithm was utilized to train the NN provided in the SPSS statistics version 21 software. To prevent over-fitting, cross validation was also applied where by ten NNs were examined using 90 percent of the sample for training and the remaining 10 percent for testing (Leong *et al.*, 2013a). The sigmoid function was used as the activation functions for the hidden and output layers (Figure 2). The number of hidden layers was generated automatically. The accuracy of the prediction is gauged using the values of root mean square of error (RMSE). Table VI indicates that the NN models are able to predict with high accuracy since the values of RMSE are very small. The relevant of the predictors were validated based on the number of non-zero synaptic weights connected to the hidden layer as shown in Table VII. The relative importance and normalized importance of the predictors were assessed using the sensitivity analysis whereby the relative importance of a predictor is divided by the largest value of the relative importance among the independent predictors. The result of Table VIII shows that PTS is the most important predictor for BI followed by FC and EE with normalized importance of 75 and 58.3 percent, respectively. Besides that, EE is also a key determiner of PE followed by PTC which has a normalized importance of 69.6 percent. Finally, PTC is the most imperative driver for EE followed by PTS with a normalized importance of 89.1 percent.

5. Discussion

5.1 Relationship between SI, PE, EE, FC, and BI

Contrary with findings by Tan *et al.* (2014a) and Yu (2012), our research suggested that SI is an insignificant construct. The mobility community enables mobile phone users to make independent adoption decision without the influence from the social perspectives. Similarly, PE was found to have insignificant relationship with BI. The finding is in line with Teo *et al.* (2012) but, contrary with Yu (2012). Mobile phone users may not be attracted with the usefulness gained from the use of m-payment. This could be explained whereby mobile phone users are more focus on activities such as phoning, gaming, texting, social networking which does not involved any monetary transactions (Chong, 2013c). On the other hand, our findings indicate that EE is the third most important constructs to draw mobile phone users' attention. This is similar with Tan *et al.* (2014a). As m-payment required setup (i.e. download m-payment applications), hence, this leads to the discovery. In other words, the friendly interface of m-payment

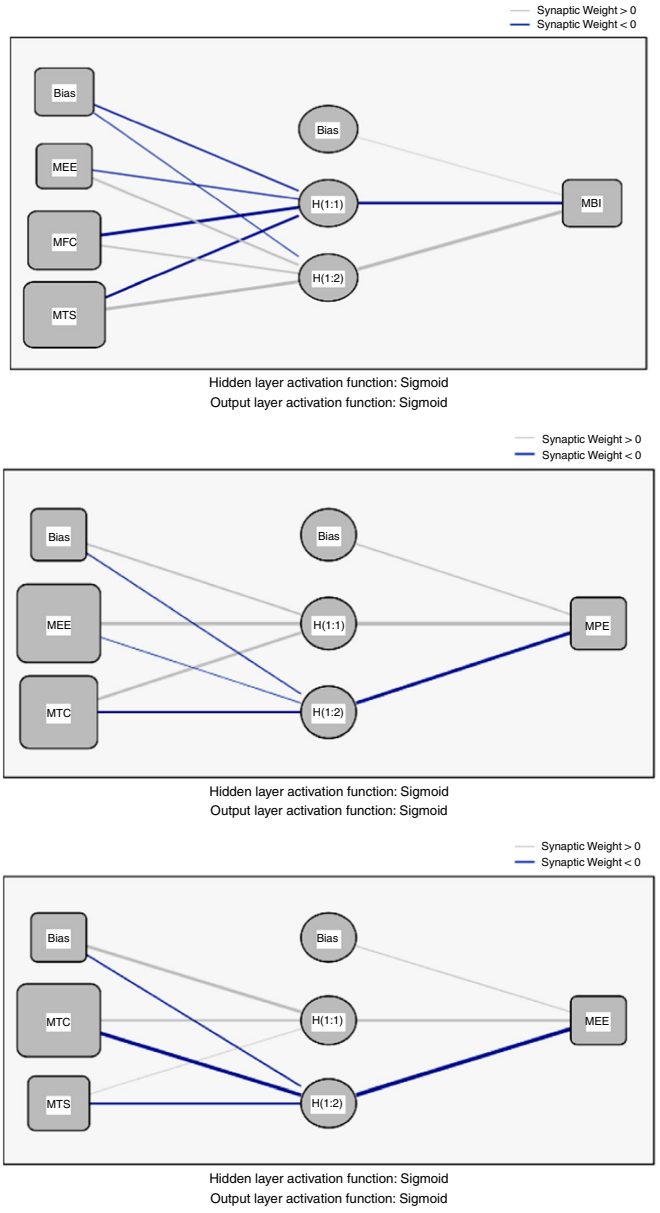

Figure 2.
NN of m-payment adoption

often draws users' intention to use. Next, our findings also supported the positive relationship between FC and BI. The findings are different from Yu (2012). Contrary to the findings by Chong (2013b) that found FC to be the least important predictor, our study shows different results. We found that FC is the second most important driver for BI of m-payment. In view that our respondents do not possess the hands-on experience on m-payment, it is understandable that they will need more information. The findings

Table VI.
Root mean square errors (RMSE) values of ten neural networks

Neural Networks	Model 1 Input nodes: EE, FC, PTS Output node: BI Training	Testing	Model 2 Input nodes: EE, PTC Output node: PE Training	Testing	Model 3 Input nodes: PTC, PTS Output node: EE Training	Testing
NN1	0.1028	0.0810	0.1191	0.0946	0.1169	0.1746
NN2	0.0966	0.1115	0.1074	0.0992	0.1237	0.1247
NN3	0.1133	0.0986	0.1122	0.0910	0.1258	0.1318
NN4	0.1083	0.0946	0.1065	0.1157	0.1242	0.1236
NN5	0.1004	0.0587	0.1068	0.1419	0.1223	0.1387
NN6	0.1137	0.0710	0.1101	0.1219	0.1248	0.1231
NN7	0.1003	0.1006	0.1084	0.0979	0.1212	0.1451
NN8	0.1043	0.0753	0.1094	0.0830	0.1252	0.1127
NN9	0.1033	0.1036	0.1125	0.0867	0.1218	0.1471
NN10	0.0988	0.1091	0.1046	0.1304	0.1299	0.1209
Mean	0.1042	0.0904	0.1097	0.1062	0.1236	0.1342
Standard deviation	0.0058	0.0178	0.0041	0.0200	0.0034	0.0180

Notes: PE, performance expectancy; EE, effort expectancy; FC, facilitating conditions; PTS, perceived transaction speed; PTC, perceived transaction cost; BI, behavioral intention

Table VII.
Connection of non-zero synaptic weight with hidden nodes

Model	Predictor Variable	Dependent Variable	Neural networks NN1	NN2	NN3	NN4	NN5	NN6	NN7	NN8	NN9	NN10
1	EE	BI	√	√	√	√	√	√	√	√	√	√
	FC		√	√	√	√	√	√	√	√	√	√
	PTS		√	√	√	√	√	√	√	√	√	√
2	EE	PE	√	√	√	√	√	√	√	√	√	√
	PTC		√	√	√	√	√	√	√	√	√	√
3	PTC	EE	√	√	√	√	√	√	√	√	√	√
	PTS		√	√	√	√	√	√	√	√	√	√

Notes: PE, performance expectancy; EE, effort expectancy; FC, facilitating conditions; PTS, perceived transaction speed; PTC, perceived transaction cost; BI, behavioral intention; √ indicates non-zero synaptic weight connected to hidden nodes

of PE mediates the relationship between EE and BI of m-payment has long been validated and confirmed through TAM- and UTAUT-based studies such as Teo *et al.* (2012) and Venkatesh *et al.* (2003). The high PE is derived from the EE of m-payment.

5.2 Relationship between PTC, PTS and PE, EE, and BI

Our findings do not support the positive relationship between PTC and BI. The result is inconsistent with mobile-application studies such as Luarn and Lin (2005). As our respondents are inexperienced with m-payment services, this leads to the perception of inconvenienced. Our results revealed on the positive relationship between PTC and PE and PTC and EE. The result is in line with Hayashi (2012) and Chen (2008). With the advancement of mobile technologies and wireless networks, the convenience of m-payment in terms of portability and flexibility will lead to higher perception of EE and PE. More specifically, the single payment method of m-payment that replaces the multiple payment methods may increase the ease to transact. In another similar study

Neural networks	Model 1 Output node: BI EE	FC	PTS	Model 2 Output node: EE EE	PTC	Model 3 Output node: PE PTC	PTS
NN1	0.192	0.360	0.448	0.560	0.440	0.621	0.379
NN2	0.210	0.356	0.435	0.648	0.352	0.573	0.427
NN3	0.277	0.396	0.327	0.628	0.372	0.409	0.591
NN4	0.240	0.305	0.454	0.584	0.416	0.517	0.483
NN5	0.249	0.323	0.428	0.673	0.327	0.511	0.489
NN6	0.327	0.330	0.343	0.528	0.472	0.605	0.395
NN7	0.264	0.341	0.395	0.613	0.387	0.514	0.486
NN8	0.211	0.284	0.505	0.564	0.436	0.466	0.534
NN9	0.362	0.113	0.524	0.533	0.467	0.460	0.540
NN10	0.166	0.406	0.428	0.566	0.434	0.613	0.387
Average importance	0.250	0.321	0.429	0.590	0.410	0.529	0.471
Normalized importance (%)	58.3	75.0	100.0	100.0	69.6	100.0	89.1

Notes: PE, performance expectancy; EE, effort expectancy; FC, facilitating conditions; PTS, perceived transaction speed; PTC, perceived transaction cost; BI, behavioral intention

Table VIII.
Sensitivity analysis

by Chen (2008) that examined PTC and PTS in m-payment, PTC was found to be more important than PTS. Surprisingly, our findings found that PTS is the most important driver for BI of m-payment. Lastly, our findings revealed that PTS positively influence EE, but not PE. The faster the speed of internet connection and data transaction, this will eventually assist user to complete the payment tasks quicker and hence contributes to higher EE. Similarly with PTC and BI, the insignificant relationship between PTS and PE is due to the inexperience respondents on the perceived benefits of m-payment.

6. Implications

As PTC and PTS are critical constructs in the payment industry, the inclusion of these constructs has theoretically contributed to its current limited research and UTAUT-based research findings. From the managerial perspective, mobile stakeholders should continuously develop the system that is easy with friendly user interface due to positive significant relationship between EE and BI. Facebook, for example has minimized the friction related with signing up for new account which contributes to a higher percentage of sign up completions. In addition, mobile stakeholders should provide sufficient information and guidelines in view of the positive relationship between FC and BI. As users are more likely to maintain their existing payment methods, continuous campaigns to educate and raise the awareness is important. Hence, creative and entertaining elements should be incorporated into their brochures, video-sharing web sites, and social media sites. Drawing from the findings, mobile stakeholders should also pay attention on the relationship between EE and PE. To increase PE, the m-payment must always be simple and hassle-free. This may be done by simplifying the registration process and to provide customer supports online and offline with competent personnel. Besides, attention should also be given on the significant relationship between PTC and EE and as well as PTC and PE. Mobile stakeholders via integrated campaigns may portray the different scenes of transaction convenience of m-payment and traditional payment methods. The promotional message should also stress on the ease and benefits gained from

transactional convenience of m-payment. Lastly, mobile stakeholders should also pay attention to the construct of PTS. As PTS significantly influence BI and EE, mobile stakeholders (i.e. mobile network operators and service providers) should constantly search and develop new infrastructures and applications to improve user's experience in terms of speed of transaction.

7. Limitations and future studies

Despite the rolled-out of various forms of m-payment, m-payment has yet to go mainstream. This has invoked our interest in understanding the factors that drive mobile phone users towards BI. Nevertheless, several limitations remain presence. First, the perceptions on m-payment vary from different users groups, the research findings may not able to provide a holistic view on BI of m-payment. As such, future studies may consider conducting a comparative study between two different users group, e.g., mobile phone users from different age groups. Second, although the study successfully extended UTAUT model with two constructs, PTC and PTS, our research findings may not be able to generalize to other nations. Apparently, different cultures and the level of development of m-payment may leads to different determinants. Hence, future studies may consider exploring PTC and PTS in a different context. Lastly, BI does not necessarily turn into the continuous intention and usage of m-payment. Therefore, the future study may investigate the determinants and the continuous intention (Zhou, 2013a) or usage.

References

Ajzen, I. (1985), "From intentions to actions: a theory of planned behavior", in Kuhl, J. and Beckman, J. (Eds), *Action-Control: From Cognition to Behavior*, Springer, Heidelberg, pp. 11-39.

Armstrong, J.S. and Overton, T.S. (1977), "Estimating non-response bias in mail surveys", *Journal of Marketing Research*, Vol. 14 No. 3, pp. 396-402.

Barki, H. (2007), "Quo vadis TAM?", *Journal of the AIS*, Vol. 8 No. 1, pp. 211-218.

Baş, D. and Boyacı, İ.H. (2007), "Modeling and optimization II: comparison of estimation capabilities of response surface methodology with artificial neural networks in a biochemical reaction", *Journal of Food Engineering*, Vol. 78 No. 3, pp. 846-854.

Berry, L.L., Seiders, K. and Grewal, D. (2002), "Understanding service convenience", *Journal of Marketing*, Vol. 66 No. 3, pp. 1-17.

Betiku, E. and Ajala, S.O. (2014), "Modeling and optimization of *Thevetia peruviana* (yellow oleander) oil biodiesel synthesis via *Musa paradisiacal* (plantain) peels as heterogeneous base catalyst: a case of artificial neural network vs. response surface methodology", *Industrial Crops and Products*, Vol. 53, February, pp. 314-322.

Bingöl, D., Hercan, M., Elevli, S. and Kılıç, E. (2012), "Comparison of the results of response surface methodology and artificial neural network for the biosorption of lead using black cumin", *Bioresource Technology*, Vol. 112, May, pp. 111-115.

Brown, L.G. (1990), "Convenience in services marketing", *Journal of Services Marketing*, Vol. 4 No. 1, pp. 53-59.

Brown, S.A., Venkatesh, V. and Goyal, S. (2012), "Expectation confirmation in technology Juse", *Information Systems Research*, Vol. 23 No. 2, pp. 474-487.

Brown, S.A., Venkatesh, V., Kuruzovich, J. and Massey, A.P. (2008), "Expectation confirmation: an examination of three competing models", *Organizational Behavior and Human Decision Processes*, Vol. 105 No. 1, pp. 52-66.

Carlsson, C., Walden, P. and Bouwman, H. (2006), "Adoption of 3G+ services in Finland", *International Journal of Mobile Communications*, Vol. 4 No. 4, pp. 369-385.

Chen, L.D. (2008), "A model of consumer acceptance of mobile payment", *International Journal of Mobile Communications*, Vol. 6 No. 1, pp. 32-52.

Chen, K.Y. and Chang, M.L. (2013), "User acceptance of 'near field communication' mobile phone service: an investigation based on the 'unified theory of acceptance and use of technology model", *The Service Industries Journal*, Vol. 33 No. 6, pp. 609-623.

Chiang, W.K., Zhang, D. and Zhou, L. (2006), "Predicting and explaining patronage behavior toward web and traditional stores using neural networks: a comparative analysis with logistic regression", *Decision Support Systems*, Vol. 41 No. 2, pp. 514-531.

Chong, A.Y.L. (2013a), "A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption", *Expert Systems with Applications*, Vol. 40 No. 4, pp. 1240-1247.

Chong, A.Y.L. (2013b), "Predicting m-commerce adoption determinants: a neural network approach", *Expert Systems with Applications*, Vol. 40 No. 2, pp. 523-530.

Chong, A.Y.L. (2013c), "Understanding mobile commerce continuance intentions: an empirical analysis of Chinese consumers", *Journal of Computer Information Systems*, Vol. 53 No. 4, pp. 22-30.

Copeland, M.T. (1923), "Relation of consumers' buying habits to marketing methods", *Harvard Business Review*, Vol. 1 No. 3, pp. 282-289.

Davis, F.D. (1989), "Perceived usefulness, perceived ease of use, and user acceptance of information technology", *MIS Quarterly*, Vol. 13 No. 3, pp. 319-349.

Deng, Z., Mo, X. and Liu, S. (2014), "Comparison of the middle-aged and older users' adoption of mobile health services in China", *International Journal of Medical Informatics*, Vol. 83 No. 3, pp. 210-224.

Doong, H.S. and Wang, H.C. (2011), "Do males and females differ in how they perceive and elaborate on agent-based recommendations in internet-based selling?", *Electronic Commerce Research and Applications*, Vol. 10 No. 5, pp. 595-604.

Eastin, M.S. (2002), "Diffusion of e-commerce: an analysis of the adoption of four e-commerce activities", *Telematics and Informatics*, Vol. 19 No. 3, pp. 251-267.

Farooq Anjum, M., Tasadduq, I. and Al-Sultan, K. (1997), "Response surface methodology: a neural network approach", *European Journal of Operational Research*, Vol. 101 No. 1, pp. 65-73.

Fishbein, M. and Ajzen, I. (1975), *Belief, Attitude, Intention, and Behavior: an Introduction to Theory and Research*, Addison-Wesley, Reading, MA.

Fornell, C. and Larcker, D.F. (1981), "Evaluating structural equation models with unobservable variables and measurement error", *Journal of Marketing Research*, Vol. 18 No. 1, pp. 39-50.

Geert-hofstede.com (n.d.), available at: http://geert-hofstede.com/malaysia.html (accessed October 1, 2014).

Gefen, D. and Straub, D.W. (2000), "The relative importance of perceived ease of use in IS adoption: a study of e-commerce adoption", *Journal of the Association for Information Systems*, Vol. 1 No. 8, pp. 1-30.

Ghezzi, A., Renga, F., Balocco, R. and Pescetto, P. (2010), "Mobile payment applications: offer state of the art in the Italian market", *Info*, Vol. 12 No. 5, pp. 3-22.

Gonggrijp, S., Geerling, M. and Mallekoote, P. (2013), "Successful introduction of new payment methods through 'co-opetition'", *Journal of Payments Strategy & Systems*, Vol. 7 No. 2, pp. 136-149.

Hayashi, F. (2012), "Mobile payments: What's in it for consumers?", available at: http://businessinnovation.berkeley.edu/Mobile_Money/documents/empirical-studies/Hayashi%20on%20consumer%20benefits%20of%20mobile%20payments.pdf (accessed February 18, 2014).

Haykin, S.S. (2007), *Neural Networks: A Comprehensive Foundation*, Prentice Hall, Englewood Cliffs, NJ.

Holden, W. (2012), "Press release: mobile payments to reach $1.3tn annually by 2017, as NFC and physical goods sales accelerate", available at: www.juniperresearch.com/viewpressrelease.php?pr=332 (accessed January 20, 2014).

Hsieh, C.T. (2007), "Mobile commerce: assessing new business opportunities", *Communications of the IIMA*, Vol. 7 No. 1, p. 9.

Jih, W.J. (2007), "Effects of consumer-perceived convenience on shopping intention in mobile commerce: an empirical study", *International Journal of E-Business Research (IJEBR)*, Vol. 3 No. 4, pp. 33-48.

Kahneman, D. and Tversky, A. (1979), "Prospect theory: an analysis of decision under risk", *Econometrica*, Vol. 47 No. 2, pp. 263-291.

Kankanhalli, A., Teo, H.H., Tan, B.C. and Wei, K.K. (2003), "An integrative study of information systems security effectiveness", *International Journal of Information Management*, Vol. 23 No. 2, pp. 139-154.

Karahanna, E., Straub, D.W. and Chervany, N.L. (1999), "Information technology adoption across time: a cross-sectional comparison of pre-adoption and post-adoption beliefs", *MIS Quarterly*, Vol. 23 No. 2, pp. 183-213.

Kharif, O. (2012), "Who's fastest? Google measures web speeds around the world", available at: http://go.bloomberg.com/tech-blog/2012-04-19-whos-fastest-google-measures-web-speeds-around-the-world/ (accessed December 17, 2014).

Kim, C., Mirusmonov, M. and Lee, I. (2010), "An empirical examination of factors influencing the intention to use mobile payment", *Computers in Human Behavior*, Vol. 26 No. 3, pp. 310-322.

Krishnan, S., Teo, T.S. and Lim, V.K. (2013), "Examining the relationships among e-government maturity, corruption, economic prosperity and environmental degradation: a cross-country analysis", *Information & Management*, Vol. 50 No. 8, pp. 638-649.

Lee, V.H., Leong, L.Y., Hew, T.S. and Ooi, K.B. (2013), "Knowledge management: a key determinant in advancing technological innovation?", *Journal of Knowledge Management*, Vol. 17 No. 6, pp. 848-872.

Leong, L.Y., Hew, T.S., Ooi, K.B. and Lin, B. (2012), "The determinants of customer loyalty in Malaysian mobile telecommunication services: a structural analysis", *International Journal of Services, Economics and Management*, Vol. 4 No. 3, pp. 209-235.

Leong, L.Y., Hew, T.S., Tan, G.W.H. and Ooi, K.B. (2013a), "Predicting the determinants of the NFC-enabled mobile credit card acceptance: a neural networks approach", *Expert Systems with Applications*, Vol. 40 No. 14, pp. 5604-5620.

Leong, L.Y., Ooi, K.B., Chong, A.Y.L. and Lin, B. (2013b), "Modelling the stimulators of the behavioral intention to use mobile entertainment: does gender really matter?", *Computers in Human Behavior*, Vol. 29 No. 5, pp. 2109-2121.

Liao, Z. and Cheung, M.T. (2002), "Internet-based e-banking and consumer attitudes: an empirical study", *Information & Management*, Vol. 39 No. 4, pp. 283-295.

Liébana-Cabanillas, F., Sánchez-Fernández, J. and Muñoz-Leiva, F. (2014), "Antecedents of the adoption of the new mobile payment systems: the moderating effect of age", *Computers in Human Behavior*, Vol. 35, June, pp. 464-478.

Lightner, N.J., Yenisey, M.M., Ozok, A.A. and Salvendy, G. (2002), "Shopping behavior and preferences in e-commerce of Turkish and American university students: implications from cross-cultural design", *Behaviour & Information Technology*, Vol. 21 No. 6, pp. 373-385.

Lin, C.C. and Lu, H. (2001), "Towards an understanding of the behavioral intention to use a web site", *International Journal of Information Management*, Vol. 20 No. 3, pp. 197-208.

Lin, Y. and Bei, L. (2008), "The perceived value of time in a transaction", *Advances in Consumer Research*, Vol. 35 No. 2008, pp. 720-721.

Lu, J., Yu, C.S. and Liu, C. (2009), "Mobile data service demographics in urban China", *Journal of Computer Information Systems*, Vol. 50 No. 2, pp. 117-126.

Lu, Y., Yang, S., Chau, P.Y. and Cao, Y. (2011), "Dynamics between the trust transfer process and intention to use mobile payment services: a cross-environment perspective", *Information & Management*, Vol. 48 No. 8, pp. 393-403.

Luarn, P. and Lin, H.H. (2005), "Toward an understanding of the behavioral intention to use mobile banking", *Computers in Human Behavior*, Vol. 21 No. 6, pp. 873-891.

Moosmayer, D.C., Schuppar, B. and Siems, F.U. (2012), "Understanding price negotiation outcomes in business-to-business relationships – an empirical perspective from the chemical industry", *Journal of Supply Chain Management*, Vol. 48 No. 1, pp. 92-106.

O'donoghue, R. (2014), "M-commerce insights: give users what they want, and make it fast", available at: http://mobiforge.com/research-analysis/m-commerce-insights-give-users-what-they-want-and-make-it-fast (accessed December 15, 2014).

Ondrus, J. and Pigneur, Y. (2009), "Near field communication: an assessment for future payment systems", *Information Systems and E-Business Management*, Vol. 7 No. 3, pp. 347-361.

Pagani, M. (2004), "Determinants of adoption of third generation mobile multimedia services", *Journal of Interactive Marketing*, Vol. 18 No. 3, pp. 46-59.

Pijpers, G.G.M., Bemelmans, T.M.A., Heemstra, F.J. and van Montfort, K.A.G.M. (2001), "Senior executives use of information technology", *Information and Software Technology*, Vol. 43 No. 15, pp. 959-971.

Pilkington, J.L., Preston, C. and Gomes, R.L. (2014), "Comparison of response surface methodology (RSM) and artificial neural networks (ANN) towards efficient extraction of artemisinin from artemisia annua", *Industrial Crops and Products*, Vol. 58, pp. 15-24.

Ranganathan, C., Teo, T.S. and Dhaliwal, J. (2011), "Web-enabled supply chain management: key antecedents and performance impacts", *International Journal of Information Management*, Vol. 31 No. 6, pp. 533-545.

Schierz, P.G., Schilke, O. and Wirtz, B.W. (2010), "Understanding consumer acceptance of mobile payment services: an empirical analysis", *Electronic Commerce Research and Applications*, Vol. 9 No. 3, pp. 209-216.

Scott, J.E. and Walczak, S. (2009), "Cognitive engagement with a multimedia ERP training tool: assessing computer self-efficacy and technology acceptance", *Information & Management*, Vol. 46 No. 4, pp. 221-232.

Sheng, M.L. and Teo, T.S. (2012), "Product attributes and brand equity in the mobile domain: the mediating role of customer experience", *International Journal of Information Management*, Vol. 32 No. 2, pp. 139-146.

Sim, J.J., Tan, G.W.H., Ooi, K.B. and Lee, V.H. (2011), "Exploring the individual characteristics on the adoption of broadband: an empirical analysis", *International Journal of Network and Mobile Technologies*, Vol. 2 No. 1, pp. 1-14.

Sim, J.J., Tan, G.W.H., Wong, J.C.J., Ooi, K.B. and Hew, T.S. (2014), "Understanding and predicting the motivators of mobile music acceptance – a multi-stage MRA-artificial neural network approach", *Telematics and Informatics*, Vol. 31 No. 4, pp. 569-584.

Sipior, J.C., Ward, B.T. and Connolly, R. (2011), "The digital divide and t-government in the United States: using the technology acceptance model to understand usage", *European Journal of Information Systems*, Vol. 20 No. 3, pp. 308-328.

Smith, C. (2014), "Shopping cart abandonment: online retailers' biggest headache is actually a huge opportunity", available at: www.businessinsider.my/heres-how-retailers-can-reduce-shopping-cart-abandonment-and-recoup-billions-of-dollars-in-lost-sales-2014-4/#.VI1UMiuUdMs (accessed December 10, 2014).

Stofega, W. and Llamas, R.T. (2009), "Worldwide converged mobile device phone 2009-2013 forecast update", IDC Document No. 217209, IDC.

Svozil, D., Kvasnicka, V. and Pospichal, J. (1997), "Introduction to multi-layer feed forward neural networks", *Chemometrics and Intelligent Laboratory Systems*, Vol. 39 No. 1, pp. 43-62.

Tan, G.W.H., Ooi, K.B., Chong, S.C. and Hew, T.S. (2014a), "NFC mobile credit card: the next frontier of mobile payment?", *Telematics and Informatics*, Vol. 31 No. 2, pp. 292-307.

Tan, G.W.H., Ooi, K.B., Leong, L.Y. and Lin, B. (2014b), "Predicting the drivers of behavioral intention to use mobile learning: a hybrid SEM-neural network approach", *Computers in Human Behavior*, Vol. 36, July, pp. 198-213.

Teo, T.S. and Bhattacherjee, A. (2014), "Knowledge transfer and utilization in IT outsourcing partnerships: a preliminary model of antecedents and outcomes", *Information & Management*, Vol. 51 No. 2, pp. 177-186.

Teo, A.C., Cheah, C.M., Leong, L.Y., Hew, T.S. and Shum, Y.L. (2012), "What matters most in mobile payment acceptance? A structural analysis", *International Journal of Network and Mobile Technologies*, Vol. 3 No. 3, pp. 49-69.

Venkatesh, V. and Goyal, S. (2010), "Expectation disconfirmation and technology adoption: polynomial modeling and response surface analysis", *MIS Quarterly*, Vol. 34 No. 2, pp. 281-303.

Venkatesh, V., Morris, M.G., Davis, G.B. and Davis, F.D. (2003), "User acceptance of information technology: toward a unified view", *MIS Quarterly*, Vol. 27 No. 3, pp. 425-478.

Venkatesh, V., Thong, J. and Xu, X. (2012), "Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology", *MIS Quarterly*, Vol. 36 No. 1, pp. 157-178.

Witek-Krowiak, A., Chojnacka, K., Podstawczyk, D., Dawiec, A. and Pokomeda, K. (2014), "Application of response surface methodology and artificial neural network methods in modelling and optimization of biosorption process", *Bioresource Technology*, Vol. 160, May, pp. 150-160.

Wong, C.H., Tan, G.W.H., Loke, S.P. and Ooi, K.B. (2014), "Mobile TV: a new form of entertainment?", *Industrial Management & Data Systems*, Vol. 114 No. 7, pp. 1050-1067.

Yale, L. and Venkatesh, A. (1986), "Toward the construct of convenience in consumer research", *Advances in Consumer Research*, Vol. 13 No. 1, pp. 403-408.

Yang, A.S. (2009), "Exploring adoption difficulties in mobile banking services", *Canadian Journal of Administrative Sciences/Revue Canadienne Des Sciences de l'Administration*, Vol. 26 No. 2, pp. 136-149.

Yang, K.C. (2005), "Exploring factors affecting the adoption of mobile commerce in Singapore", *Telematics and Informatics*, Vol. 22 No. 3, pp. 257-277.

Yoon, C. and Kim, S. (2007), "Convenience and TAM in a ubiquitous computing environment: the case of wireless LAN", *Electronic Commerce Research and Applications*, Vol. 6 No. 1, pp. 102-112.

Yu, C.S. (2012), "Factors affecting individuals to adopt mobile banking: empirical evidence from the UTAUT model", *Journal of Electronic Commerce Research*, Vol. 13 No. 2, pp. 104-121.

Zhou, T. (2013a), "Understanding usage of mobile sites", *Industrial Management & Data System*, Vol. 113 No. 9, pp. 1286-1299.

Zhou, T. (2013b), "An empirical examination of continuance intention of mobile payment services", *Decision Support Systems*, Vol. 54 No. 2, pp. 1085-1091.

Zhou, T., Lu, Y. and Wang, B. (2010), "Integrating TTF and UTAUT to explain mobile banking user adoption", *Computers in Human Behavior*, Vol. 26 No. 4, pp. 760-767.

About the authors

Aik-Chuan Teo is a Lecturer in the Faculty of Business and Finance, the Universiti Tunku Abdul Rahman, Malaysia. He received his Bachelor of Business Administration (Marketing) and MBA from the University Utara Malaysia. His current research includes the area of mobile commerce, green marketing and service management.

Garry Wei-Han Tan is the Chairperson of the Centre for Business and Management at the Faculty of Business and Finance, the Universiti Tunku Abdul Rahman, Malaysia. He obtained his Master of Science in Management from the University of Edinburgh, UK, in 2008 and in 2005 a Bachelor degree in Economics (Hons) from the University of Malaya, Malaysia. He also holds two insurance diplomas with Honors from LOMA Society, USA. Currently, he is also the SiRC visiting scholar at Wee Kim Wee School of Communication and Information, the Nanyang Technology University, Singapore. Garry Wei-Han Tan is the corresponding author and can be contacted at: garrytanweihan@gmail.com

Dr Keng-Boon Ooi is a Professor at the Faculty of Business, Management and Accountancy, the Linton University College, Malaysia. He has published over 80 articles in international refereed journals.

Teck-Soon Hew holds a Master's Degree in Information Technology (Distinction) from the Faculty of Information Technology and Multimedia Communications, the Open University Malaysia (OUM). He graduated with a first-class honours degree in Educational Science from the University of Technology Malaysia and received the OUM Chancellor Foundation Award in 2010 as well as Excellence Service Award by the Ministry of Education, Malaysia, in 2007. Currently, he is a PhD scholar at the Faculty of Business and Accountancy, the University of Malaya. His research interests are in the areas of technology adoption, mobile applications, applied statistics, neural networks and virtual learning environment.

King-Tak Yew is a Senior Lecturer at the Faculty of Business and Finance, the Univeristi Tunku Abdul Rahman, Malaysia. He received his Master of Information Technology from Charles Sturt University, Australia. His research interests are in the area of Expert Systems, Knowledge Management Systems, Information Systems and E-Commerce Strategies.

This article has been cited by:

1. Hongyu Shen, Pan Liu, Shuping YiTrust Transfer Mechanism and Intention on Accepting NFC Mobile Payment: An Empirical Research 363-376. [CrossRef]
2. Pan Liu, Shu-ping YiThe Effects of Extend Compatibility and Use Context on NFC Mobile Payment Adoption Intention 57-68. [CrossRef]
3. Voon-Hsien Lee, Alex Tun-Lee Foo, Lai-Ying Leong, Keng-Boon Ooi. 2016. Can competitive advantage be achieved through knowledge management? A case study on SMEs. *Expert Systems with Applications* **65**, 136-151. [CrossRef]
4. Teck-Soon Hew, Sharifah Latifah Syed Abdul Kadir. 2016. Behavioural intention in cloud-based VLE: An extension to Channel Expansion Theory. *Computers in Human Behavior* **64**, 9-20. [CrossRef]
5. Keng-Boon Ooi, Garry Wei-Han Tan. 2016. Mobile technology acceptance model: An investigation using mobile users to explore smartphone credit card. *Expert Systems with Applications* **59**, 33-46. [CrossRef]
6. Teck-Soon Hew, Sharifah Latifah Syed Abdul Kadir. 2016. Understanding cloud-based VLE from the SDT and CET perspectives: Development and validation of a measurement instrument. *Computers & Education* **101**, 132-149. [CrossRef]
7. HewTeck-Soon Teck-Soon Hew Syed Abdul KadirSharifah Latifah Sharifah Latifah Syed Abdul Kadir Faculty of Business and Accountancy, University of Malaya, Kuala Lumpur, Malaysia Department of Operation and Management Information System, Faculty of Business and Accountancy, University of Malaya, Kuala Lumpur, Malaysia . 2016. Predicting instructional effectiveness of cloud-based virtual learning environment. *Industrial Management & Data Systems* **116**:8, 1557-1584. [Abstract] [Full Text] [PDF]
8. June Lu, June Wei, Chun-sheng Yu, Chang Liu. 2016. How do post-usage factors and espoused cultural values impact mobile payment continuation?. *Behaviour & Information Technology* 1-25. [CrossRef]
9. Tiago Oliveira, Manoj Thomas, Goncalo Baptista, Filipe Campos. 2016. Mobile payment: Understanding the determinants of customer adoption and intention to recommend the technology. *Computers in Human Behavior* **61**, 404-414. [CrossRef]
10. Gwarlann de Kerviler, Nathalie T.M. Demoulin, Pietro Zidda. 2016. Adoption of in-store mobile payment: Are perceived risk and convenience the only drivers?. *Journal of Retailing and Consumer Services* **31**, 334-344. [CrossRef]
11. Choy-Har Wong, Garry Wei-Han Tan, Teck-Soon Hew, Keng-Boon Ooi. 2016. Can mobile TV be a new revolution in the television industry?. *Computers in Human Behavior* **55**, 764-776. [CrossRef]
12. Lai-Ying Leong, Teck-Soon Hew, Voon-Hsien Lee, Keng-Boon Ooi. 2015. An SEM–artificial-neural-network analysis of the relationships between SERVPERF, customer satisfaction and loyalty among low-cost and full-service airline. *Expert Systems with Applications* **42**:19, 6620-6634. [CrossRef]
13. Choy-Har Wong School of Business and Administration, Wawasan Open University, Ipoh, Malaysia Garry Wei-Han Tan Faculty of Business and Finance, Universiti Tunku Abdul Rahman, Kampar, Malaysia Siew-Phaik Loke Faculty of Business Management, Universiti Teknologi MARA Perak, Bandar Seri Iskandar, Malaysia Keng-Boon Ooi Faculty of Business & Information

Science, UCSI University, Kuala Lumpur, Malaysia . 2015. Adoption of mobile social networking sites for learning?. *Online Information Review* **39**:6, 762-778. [Abstract] [Full Text] [PDF]

14. Jun-Jie Hew Faculty of Business and Finance, Universiti Tunku Abdul Rahman, Kampar, Malaysia Voon-Hsien Lee Faculty of Business and Finance, Universiti Tunku Abdul Rahman, Kampar, Malaysia Keng-Boon Ooi Faculty of Business & Information Science, UCSI University, Kuala Lumpur, Malaysia June Wei College of Business, University of West Florida, Pensacola, Florida, USA . 2015. What catalyses mobile apps usage intention: an empirical analysis. *Industrial Management & Data Systems* **115**:7, 1269-1291. [Abstract] [Full Text] [PDF]
15. Alain Yee Loong Chong, Eugene Ch'ng, Martin J. Liu, Boying Li. 2015. Predicting consumer product demands via Big Data: the roles of online promotional marketing and online reviews. *International Journal of Production Research* 1-15. [CrossRef]