Factors that Drive Consumer Adoption of Mobile Wallet

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Abstract

The widespread use of smartphones and technological advances in near-field communication technologies are quickly transforming mobile payment systems. These technologies have made it possible for consumers to use their smartphones to pay for their purchases through various payments systems such as Google Wallet, PayPal, Square Wallet, and Apple Pay. These mobile payment systems, commonly referred to as mobile wallets, are designed to eliminate the need for consumers to carry multiple credit cards or cash in their wallets, thereby making it more convenient for consumers to shop. Mobile wallets is a major innovation in mobile marketing because they are another major channel through which marketers can better reach and serve customers in a very personalized way. Realizing the potential benefits of mobile wallets for both marketers and consumers depends on the speed of adoption of this new technology. This study examines the factors that influence consumers' decision to adopt mobile wallets. Drawing on the theoretical technology adoption and diffusion literatures, a model of the factors that influence mobile wallet adoption is proposed and tested with data collected from 530 respondents. The results show that mobile wallet adoption is driven by factors such as trialability, perceived usefulness of the technology and perceived ease of use. Interestingly, privacy and security and social norms did not influence adoption decisions. However, social norm is significant only though peer pressures.

Keywords

Mobile Wallets, Technology Acceptance, Diffusion of Innovations,

1. Introduction

Mobile wallets allow consumers to use their smartphones to make payments for purchases of goods and services. In order for consumers to use their smartphones as mobile wallets, they need to download the service provider's mobile wallet app and enter their credit and debit cards information. Once this is done, consumers can make payments by simply having their smartphone scanned by service providers NFC readers. In addition to payment capabilities, mobile wallets offer consumers *inter alia* the ability to link their loyalty cards to their mobile wallets, store online shopping accounts and details, receive product information, coupons, special offers and promotions, and make price comparison. Mobile wallets can support various transactions, including consumer-to-consumer, consumer-to-business, consumer-to-machine (i.e., paying for parking meter), and consumer-to-online. Mobile wallets offer faster processing at the point of sale and increased opportunity for impulse buying. These functionalities not only offer consumers convenience and other benefits but also provide marketers with a wealth of consumer shopping behaviour information, which could be used by marketers to enhance consumers' shopping experiences. Basically, mobile wallets enable marketers to develop close relationships with its customers. A few examples of mobile wallet apps include Google Wallet, PayPal, Square Wallet, and Apple Pay.

Mobile wallets represent another major advance in mobile marketing since they significantly enhance consumer convenience and provide marketers with a wide range of opportunities to better reach and serve consumers in a personalized way. However, consumer adoption is crucial for the success of mobile wallets. Currently, consumer adoption of mobile wallets is in the early stages but marketers are eager to see widespread adoption of this new technology (MasterCard, 2012). Thus, there is a real practical need for a better understanding of the factors that could influence mobile wallet adoption. Further, although much research has been conducted on various aspects of mobile commerce and payment systems, research on the adoption of mobile wallets is limited. The goal of this study is to add to the emerging research on mobile wallet by investigating consumer adoption of this technology.

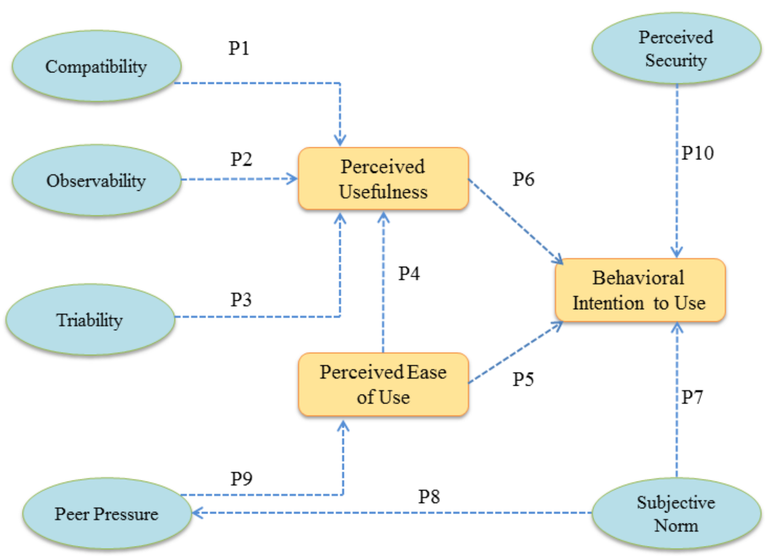
The main focus of this study is to identify the main factors that are likely to influence consumer adoption of mobile wallets. The analytical framework utilized in this study is based on two established technology adoption literatures, namely, technology acceptance models (TAM) and innovation diffusion theory (IDT). Relevant factors from these models are tested in the context of mobile wallet adoption.

The remainder of this paper is structured into five sections. The next section describes the conceptual framework. Section three describes the methodology employed in the study. Section four presents the results and Section five discusses the research and managerial implications. This is followed by the conclusion.

2. Conceptual Framework

This study uses a theoretical model that integrates relevant components of both TAM and IDT theories. The model is shown in Figure 1 below. The constructs *compatibility*, *trialability* and *observability* are adopted from innovation diffusion theory while the remaining constructs are from the TAM literature. As depicted in Figure 1, three *compatibility*, *trialability* and *observability*, influences consumers' perception of the *perceived usefulness* and *perceived ease of use,* which in turn influence consumers' *intention to use* mobile wallets. Further, *subjective norms* and *perceived security* affect consumers' *intention to use* mobile wallets and *subjective norms* influence *peer pressure* and *perceived ease of use*. Each of the constructs and relationships shown in Figure 1 is describe in more detail below.

Figure 1 Conceptual Model



Compatibility

Compatibility refers to the degree to which innovation is regarded as being consistent with the potential end-users' existing values, prior experiences, and needs (Lee, Hsieh, & Hsu, 2011). Agarwal, (2000) reported a positive relationship between an individual's prior compatible experiences and the new information technology acceptance. They confirmed that the extent of prior experience with similar technologies was positively associated with an information technology use. Moreover, Chau & Hu (2001), argued that the effect of compatibility was found to be significant related to *perceived usefulness*. Later, Wu & Wang (2005) and Change & Tung (2008) found that compatibility had a significant positive and direct effect on perceived usefulness. Therefore, the following relationship is proposed.

Hypothesis 1: Compatibility has a positive effect on the perceived usefulness of mobile wallets.

Observability

In previous studies combining TAM and IDT, when the users perceived a system as being easier to be observed or described, they tended to perceive the system as more useful (Huang 2004; Yang, 2007). Therefore, we proposed that observability has a positive effect on perceived usefulness of mobile wallets. The following relationship is tested:

Hypothesis 2: Observability has a positive effect on the perceived usefulness of mobile wallets.

Trialability

Some studies have empirically tested the association between trialability and the intention to use the system (Lee, 2007). They found that trialability had a positive effect on the intention to use the system. However, Yang (2007) reported that when the users perceived higher trialability, they also perceived higher levels of usefulness of the system. Thus, we test the following relationship.

Hypothesis 3: Trialability has a positive effect on perceived usefulness of mobile wallets.

Perceived Ease of Use (PEU)

PEU is the degree to which an individual believes that using a particular system would be free of effort (Davis, 1989). Information system researchers have indicated that PEU has a positive effect on the end-users' behavioral intention as well as the perceived usefulness of the system (Chin & Todd, 1995). Yang (2005) study on users in Singapore showed that perceived ease of use has a significant influence on perceived usefulness. Lu, Liu & Yao (2003) also found that perceived usefulness influences users' intention through perceived ease of use. When mobile payment users perceive a comparatively high ease of use, they will be more likely to recognize the convenience of mobile payments and to try different mobile payment services, experiencing a higher level of usefulness.

In addition, researchers using TAM have shown that perceived ease of use has a significant influence on user's behavioral intention (Chang & Tung, 2008; Venkatesh & Davis, 2000; Shi, Shambare, & Wang, 2008). In some studies, perceived ease of use and perceived usefulness have been found to have significant impact on adoption behavior. Yang (2005) found that perceived ease of use affected the attitude of users towards mobile commerce, coupled with the individual's creativity, past experience, relevant knowledge, technology groups, gender, age, and occupation. Therefore the following two hypotheses are proposed.

Hypothesis 4: PEU has a positive effect on the *perceived usefulness* of mobile wallets.
Hypothesis 5: PEU has a positive effect on the Behavioral Intention to use mobile wallets.

Perceived Usefulness

PU is the degree to which an individual believes that a particular system would enhance his or her job performance within an organizational context (Davis, 1989). Information system researchers have investigated TAM, and asserted that PU was valid in predicting the individual's acceptance of various systems (Venkatesh & Davis, 2000; Chin & Todd, 1995). Mobile payment can be used in virtually any shopping context, which greatly increases its usefulness (Liu & Li (2010). Thus, the following hypothesis is proposed.

Hypothesis 6: PU will have a positive effect on the behavioral intention to use mobile wallets.

Subjective Norms

Subjective Norm refers to "a person's perception that most people who are important to him/her think he/she should or should not perform the behavior in question" (Fishbein & Ajzen, 1975). Subjective Norms, which is similar to the construct Attitude in the original TAM model is found to predict adoption behavior. Venkatesh & Davis (2000) indicate that Subjective Norm significantly influences users' acceptance of technology while Riemenschneider et al. (2003) found that Subjective Norms affect adoption decisions. Further, Celuch, Walz, Saxby, & Ehlen (2011) observed that Subjective Norm positively influence intention to use the Internet for purchasing and information management. In another study, Chakraborty, Ball, Gaeth, & Jun (2002) contend that 80% of technology purchasers tend to buy technology that is used by others, even at higher cost. Those who have had no mobile payment experience decide to try it on their subjective assessments, which are influenced by family, friends, colleagues, and even their leaders. Mobile users are a group of users who quickly accept new technologies (Hildebrand, 2014). Therefore, when they are aware of other people using mobile payments, they are more likely to adopt that method in order to conform to their community. Consequently, the following hypotheses are proposed.

Hypothesis 7: Subjective Norm will have a positive effect on the behavioral intention to use the mobile wallets

Hypothesis 8: Subjective Norm will have a positive effect on Peer Pressure to use mobile wallets

Peer Pressure

Influence from others can be direct and explicit, as in the case of peer pressure, where one or more people cajole, bully, or outright command others to change their behavior to conform to the group (Shepherd, Lane, Tapscott, & Gentile (2011). Social influence can also be subtle; the mere presence of others or the perception of their preferences can create a motivation to change one's behavior to align with the group (Aronson, Wilson, & Akert, 2013). According to Salajan, Welch, Peterson, & Ray (2011), people perceive increased pressure to be proficient with the technology, which can affect their decisions whether or not to use a technology. In another research conducted by Chismar & Wiley-Patton (2003), participants believed that the peer pressures influenced them to adopt technologies. Thus, the following hypothesis is proposed.

Hypothesis 9: Peer Pressure will have a positive effect on the PEU to use mobile wallets.

Perceived Security

One of the concerns in mobile wallet is security to support mobile cash transactions. Near Field Communications (NFC) provides a secure environment for convenient and efficient business transactions. NFCs enable fast and easy wireless connection between electronic devices in short-range distance (Chen & Chang, 2013). Given the rising concerns over mobile security, this study explores the effect of users' perceived security on intention to use a mobile wallet. Perceived security is defined as the degree to which a customer believes using a particular mobile payment procedure will be secured (Shin, 2005; Yenisey, Ozok, & Salvendy, 2005). Security in interactive spaces does not depend on technical security measures alone. Shin and Kim (2008) show that the feeling of security is largely determined by the users' feeling of control of the interactive system. In a survey, Zimenkov & Ahmad, (2012) reported that 91% of respondents were "very concerned" about their information security and privacy. Cheong, Park, & Hwang (2008) examined barriers to mobile payment adoption and reported that the lack of security is the most frequent reason for refusing to use the system. Thus, the following hypothesis is proposed.

Hypothesis 10: Perceived security influences the intention to use mobile wallets.

3. Methodology

The data for this study was gathered through an online survey using Qualtrics survey software. Targeted participants were sent an email invitation requesting them to participate in the study and the link to the survey was provided in the email. A sample frame of about 800 adult participants was created from several sources including participants from a previous study and the researchers' personal and professional contacts. The email invitation clearly stated that respondents were under no obligation to participate in the survey, their identity will be kept anonymous and their responses will be kept confidential and only used in aggregate form. A total of 530 fully completed and usable responses were received. Thus, the response rate is approximately sixty-six percent.

The survey instrument consisted of both Likert scale and demographic questions. All the constructs used in the theoretical model were measured on a 1 to 7 strongly disagree to strongly agree Likert scale, where 1 indicates strongly disagree and 7 indicates strongly agree. The items for the various constructs were extracted from previous studies that reported high reliabilities and validities of the items. Demographic questions pertain to participants' age, gender, education, income, and occupation as well as their shopping styles, payment methods and preferences, and whether or not they currently use mobile wallet.

The data analysis was executed in two stages. First, descriptive statistics (e.g., means, standard deviations, and frequencies) were generated for all the variables in the questionnaire. This was done in order to obtain insights into the nature of the dataset and to ascertain whether there are any anomalies. The second stage involves the use of Structural Equation Modeling (SEM) to examine the relationships proposed in our theoretical model. SEM is widely used to simultaneously evaluate complex relationships among unobserved latent variables (Jöreskog, Sörbom, & Magidson, 1979; Wothke, 2010). The analysis in this study is conducted by Partial Least Square (PLS), a variance-based SEM analytical method (Wong, 2013), using SmartPLS.

4. Results

The demographic profile of our sample of respondents is presented in Table 1. As show in Table 1, the sample is almost equally weighted in terms of men and women who participated in the study. About half of the participants are between 18-24 years old and almost three-quarters are under 35 years old, which reflects an overall young sample in our study. About 44% of the respondents are students while about 48% are employed full-time or part-time. Over 46% of the participants earn more than $40,000 and approximately two-thirds have at least a university degree either Bachelor's, Master's or PhD, or professional qualifications. Thus, our sample can be described as a group of people who are employed, highly educated and have relatively high incomes.

Variable		Percentage (%)
Gender	Male	48.1
	Female	51.9
Age	18-24	50.2
	25-34	23.4
	35-44	8.6
	45-54	13.7
	55-64	3
	65 or above	1.1
Occupation	Employed Full-time	34.4
	Employed Part-time	13.9
	Unemployed	4.4
	Retired	2.5
	Student	44.7
Household Income	Less than $19,999	34.4
	$20000-29,999	11.2
	$30,000-39,999	8
	$40,000-49,999	6.1
	$50,000 or more	40.3
Level of Education	High school	20.3
	College	14.3
	Bachelor degree	47.7
	Master's and/or PhD	15.2
	Professional qualification	2.5

In terms of the SEM analysis, the model was assessed in two steps as recommended by Hair, Ringle and Sarstedt (2011). The first step involves assessing the measurement or outer model fit to determine the reliability and validity of this model. Once the measurement model is assessed to be a good fit with the data, the second step involves assessing the inner or structural model. In assessing the measurement model, the focus is on the reliability and validity of the constructs. Reliability gives an indication of the internal consistency of the items used to measure the construct while validity gives an indication of whether the model constructs are different from each other. Validity is generally evaluated by assessing their discriminant and convergent validities. Convergent validity indicates whether all the items that are theoretically supposed to be related to each other are in fact related while discriminant validity indicate whether the items that are not supposed to be related are in fact not related.

Table 2 illustrates the matrix of loadings and cross-loadings of two models with a high degree of significance for each item (average loading > 0.7) on its respective construct. The shaded area shows the cross-loadings of the items with their own construct and unshaded area shows loadings of the items with the other constructs. Convergent validity requires that the items of a construct be strongly correlated with their associated construct and weakly correlated with the other constructs in the model (Straub, Boudreau et al, 2004). As shown in Table 2, the item correlations of the respective constructs satisfy this condition, so we conclude that the measurement model demonstrate adequate convergent validity. In order to assess the discriminant validity, the correlations among the latent variables are evaluated. For this purpose, the square root of Average Variance Extracted (AVE) is compared with the calculated correlations. According to Fornell & Larcker (1981), Chin (1998a), and Pavlou & Gefen (2004), the discriminant validity of the model is verified when the square root of the AVE is greater than the correlations. As presented in Table 3, the square root values displayed on the diagonal of the matrix are larger than the correlation values presented in the same row and the same column. Thus, we conclude that there is adequate discriminant validity among the constructs.

Table 2: Matrix of Loadings and Cross Loadings

	BI	Com.	Obs	PEOU	PP	PU	S & P	SN	Tri
BI1	0.824	0.595	0.612	0.666	0.502	0.716	0.251	0.586	0.677
BI2	0.926	0.629	0.631	0.798	0.625	0.787	0.365	0.712	0.736
BI3	0.912	0.586	0.637	0.794	0.687	0.752	0.348	0.733	0.652
Com1	0.673	0.828	0.586	0.686	0.414	0.775	0.403	0.576	0.778
Com2	0.386	0.777	0.463	0.468	0.480	0.491	0.564	0.456	0.548
Com3	0.460	0.729	0.502	0.542	0.538	0.509	0.672	0.518	0.543
Obs1	0.525	0.552	0.783	0.544	0.582	0.611	0.317	0.527	0.576
Obs2	0.517	0.522	0.849	0.577	0.636	0.560	0.296	0.654	0.491
Obs3	0.671	0.563	0.810	0.682	0.663	0.617	0.396	0.744	0.540
PEOU1	0.719	0.708	0.668	0.825	0.573	0.800	0.346	0.653	0.735
PEOU2	0.713	0.621	0.562	0.833	0.604	0.689	0.493	0.640	0.666
PEOU3	0.696	0.532	0.621	0.848	0.709	0.664	0.321	0.731	0.519
PP1	0.442	0.461	0.629	0.528	0.786	0.505	0.283	0.550	0.418
PP2	0.650	0.529	0.677	0.697	0.912	0.606	0.435	0.741	0.502
PP3	0.660	0.549	0.694	0.710	0.890	0.630	0.390	0.769	0.482
PU1	0.682	0.719	0.579	0.670	0.434	0.849	0.371	0.537	0.772
PU2	0.638	0.612	0.671	0.704	0.648	0.825	0.348	0.668	0.626

PU3	0.817	0.676	0.622	0.806	0.632	0.867	0.472	0.712	0.738
S&P1	0.360	0.589	0.393	0.423	0.447	0.427	0.901	0.413	0.515
S&P2	0.365	0.576	0.375	0.456	0.416	0.438	0.916	0.433	0.519
S&P3	0.207	0.601	0.315	0.315	0.242	0.370	0.800	0.307	0.463
SN1	0.732	0.619	0.701	0.758	0.745	0.685	0.428	0.923	0.572
SN2	0.711	0.572	0.719	0.739	0.770	0.674	0.419	0.914	0.544
SN3	0.585	0.599	0.688	0.651	0.612	0.659	0.332	0.825	0.547
Tri1	0.665	0.749	0.597	0.664	0.417	0.764	0.467	0.550	0.878
Tri2	0.659	0.632	0.573	0.625	0.480	0.685	0.339	0.480	0.832
Tri3	0.635	0.700	0.498	0.653	0.482	0.678	0.645	0.545	0.818

BI = Behavioral intention; Com = compatibility; Obs = Observability; PEOU = Perceived ease of use; PP= Peer pressure; PU = Perceived usefulness; S&P = Security & privacy; SN = Subjective norm; Tri = Trialability

Table 1: Average Variance Extracted and Inter-Construct Correlations

	BI	**Com.**	**Obs.**	**PP**	**PEOU**	**PU**	**S & P**	**SN**	**Tri.**
BI	0.889								
Com.	0.679	0.779							
Obs.	0.705	0.672	0.814						
PP	0.684	0.595	0.771	0.864					
PEOU	0.805	0.744	0.740	0.752	0.835				
PU	0.846	0.790	0.734	0.675	0.801	0.847			
S&P	0.364	0.668	0.415	0.432	0.461	0.473	0.874		
SN	0.765	0.670	0.790	0.802	0.808	0.756	0.445	0.888	
Tri.	0.774	0.624	0.661	0.542	0.768	0.842	0.571	0.623	0.843

Table 4 presents the internal consistency of the constructs, which are measured the constructs composite reliabilities and Cronbach's Alpha. The Table also shows the AVE of the constructs in our models. For adequate reliability, both the composite reliability (CR) and Cronbach's Alpha must exceed the minimum threshold of 0.70 (Nunnally, 1978). In addition, the AVE should exceed 0.5 to ensure adequate convergent validity (Fornell & Larcker, 1981; Chin, 1998; Gefen et al, 2000). The values displayed in Table 4 exceed these thresholds by substantial margins. Thus, we conclude the constructs demonstrate adequate reliability and validity.

Table 4: Reliability and Convergent Validity of Model Constructs

	AVE	Composite Reliability	Cronbach's Alpha
Behavioral Intention to Use	0.790	0.918	0.866
Compatibility	0.606	0.822	0.687
Observability	0.663	0.855	0.745
Peer Pressure	0.747	0.898	0.829
Perceived Ease of Use	0.698	0.874	0.783
Perceived Usefulness	0.718	0.884	0.804
Security & Privacy	0.763	0.906	0.845
Subjective Norms	0.789	0.918	0.865
Triability	0.711	0.881	0.796

Now that the measurement model has been show to be both reliable and valid, the next step is to assess the structural model. This requires and evaluation of the R^2 measures and the level and significance of the path coefficients (Hair, Ringle & Sarstedt, 2011). Generally, in marketing research R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables in the structural model can, as a rule of thumb, be described as substantial, moderate, or weak, respectively (Hair, Ringle & Sarstedt, 2011). The significance of the path coefficients is assessed by bootstrapping. PLS‑SEM does not presume normality of the data. Consequently, it uses nonparametric bootstrapping to obtain standard errors for hypothesis testing (Hair, Ringle & Sarstedt, 2011). Bootstrapping involves repeated random sampling with replacement from the original sample to create a bootstrap sample. The bootstrap sample enables the estimated coefficients in PLS‑SEM to be tested for their significance (Henseler, Ringle, and Sinkovics 2009). Paths that are nosignificant or has a sign that is different from what was originally hypothesized mean that the particular hypotheses are not supported. Paths that are significant and are in the hypothesized directions support the hypothesized relationships.

Table 5 presents the R^2 values of the endogenous constructs of the model. Based on the preceding rules of thumb, it is concluded that the models have substantial explanatory since they are close to or exceed the 0.75 threshold.

Table 5: Model R-Square

	R-Square
Behavioral Intention	0.781
Compatibility	NA (Exogenous)
Observability	NA (Exogenous)
Peer Pressure	0.648
Perceived Ease of Use	0.684
Perceived Usefulness	0.835
Security & Privacy	NA (Exogenous)
Subjective Norms	NA (Exogenous)
Triability	NA (Exogenous)

In order to assess the significance of the path coefficients, bootstrapping with SmartPLS was performed. The results are presented in Table 6. In order for a path to be deemed significant, the t-value must be ≥ 1.96 and the p value ≤ 0.05. Based on these criteria, it is observed that four of the paths are not statistically significant and thus the associated hypotheses are rejected. The remaining parts are statistically significant and therefore support our hypothesized relationships.

These results show that three of the four nonsignificant paths relate to the construct perceived usefulness. That is, compatibility, observability, and security and privacy do not seem to influence consumers' perceptions of the usefulness of mobile wallets. This suggests that these features of the mobile wallets have very little impact on consumers' perception of its usefulness in their lives. In similarly vein, subjective norm, which reflects the influence of others on adoption decisions, does not influence consumers' decision to adopt mobile wallets to transact or interact with marketers. On the other hand, the results indicate that trialability influences perceived usefulness, which in turn influences intention to adopt mobile wallets. Similarly, peer pressure influences perceived ease of use, which in turn influences intention to adopt mobile wallets.

Table 6: Path Coefficients and Hypothesis

Hypothesis (Model Paths)	Betas	t	p	Hypothesis
Compatibility -> PU	0.1589	1.6577	0.098	Rejected
Observability -> PU	0.1112	1.4694	0.142	Rejected
Peer Pressure -> PEOU	0.2952	2.8799	0.004	Supported
Perceived Ease of Use -> BI	0.3744	2.7947	0.005	Supported
Perceived Ease of Use -> PU	0.4175	4.8661	0.000	Supported
Perceived Usefulness -> BI	0.4068	3.6202	0.000	Supported
Security & Privacy -> PU	-0.0801	1.2667	0.206	Rejected
Subjective Norms -> BI	0.1551	1.4363	0.152	Rejected
Subjective Norms -> PP	0.8049	17.8624	0.000	Supported
Subjective Norms -> PEOU	0.5706	5.7598	0.000	Supported
Trialability -> PU	0.3638	3.9561	0.000	Supported

5. Discussion

The mobile wallet is a recent technological advance in the mobile marketing arena. Although it is often viewed as a mobile payment system that offer consumers tremendous convenience when shopping, it can do much more than payments. Mobile wallets can facilitate personalized marketing where consumers can get marketing messages and product information tailored to them based on their location, unique socio-demographic characteristics, and shopping patterns and preferences. This can enhance the efficiency of the consumer buying process while simultaneously providing marketers with lots of information about consumers. The information collected could be used to build better consumer relationships and better serve their needs. Thus, understanding the drivers of adoption of mobile wallets is an important concern for marketers. In addition, our literature search indicates that there is a lack of academic research on mobile wallets. Thus, the goal of this study was to identify the factors that are likely to drive the adoption of mobile wallets. Following a review of the technology adoption literature, it was determined that the technology adoption model (TAM) and innovation diffusion theory (IDT) maybe relevant since they have been used in several similar studies of technology adoption. Relevant factors from these two models were combined to form a theoretical model, which guided our data collection and analysis.

The results of this study have several important implications for marketers and researchers. From a marketing perspective, the significance of trialability on perceived usefulness and ultimately adoption intention means that marketers can enhance the pace of mobile wallets adoption by using trials to show customers the benefits of mobile wallets. In addition, the fact that privacy and security concerns were not significant influencers in consumers' adoption decision should not necessarily be interpreted as these factors are not important. Rather, it seems that consumers appear willing to lay these concerns aside in order to enjoy the benefits of mobile wallets. Thus, marketing strategies should emphasize that mobile wallets do not only offer many benefits but that they are also safe and secure. The nonsignificant direct effect of social norms on adoption was surprising but the effects seem to be indirect through peer pressure, which suggests that mobile wallet adoption can be increased by using marketing tactics that emphasize the impact of others, for example by using advertisements that show peers and opinion leaders are happy with and comfortable using mobile wallets. These marketing communication messages should not only emphasize the benefits but also how easy it is to use mobile wallets.

From a theoretical perspective, this study is one of the earliest attempts to study the drivers of mobile wallet adoption. Further, it is one of a handful of studies to combine social norms and peer pressure in the same study as recommended by Celuch et al. (2011) and Salajan et al. (2011). The results suggest that when combined, social norms effect on adoption decision works indirectly through peer-pressure rather than directly. That is, peer pressure seems to reduce the direct effect of social norms, which is inconsistent with prior studies using TAM. Clearly, further testing is required to validate this finding. In addition, the lack of statistical significance of compatibility and observability suggest that some rethinking of the usefulness of these variables in future research may be warranted. One possible explanation for the lack of significance of these two variables could be because today's consumers are tech-savvy and uses a wide range of mobile technologies on a daily basis. Thus, their effects are nullified.

6. Conclusion

Mobile wallet is a recent innovation in mobile marketing. Mobile wallets are often described as convenient payment systems that eliminate the need for customers to carry credit cards, cash, and debit cards. However, it is has the potential to offer a wider range of benefits including the ability to link their loyalty cards to their mobile wallets, store online shopping accounts and details, receive product information, coupons, special offers and promotions, make price comparisons, and enhance the customer shopping experience. For marketers, it provides information which can be used to build customer relationships and better serve their needs. However, before these benefits can be realized, consumers must adopt mobile wallets. This study aims to identify the factors that influence consumers' decision to adopt mobile wallets. A theoretical framework that combines elements from both the technology adoption model and the theory of innovation diffusion was developed and empirically tested using survey data obtained from 530 respondents. The results indicate that consumers' ability to try mobile wallets, perceived usefulness of mobile wallets as well as perceived ease of use are key factors that influence the adoption of mobile wallets. Interestingly, privacy and security did not affect consumers' adoption decisions. Similarly, social norms did not directly influence adoption decisions but its effect can be observed indirectly through peer pressure. The inclusion of both peer pressure and social norm in the same model was recently suggested by Celuch et al. (2011) and Salajan et al. (2011) and are used in only a few studies and the results are mixed. Further testing of these two constructs need to be undertaken in order to corroborate prior research. The results also provide insights that marketers could use to develop marketing communications strategies to encourage the adoption of mobile wallets.

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