A two-stage SEM-neural network analysis to predict drivers of m-commerce in India

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Abstract: The rapid developments in the field of mobile technologies and deep penetration of smartphones have created tremendous opportunities for m-commerce worldwide. The purpose of this study is to investigate factors that predict consumer's intention to adopt m-commerce. The study identifies variables relevant for m-commerce environment and empirically establishes their influence on m-commerce *adoption intention*. A two-stage analysis comprising of *structural equation modelling (SEM)* and *neural network (NN)* technique is employed to test the proposed model. The results obtained from SEM analysis observed that perceived risk is the strongest predictor of m-commerce adoption decision, followed by *performance expectancy*, *variety of services* and *perceived critical mass*. *Effort expectancy* is found to be statistically insignificant. The significant factors from *SEM* were used as inputs to *NN* model and the results established *performance expectancy* to be the most important input variable in predicting m-commerce *adoption intention* followed by *variety of services*, *perceived risk* and *perceived critical mass*. The findings of this study are useful for m-commerce marketers and service providers, in developing suitable marketing strategies to scale up their business. This study is one of the few empirical studies conducted in India to examine the *adoption intention* of m-commerce.

Keywords: m-commerce; perceived risk; variety of services; VOS; perceived critical mass; PCM; structural equation modelling; SEM; neural network; India.

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1 Introduction

The advancement in the internet technologies (3G, 4G) and the growing popularity of mobile communication devices (such as smartphones, tablets, netbooks, and laptops), has unlocked the power of m-commerce (also known as mobile commerce) as an alternative business model during the recent years. Mobile phone today is not just a tool to connect but a complex device offering wireless internet access, data transfer and numerous other advanced mobile services (Marinkovic and Kalinic, 2017; Thakur and Srivastava, 2013). Its usage has gone far beyond the function of merely connecting people to a host of other functions such as internet surfing, entertainment, online shopping and the like. All these reasons account for its increased popularity.

The term m-commerce was defined for the first time as "the delivery of electronic commerce capabilities directly into the consumer's hand, anywhere, via wireless technology" (Duffey, 1997). M-commerce and e-commerce have common fundamental principles for conducting business, i.e., conducting commercial transactions through an electronic medium. However, m-commerce can be considered as a step ahead (Coursaris and Hassanein, 2002). The name 'm-commerce' implies undertaking business transactions using wireless electronic devices. Many researchers define it as "enabling business transactions through wireless devices" (Dholakia and Rask, 2002; Müller-Veerse, 1999; Tiwari and Buse, 2007). It offers an additional advantage of mobility in combination with the advantages offered by the traditional e-commerce. It involves providing mobile devices such as smartphones, tablets, PDAs, etc. with the ability to transact (Antovski and Gusev, 2008).

The increasing penetration of mobile phones and changing preferences of consumers have led marketers to develop various mobile based applications, enabling consumers to enter into transactions using their mobile devices. The trend today has shifted from wired to wireless networks. However, according to various researchers, the growth of m-commerce varies from country to country (Marinkovic and Kalinic, 2017). This implies that there exist certain inherent factors which affect m-commerce adoption.

Previous research in this field indicated a fair success of m-commerce in developing economies like China, Malaysia, Kenya and the Philippines as compared to a large number of other nations with similar socio-economic and demographic characteristics (Qiang, 2009). This difference is largely attributed to the fact that in developing nations

mobile phones are more widely penetrated whereas penetration of financial services such as banking, insurance, and trading services is still limited. India is a developing nation and having mobile phone penetration of almost 74% (wireless teledensity of 74.16%) (TRAI Press Release, 2014), has a great potential for m-commerce services. However, actual adoption is still low (Thyagarajan, 2015). This shows that there exist certain factors hindering its adoption among Indian consumers.

India's m-commerce market is still in the phase of infancy. The problem lies at the consumers' end with respect to their intention to accept new technology (Faqih, 2016; Wu and Wang, 2005). It is expected that with a deeper understanding of factors influencing consumers' decision to undertake purchase and sale transactions over mobile devices, m-commerce opportunities will continue to multiply.

Most of the researches so far have utilised analysis methods such as regression and structural equation modelling (SEM), to map factors affecting m-commerce adoption (Chong et al., 2012; Islam et al., 2011; Lin and Wang, 2005; Marinkovic and Kalinic, 2017; Sreenivasan and Noor, 2010). Such methods aim at establishing relationship between these factors and m-commerce adoption. Only a few have attempted to use predictive modelling methods such as neural network (NN) technique to predict factors affecting m-commerce. NN technique is believed to be more accurate in predicting and capturing non-linear numerical relationships between the predicting variables and the output (Chong, 2013a, 2013b). Hence the purpose of this study is threefold. First, the study identifies various factors that influence new technology adoption such as m-commerce. Second, it proposes an integrated framework predicting *adoption intention* (AI) in m-commerce domain. Third, it empirically examines the framework by explanatory and predictive modelling methods.

This study is organised into three major parts. The first part deals with the identification of important factors affecting m-commerce adoption through reviewing the available literature on technology adoption. The second part includes the proposed framework of the study, and its analysis. The discussion and conclusion is presented in the final part of the study. The findings of this study can help marketers and service providers in designing appropriate marketing interventions to improve the scope of m-commerce as an alternative business model.

2 Literature review

2.1 m-commerce

The term 'm-commerce' was used for the first time in 1997, since then numerous researchers have defined m-commerce in many ways. Most researchers argued m-commerce to be any monetary transaction (i.e., buying and selling of goods and services) conducted using mobile devices over mobile telecommunication network (Chong, 2013a; Dholakia and Rask, 2002; Müller-Veerse, 1999; Tiwari and Buse, 2007). A broader view of m-commerce defines it as a wide range of business activities that precede and follow the actual transaction of sale (Adam et.al., 1998; Turban et al., 2000). It involves all such activities that are related to a potential commercial transaction

conducted over a wireless network via some handheld mobile device such as a smartphone, laptop, palmtop or tablet (Tarasewich et.al., 2002). Another view which considers m-commerce to be an extension or a step forward of e-commerce defines m-commerce as 'an e-commerce for users on the move' (Vittet-Pilippe and Navarro, 2000).

M-commerce involves a new set of services, business models, and technologies. It is different from the traditional e-commerce in a way that it is a step ahead. E-commerce is the electronic exchange (delivery or transaction) of information, goods, services, and payments over telecommunications networks (Adam et al., 1998; Turban et al., 2000). M-commerce, along with the advantages of traditional e-commerce also offer additional advantages of mobility and locatabilty (Dholakia and Rask, 2002). The difference between e-commerce and m-commerce exists in the mode of communication (wired local area network in case of e-commerce and wireless network in case of m-commerce), the types of internet access devices (wired devices in case of e-commerce such as desktops, laptops, etc. and wireless devices in case of m-commerce such as mobile phones, PDAs, etc.) the development languages and communication protocols (HTML in case of e-commerce and WML or cHTML in case of m-commerce), as well as technologies supporting each environment (Coursaris and Hassanein, 2002).

Undoubtedly the constraints imposed by mobile devices such as smartphones, are very different from those imposed by desktop computers. Small screen sizes, limited bandwidth, are few of the constraints in m-commerce. However, these constraints, in fact, have led to the development of some mobile-based applications, which makes it possible to access the internet wherever you go (Sadeh, 2002).

2.2 Factors affecting adoption of m-commerce

Researchers around the globe have developed models to explain *AI* of technologies similar to m-commerce. Notable among them are *theory of reasoned action* (TRA) (Fishbein and Ajzen, 1975), *technology acceptance model* (TAM) (Davis, 1989), *technology-organisation and environment* framework (TOE) (Tornatzky and Fleischer, 1990), *theory of planned behaviour* (TPB) (Ajzen, 1991), *diffusion of innovation* (DOI) (Roger, 1995) and *unified theory of acceptance and use of technology* (UTAUT) (Venkatesh et al., 2003). Most of these theories have adopted principles from the field of psychology, marketing and IT to understand the *AI* of various *IT/IS* at individual and firm level. The robustness and explanatory power of these models vary especially in the backdrop of advancement in *IT/IS* and changing nature of consumer behaviour (Tan et al., 2013). Such frameworks have been widely used to understand the adoption and diffusion process across disciplines ranging from marketing and social psychology to a new information system (Williams et al., 2015). The present study is based on the assumption that mobile-based technological platforms are passing through a stage of rapid transformation. Therefore, it is imperative to extend the traditional theoretical framework of *IT/IS* adoption to address the requirement of frequently changing and developing mobile technology environment. Hence, it identifies variables and proposes a relevant framework to address the requirement and inherent characteristics of m-commerce ecosystem.

Table 1 Constructs and their literature support

Constructs	*Number of items*	*Sources*
Performance expectancy (PE)	4	Venkatesh et al. (2003), Bax and McGill (2003), Kleijnen et al. (2007), Sreenivasan and Noor (2010), Chong et al. (2012), Yang (2010) and Slade et al. (2015)
Effort expectancy (EE)	3	Venkatesh et al. (2003), Kleijnen et al. (2007), Sreenivasan and Noor (2010), Chong et al. (2013), Yang (2010) and Slade et al. (2015)
Perceived risk (PR)	4	Turban et al. (2000), Kleijnen et al. (2004), Wu and Wang (2005), Wei et al. (2009), Islam et al. (2011), Zhang et al. (2012), Thakur and Srivastava (2013), Chong et al. (2012) and Chong (2013a, 2013b)
Variety of services (VOS)	4	Sadeh (2002), Anckar (2002), Islam et al. (2011) Chong et al. (2012) and Chong (2013a, 2013b)
Perceived critical mass (PCM)	3	Hsu and Lu (2004), Cheng et al. (2012) and Hsu and Lin (2016)
Adoption intention (AI)	3	Riquelme and Rios (2010), Islam et al. (2011), Chong (2013a, 2013b), Thakur and Srivastava (2013), Zhang et al. (2012) and Hanafizadeha et al. (2012)

2.2.1 Performance expectancy

It refers to the extent to which users consider using a new system or new technology useful in improving their job performance (Venkatesh et al., 2003). It was introduced as an important construct in the *TAM* (Davis, 1989) with the name *perceived usefulness*. *TAM2* (Venkatesh and Davis, 2000) as well as, *TAM3* (Venkatesh and Bala, 2008), also included this factor. It was also considered by the *UTAUT* model (Venkatesh et al., 2003) and its extended version *UTAUT 2* (Venkatesh et al., 2012). Other than the mentioned models, various researchers have also considered the role of this factor to be significant in determining *AI* for various *IT/IS*, (Bax and McGill, 2003; Chong et al., 2012; Kleijnen et al., 2007; Madan and Yadav, 2016; Sreenivasan and Noor,2010; Sharma and Yadav, 2011; Slade et al., 2015; Yang, 2010).In the context of m-commerce, increased time effectiveness, mobility as well as anytime, anywhere usage options offered by it, might enhance performance levels of an individual in his daily job. Consumers can easily search for information about a specific product, such as the detailed ingredients of a food item or the detailed specifications of a technical device on their mobile devices (Shaw and Sergueeva, 2016). Hence, this study proposes that:

H1 *Performance expectancy (PE)* has a positive influence on consumer's m-commerce *AI*.

2.2.2 Effort expectancy

Effort expectancy (EE) refers to the degree of ease in using a system or technology (Venkatesh et al., 2003). Previous researchers have considered *EE* as another important factor influencing *AI* of similar technologies (Chong, 2013a, 2013b; Kleijnen et al., 2007;

Sreenivasan and Noor, 2010; Slade et al., 2015; Yang, 2010). It was another important factor in TAM (Davis, 1989) with the name *perceived ease of use*. It refers to the extent to which a new technology or system is useful and easy enough for consumers to adopt. The variable is also included in *TAM2* model, an extension of *TAM* (Venkatesh and Davis, 2000) as well as *TAM3* (Venkatesh and Bala, 2008). The *UTAUT* model (Venkatesh et al., 2003) for organisation information system, also considers *EE* to be an important factor in determining consumers' *AI*. Mobile commerce requires transacting via mobile apps. With this wide variety of apps, users will try new functionality, only if it is easy to use (Shaw and Sergueeva, 2016). The ease with which users can transact over mobile devices via mobile apps will influence their decision to adopt mobile commerce. Hence, this study proposes that:

H2 *EE* has a positive influence on consumer's m-commerce *AI*.

2.2.3 Perceived risk

Perceived risk (PR) refers to financial, social, physical, psychological, time and product associated risks consumers undertake while making transactions online (Wu and Wang, 2005). Important personal information is usually stored on users' mobile phones, and therefore security and privacy risks involved in m-commerce transactions can be quite high (Chong, 2013a). M-commerce involves undertaking financial transaction over mobile devices, which is perceived to be risky by the users. Numerous researchers have considered this factor to be significant in explaining mobile technology adoption rate (Chong et al., 2012; Islam et al., 2011; Kleijnen et al., 2004; Madan and Yadav, 2016; Natarajan et al., 2017; Thakur and Srivastava, 2013; Zhang et al., 2012). Another major factor considered in determining m-commerce *AI* is *trust* (Chong et al., 2012; Chong 2013a, 2013b; Marinkovic and Kalinic, 2017; Wei et al., 2009; Zhang et al., 2012). *Perceived trust* may be explained as the degree of trust consumers have on m-commerce application providers with respect to their reputation, security, and privacy policies followed by them, which influence m-commerce *AI* (Chong, 2013a, 2013b). Since trust and risk have close inter-relationships, for the purpose of this study *PR* and *trust* are combined to form one factor, i.e., *PR*. (Chong et al., 2012; Turban et al., 2000). Hence, this study proposes that:

H3 *PR* has a negative influence on consumer's m-commerce *AI*.

2.2.4 Variety of services

The variety of m-commerce services currently being offered by service providers can be classified into five major categories: firstly entertainment services (games, music, video, graphic), secondly communication services (messaging, e-mail, video conferencing and chat rooms), thirdly transaction services (shopping, banking, auctions, booking and reservations, betting, mobile wallet, voting, and competition/contests), fourthly information services (maps, news, city information, traffic and weather, mobile advertising, market data and corporate information) and lastly Database Services (telephone directory, restaurant guide, dictionary, etc.) (Islam et.al., 2011; Sadeh, 2002). Although m-commerce has many applications, the variety of services (VOS) offered by it might not be comparable to services offered by e-commerce websites (Chong et al.,

2012). Thus, variety of m-commerce services available also affects m-commerce *AI* (Anckar, 2002; Chong, 2013a, 2013b). Hence, this study proposes that:

H4 *VOS* has a positive influence on consumer's m-commerce *AI*.

2.2.5 Perceived critical mass

Perceived critical mass (PCM) is defined as the degree to which an individual believes that a particular technology or a system would be used by mass of people (Hsu and Lin, 2016). Earlier researchers have found that a users' intention of using a particular system or network increases once the number of existing participants reaches a decent number (Lin and Lu, 2011). Factors similar to this construct have been considered by various earlier researchers to determine usage intention of similar technologies related to the internet, e-commerce, mobile banking and the like (Cheng et al., 2012; Hsu and Lu, 2004; Hsu and Lin, 2016). In the context of m-commerce, the number of people using m-commerce in an individual's referent group might have an influence on his intention to use it. Hence, this study proposes that:

H5 *PCM* has a positive influence on consumer's m-commerce *AI*.

3 The conceptual model

Thus, the study proposes a conceptual framework in which *PE*, *EE*, *PR*, *VOS*, and *PCM* are treated as independent variables and analyses their impact on *AI*, a dependent variable.

Table 2 Measures/items, factor loadings and reliabilities

S. no.	*Name of dimension*	*Standardised regression weights*	*Coefficient alpha*
ID1	*Effort expectancy*		*0.792*
1	I think it is easy to learn how to use m-commerce	0.64	
2	I think less time and mental effort is required in learning how to use m-commerce.	0.79	
3	I think m-commerce is easy to use.	0.81	
ID2	*Performance expectancy*		*0.882*
1	M-commerce improves my current job performance.	0.77	
2	M-commerce increases my productivity.	0.92	
3	M-commerce increases my time effectiveness.	0.77	
4	M-commerce is useful for my work.	0.79	
ID3	*Perceived risk*		*0.902*
1	I feel my personal information provided during m-commerce transactions will be kept safe.	0.89	
2	I feel that payments made for m-commerce transactions will be processed in a secure manner.	0.86	

Table 2 Measures/items, factor loadings and reliabilities (continued)

S. no.	*Name of dimension*	*Standardised regression weights*	*Coefficient alpha*
ID3	*Perceived risk*		*0.902*
3	I feel there will be no risk involved while using my credit card or bank account details for making m-commerce payments.	0.86	
4	I think m-commerce firms follow honest practices.	0.74	
ID4	*Variety of services*		*0.909*
1	Variety of m-commerce services offered fits my current lifestyle.	0.80	
2	M-commerce services currently offered appeals to me and attracts me to avail them.	0.82	
3	M-commerce services offered are according to my requirements.	0.88	
4	Current m-commerce services offered meets my expectations.	0.88	
ID5	*Perceived critical mass*		*0.877*
1	People who are important to me frequently use mobile commerce.	0.80	
2	Most people in my community and peer group frequently use mobile commerce.	0.87	
3	Using mobile commerce is a common social trend.	0.86	
D1	*Adoption intention*		*0.932*
1	I will definitely avail m-commerce services in future.	0.97	
2	I will continue availing m-commerce services in future as well.	0.82	
3	I will refer m-commerce services to my friends and family.	0.79	

4 Research methodology

4.1 Participants

An online survey was conducted among the respondents who have entered into at least one m-commerce transaction using their mobile phone during last six months. The survey instrument was sent to 336 postgraduate students of academic institutions and working professionals of various multinationals located in Delhi NCR. Delhi NCR attracts students and professionals from all over India, representing a cosmopolitan population (Yadav et al., 2016). Also, a majority of them are young and perceived to be more technology savvy (Davis, 1989; Hanafizadeh et al., 2012; Yadav et al., 2016). Hence, the sample is considered as a good representative of the research area and population under consideration.

4.2 Constructs measurement

The study proposes the hypothetical interrelationships between five independent factors and one dependent factor. *PE*, *EE*, *PR*, *VOS* and *PCM* were considered to be independent factors affecting the dependent factor *AI*. Collectively 18 items were used to measure predictors and three items for AI (dependent variable). Items used to measure each of the independent, and dependent variables are given in Table 2. All the items were measured on a Likert Scale ranging from 1 (as strongly disagree) to 5 (as strongly agree).

4.3 Data collection and sampling

The study uses the basic framework of descriptive research design. The survey form was divided into two parts. First part obtained information on demographic and socio-cultural dimensions. The second part dealt with the collection of information on proposed model. The sampling frame considered for the study comprised of students and working professionals residing in Delhi NCR. Due to the nature of the sampling frame, conducting systematic random sampling was not feasible; hence, the present study used non-probability sampling techniques. Judgement sampling method was used to collect data in the pilot testing phase and convenience sampling for data collection for the main analysis. Such practice is in line with other studies conducted to understand the AI of different IT/IS in recent past (Chong, 2013a; Püschel et al., 2010; Tiruwa et al., 2016). During the pilot phase, an offline survey was conducted among experts and peers to get a true feeling of the research as well as to take suggestions from the respondents. In the final phase, an online survey form was used. 2013 respondents replied to the e-mail and constituted the sample for this study. However, a minimum sample size of 10 samples per independent factor was achieved (Hair et al., 2010).

4.4 Data analysis technique

For the purpose of this research, a two-staged analysis was conducted utilising *SEM* techniques and *NN*. The results obtained from *SEM* analysis were further integrated with the results of *NN* analysis to capture any non-linear relationships existing among the independent and dependent variables of this research. The factors which were found significant in the first stage of analysis, i.e., *SEM* analysis were used as input variables for the *NN* model.

4.4.1 Structural equation modelling

To capture linear relationship and to establish causal effect between the predictors and the m-commerce *AI*, *SEM* technique was utilised. A model was created in *IBM SPSS AMOS*, and the proposed hypotheses were tested. *SEM* has been widely used by earlier researchers to establish and test relationships between various independent and dependent variables. (Akturan and Tezcan, 2012; Yang et al., 2012; Chong, 2013a, 2013b; Hanafizadeh et al., 2012; Riquelme and Rios, 2010) In accordance with the previous studies conducted on similar lines, *SEM* was considered as a suitable data analysis technique to form the first stage analysis for the present study as well.

4.4.2 NN model

NN model is a tool used by researchers to map complex relationships between independent and dependent variables. "An artificial *NN* is usually defined as a network composed of a large number of simple processors that are massively interconnected, operate in parallel, and learn from experience" (Specht, 1991). Its working is similar to a human brain; the model is trained first with knowledge acquisition and then based on the training, the predictive capacity of the model is tested. Previously, *NN* has been used by researchers in various fields such as stock markets (Shen et al., 2011), m-commerce (Chong, 2013a, 2013b), internet banking (Sharma et al., 2015), mobile banking (Sharma et al., 2017a), and e-learning (Sharma et al., 2017b). The primary reason for its increased application in business research is its flexibility in terms of learning and handling varied data, its computational power to capture non-linear relationships along with the linear relationships and its ease of use (Sharma et al., 2017a, 2017b). *NN* technique is believed to be more accurate in predicting and capturing non-linear numerical relationships between the predicting variables and the output (Chong, 2013a, 2013b). Hence, *NN* modelling was used to accomplish the second stage of analysis in this study.

Table 3 Demographic analysis

Sample characteristics	*Frequency (n = 203)*	*Percent (%)*
Age		
Less than 30 years	144	71%
30–45 years	41	20%
Above 40 years	18	9%
Gender		
Male	155	76%
Female	48	24%
Family income per month		
Less than Rs. 75,000	57	28%
Rs. 75001 to Rs. 1,50,000	63	31%
Above Rs. 1,50,000	83	41%

5 Data analysis and results

5.1 Demographic profile

The demographic profile of the respondents is presented in Table 3. It is observed from the table that male respondents constituted 76% of the sample. The reason behind such a turn-out could be that females are still hesitant in using new technologies as compared to their male counter-parts (Venkatesh and Morris, 2001). Moreover, 71% respondents were below the age of 30 years. Only 9% respondents were above 45 years. This means that majority of the respondents considered for the study were youngsters. It was justified as the study required data collection from individuals who have entered into at least one m-commerce transaction using their mobile phone during last six months and younger generation is more active in using online services (McMillan and Morrison, 2006).

Finally, the average family monthly income of 72% respondents was over and above INR 75,000. This again is reasonable since mobile commerce requires accessibility to some necessary equipment, internet connection, knowledge as well as a high degree of interest in using new technology which can be observed in individuals of this income group.

5.2 Validity and reliability of constructs

Table 5 shows the results of reliability and validity test of the *measurement model*. The study tested two types of validities namely: *convergent validity* and *discriminant validity* along with the *reliability* of the constructs.

Table 4 Reliability and validity

Factors	*Cronbach's alpha*	*Average variance extracted (AVE)*	*Maximum shared squared variance (MSV)*	*Average shared squared variance (ASV)*
Effort expectancy (EE)	0.792	0.567	0.533	0.355
Performance expectancy (PE)	0.882	0.661	0.527	0.383
Perceived risk (PR)	0.902	0.705	0.530	0.358
Variety of services (VOS)	0.909	0.695	0.555	0.436
Perceived critical mass (PCM)	0.877	0.706	0.275	0.135
Adoption intention (AI)	0.932	0.835	0.555	0.452

It can be seen from Table 4 that alpha value is ranging from 0.797 to 0.933, which is greater than the widely accepted range of 0.7, therefore demonstrating reliability of data. *Average variance extracted (AVE)* is also more than 0.5 (ranging from 0.574 to 0.837) which further ensures *convergent validity* (Hair et al., 2006). *AVE* is also greater than *MSV* and *ASV*, which shows that the data has *discriminant validity* as well (Hair et al., 2006).

5.3 Measurement model

Confirmatory factor analysis was conducted in *AMOS* to test the *measurement model*. Five common model fit measures were used to assess the model's overall goodness of fit: the ratio of X^2 to degrees-of-freedom (*d.f.*), comparative fit index (*CFI*), goodness-of-fit index (*GFI*), normalised fit index (*NFI*) and root mean square error of approximation (*RMSEA*).

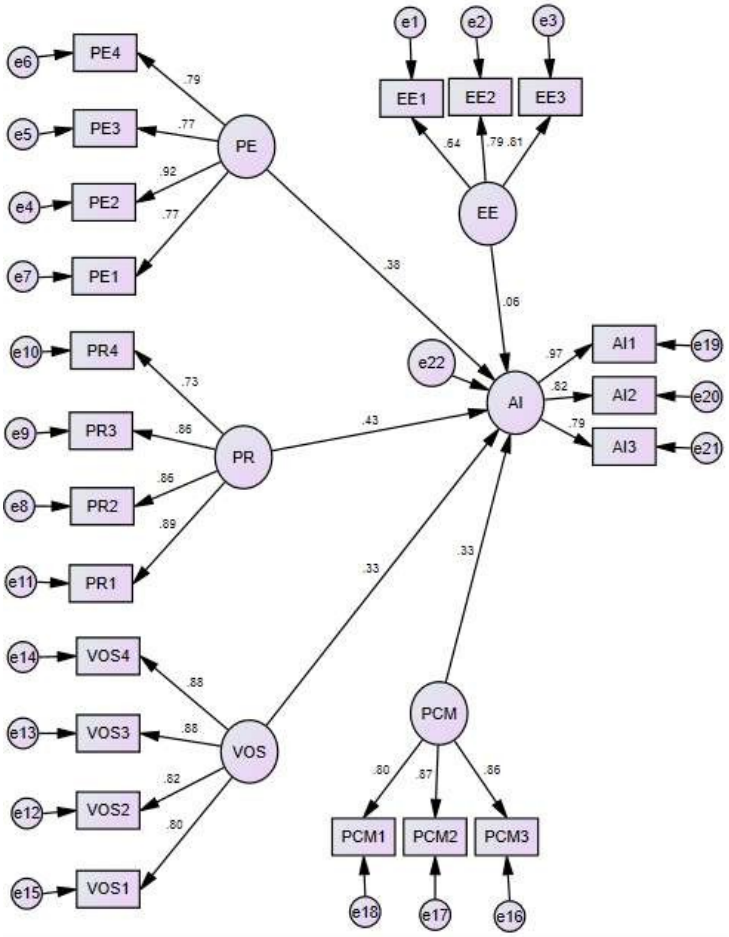
Table 5 demonstrated the model fit measures. The value of the *GFI* more than or equal to 0.9 shows a good enough fit (Baumgartner and Homburg, 1996). *CFI* and *NFI* values greater than 0.9 are widely accepted to demonstrate a good model fit. (Hu and Bentler, 1999) Since the values of *CFI*, *GFI* and *NFI* are coming out to be almost 0.9 or more than 0.9, it can be said that the *measurement model* observed a good fit with the data collected. *RMSEA* another measure used to assess goodness of fit of the proposed

model is less than 0.1which further confirms the fitness of the model (Hu and Bentler, 1999) *C-min/d.f.* value is less than 5 which again demonstrate a better model fit (Schumacker and Lomax, 2004).

Table 5 Overall fit indices for measurement model

Model elements	*Values*
C-min	360.151
Degrees of freedom (d.f.)	173
C-min/d.f.	2.082
Root mean square error of approximation (RMSEA)	0.073
Comparative fit index (CFI)	0.944
Normalised fit index (NFI)	0.899
Goodness-of-fit index (GFI)	0.855

Figure 1 Structural model constructed using AM (see online version for colours)



5.4 Structural model

Once reliability and validity of data were confirmed, a *structural model* was constructed in *AMOS* (see Figure 1) and following output was generated.

Table 6 shows *p*-values for each construct; it can be observed that *p*-values are coming out to be less than 0.05 for all the factors other than *EE*, further supporting our hypothesis *H1*, *H3*, *H4* and *H5* and rejecting hypothesis *H2*. Moreover, according to the β values, *PR* (β = 0.43) is appearing to be the strongest predictor of m-commerce adoption in this study, followed by *PE* (β = 0.38) and then *VOS* (β = 0.33) and *PCM* (β = 0.33).

Table 6 Structural results

Hypotheses	*S.E.*	*p-value*	*Remarks*
H1	0.06	< 0.001	Supported
H2	0.38	0.238	Not supported
H3	0.43	< 0.001	Supported
H4	0.33	< 0.001	Supported
H5	0.33	< 0.001	Supported

Table 7 RMSE for ten NNs

Networks	*Training*	*Testing*
ANN1	.302	.364
ANN2	.357	.206
ANN3	.325	.305
ANN4	.316	.332
ANN5	.278	.405
ANN6	.303	.388
ANN7	.330	.390
ANN8	.376	.233
ANN9	.333	.261
ANN10	.371	.323
Mean	*0.329*	*0.321*

5.5 NN model

The *NN* model developed in *SPSS* was trained using the *multilayer perceptron (MLP)* training algorithm. *RMSE* was used to measure the accuracy of the network model. Further, the model was run by varying the number of hidden nodes from one to ten. Such an act is in line with previous studies (Wang and Elhag, 2007; Chong, 2013a, 2013b; Sharma et al., 2015). Hence, a *ten-fold* cross validation algorithm was utilised to arrive at the average cross-validated *RMSE* for the training and testing model (Chong, 2013a, 2013b; Wang and Elhag, 2007). 70% of the data collected was utilised to train the *NN*, and the remaining 30% was utilised to test the trained model with respect to its predictive accuracy. The significant factors found in *SEM* analysis, i.e., *PE*, *PR*, *VOS*, and *PCM* were taken as the input variables to predict the output variable, i.e., m-commerce *AI* in

the *NN* analysis (Chong, 2013a). Table 7 shows the *RMSE* generated for the *training model* as well *testing model*. The average *RMSE* for the training model was 0.329, and for the testing model was 0.321 (see Table 7).

5.6 Sensitivity analysis

Table 8 depicts the average importance of each input variable in predicting mobile commerce *AI*, i.e., the extent to which the model predicted values varies with any change in the different input variables. From the table, it can be observed that *PE* is the most important input variable in predicting the output followed by *VOS*, *PR*, and *PCM* (see Table 8).

Table 8 Independent variable importance

Constructs	*Importance*	*Normalised importance*
Performance expectancy (PE)	.2895	1
Perceived risk (PR)	.2424	.8373
Variety of services (VOS)	.2677	.9247
Perceived critical mass (PCM)	.2004	.6922

The research methodology used for the purpose of the present study suffers from a few limiting factors. The study utilised non-probability sampling techniques such as judgment and convenience sampling for data collection. Further, the respondents belonged to different demographic categories in a disproportionate manner which might influence the results of the study.

6 Discussions

The study empirically tested the relationships between five independent and one dependent variable through a two-staged analysis. The selection of the variables was made in line with the requirement of mobile based technological processes which is perhaps, passing through the stage of rapid changes. Hence, an integrated framework was used to test the hypotheses. The *SEM* analysed the linear relationships between the independent and dependent variable and observed that *PE*, *PMC*, and *VOS* have a positive and significant influence on respondent's mobile commerce *AI*, whereas *PR* has a negative and significant influence. Surprisingly, results further observed that *EE* have no significant influence on *AI*, contradicting several previous studies. (Chong, 2013a; Pagani, 2004; Zhang et al., 2012)

The contradiction is largely attributed due to growing introduction of mobile apps which makes consumer experience with mobile phones free from major efforts. At the same time, the introduction and growing penetration of smartphones and youngster's preference towards large display size further reduce the degree of efforts one needs to put in to become skilful in using mobile phones for various purposes. Thus, it might be a reason for consumers not giving enough importance to the ease offered by mobile devices while entering into an m-commerce transaction. Issues like small screen size, low bandwidth and the like might create problems in easy browsing through mobile devices, but the benefits offered by m-commerce surely outnumber these issues.

According to the observation which is in line with past research, *PE* was found to have a significant and positive influence on *AI*. (Chong, 2013a, 2013b; Hanafizadeh et al., 2012; Madan and Yadav, 2016; Riquelme and Rios, 2010) It is mainly due to the advantages and inherent characteristics of mobile commerce. The ubiquitous use, unwired connection, degree of personalisation and retrieval of information in a convenient manner are some of the usefulness and advantages which support mobile phone user's to adopt mobile commerce more frequently.

The present study also found that *PCM* was an important variable influencing *AI* towards mobile commerce. It is observed that family, peer group, friends and virtual social communities are important change agents in the behaviour of a person. As more of these people start to use a new technology, it has a strong motivational impact on an individual's behaviour as well to adopt that technology.

The study validated the findings of previous research in which *PR* emerged as another important variable having a significant negative influence on adoption of m-commerce. (Chong et al., 2012; Islam et al., 2011; Kleijnen et al., 2004) In comparison to other *IT/IS*, m-commerce is at a nascent stage. In a typical m-commerce transaction, the information is exchanged between the customer, company, telecom service provider, and payment gateway. Any breach of trust among these stakeholders leads to high degree of risk perceived. In addition to that, there exists limited awareness among the mobile phone users regarding the regulatory and legal support mechanism available in case any dispute arises while making such transactions. The mobile commerce companies, telecom service providers, and companies involved in payment processing are required to develop foolproof and multi-layer security systems to minimise any risk. Such a process would reduce the risk perceived by users in m-commerce transactions.

Increasing numbers of marketers are now integrating mobile technology into their business processes. Mobile phone devices are no longer treated simply as a communication device. Large varieties of services are being delivered to the customers through m-commerce. Free download of the mobile app, easy installation, and usage makes people more comfortable in availing wide spectrum of services offered through mobile phones. M-commerce companies can create a competitive advantage over e-commerce by investing in technology and processes which have the ability to deliver more *VOS* and transform the mobile phone into a powerful multipurpose device. Therefore, adding *VOS* have significant positive influence on a customer's m-commerce *AI*.

PE, *PR*, *VOS* and *PCM*, found as significant factors in the first stage of analysis were taken as inputs for the *NN* analysis. *PE* came out to be the most important input in predicting the *NN* model. Such a result can be justified by the advantages and inherent characteristics of mobile commerce which are expected to improve the users' performance level while dealing with their daily tasks.

7 Conclusions and implications

Over the years, significant investments have been made by public and private sector to create superior telecommunication network for the people around the world. As a result, the adoption of mobile phones created a novel story in the history of technology adoption and became fastest in comparison to any other technology adoption during the last couple of decades. The marketers are now converting this business opportunity of widespread

mobile penetration into higher sales by facilitating transactions through mobile devices and making serious efforts to encourage more and more customers to adopt it. Therefore, the intention of this paper was to identify important predictors for m-commerce adoption and empirically examine their influence on *AI* of m-commerce services. The results observed that *PE*, *PR*, *VOS* and *PCM* are important factors predicting m-commerce *AI*. By shifting the focus on these factors, marketers are expected to benefit in terms of increased acceptance and revenue generation through m-commerce.

The results obtained in this study have significant practical, managerial and research-oriented implications. Firstly, the *two-staged* analysis observed *PR* and *PE* to be most important factors influencing *AI* of m-commerce among consumers. Hence, it is suggested that various contributors in m-commerce value-chain, i.e., service providers, app developers, marketers, as well as regulatory authorities should emphasise on reducing the risk perceived by users while transacting over mobile devices and increase performance benefits offered by m-commerce in order to accelerate the acceptance and adoption of m-commerce by users.

Secondly, the present study was conducted in a developing country wherein marketers are indulging in m-commerce businesses with the anticipation of its quick and high diffusion. However, in India m-commerce adoption is still in its nascent stage. A sound understanding of factors motivating or impeding its adoption rate would be of great help for the industry to come out with suitable strategic framework aiming the growth of m-commerce adoption.

Thirdly, the study does not attempt to establish only the causal relationship between the independent and dependent factors. Rather, it also intent to predict the factors influencing consumers' *AI* towards m-commerce. The integration of *NN* model with the *SEM* technique is a relatively new approach to data analysis which can prove to be a useful tool for the future researchers in the m-commerce domain.

Finally, the results of this study can provide guidance to various m-commerce value-chain partners in formulating strategies to improve acceptance of m-commerce services among Indian consumers. It may also provide a direction to future researchers in conducting higher level researches in this area.

8 Limitations and future scope

The present study used non-probability sampling techniques such as judgment and convenience sampling for data collection. By increasing the coverage of the study, systematic sampling techniques such as stratified sampling can be employed which might improve the applicability of the results. Only five major factors were considered in this study which might influence m-commerce AI. However, there may be other factors such as facilitating conditions, cost, perceived enjoyment and the like, which influences users AI towards m-commerce. Further, the respondents belonged to different demographic categories in a disproportionate manner which might have influenced the results of the study. Future studies in this domain should emphasise on the inclusion of these additional constructs in the research framework to predict m-commerce AI. Also, the influence of these factors can be studied taking demographics into considerations. Consumers belonging to different demographic categories might have differing AIs as well. Another limiting factor for this study is the fact that m-commerce industry is still evolving in India

and the users' adoption behaviour may change along the process of this evolution. Hence, the results of the present study cannot be generalised for a long period.

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