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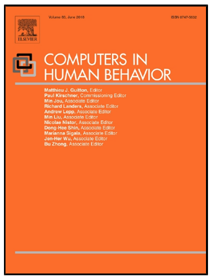

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Mobile shopping apps adoption and perceived risks: A cross-country perspective utilizing the Unified Theory of Acceptance and Use of Technology

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Abstract

Consumer adoption of mobile shopping apps is an emerging area in m-commerce which poses an interesting challenge for retailers and app developers. In this study, we adapt the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) to investigate factors predicting consumer behavioral intention (BI) and use behavior (UB) towards mobile shopping apps, considering the impact of two manifestations of consumer's perceived risk: Privacy Risk and Security Risk. Because cultural characteristics may moderate the impact of these risks on behavioral intention and use behavior, we conduct two studies from two consumer panels from countries with significant difference in technology use as captured by the Computer-Based Media Support Index (CMSI), namely India (high CMSI) and USA (low CMSI). For both countries, the baseline UTAUT 2 constructs predict the Behavioral Intention to use mobile shopping apps (and subsequently use behavior). However, the manifestations of perceived risk are significant only for the country with the highest CMSI score, suggesting that cultural influences play a strong role in the adoption of m-shopping. Our study has practical implications for theory as it poses the use of m-shopping apps in a cross-cultural context, suggesting that privacy and security moderate intention to use differently across cultures as predicted by the CMSI. From that perspective, it also has practical implications for consumer behavior researchers and app developers challenged with app localization as well as retailers designing mobile shopping apps for an intercultural audience.

Keywords Mobile shopping apps, UTAUT2, Privacy Risk, Security Risk, India, USA

1. Introduction

Mobile devices such as smartphones and tablets have substantially altered the user experience in electronic commerce, leading to the establishment of a whole new channel which retailers can use to provide more targeted offerings to their customers. This has given rise to m-commerce as "*an extension of e-commerce where business activities are performed in a wireless environment using mobile devices*" (Zhang et al., 2012). While m-commerce is rapidly growing and currently representing over one-third of global e-commerce transactions (eMarketer, 2016), several industry reports highlight its contributing importance as an initiation for conversion to other channels (e.g. in the case of Omni-channel shopping)[1]. However when compared with traditional web-based interfaces, mobile shoping has a significantly lower conversion rate in terms of customer checkout rates (Bhalla, 2016). From a digital marketing viewpoint, some researchers suggest that this can be due to the nature of mobile shopping as acting in the early stages of the purchase funnel (Ghose et al., 2012) where consumers search for products and assess their purchase fit. Nevertheless, limitations in interface navigation and network performance can also be considered as a major factor, with interruptions often cited as a contributing factor (T. Zhou, 2013). In that direction, companies are committing high levels of investment in creating and redefining their online shopping offerings through customized mobile shopping apps which are adapted to the interface cues of the mobile devices and allow features that can enhance customer convenience (e.g. the integration of checkout with in-device payment methods such as Apple Pay).

Nonetheless, a significant body of literature suggests that due to issues related to privacy and security, consumers are less committed to complete their purchases through their mobile

[1] Google and Nielsen (2013) Mobile search moments study. Available at: https://www.thinkwithgoogle.com/research-studies/creating-moments-that-matter.html

devices and as such they tend to complete their shopping journey on a medium that has more trustworthy features (Luo et al., 2010).

However, does this always hold true? Considering the global implications of digital channels, an ever-growing set of past research has identified the influence of cultural moderators on how a user's perceived risk is manifested through interacting with the interface and how this affects her usage behavior. This becomes important when an app's interface design decisions are considered and in particular how interface affordances can be designed to minimize users perceived risk, for example in the context of an app localization (Hoehle et al., 2016).

While m-shopping adoption has been studied in different contexts, not many studies have focused on the specific context that mobile apps aim to address (S. C. Kim et al., 2014). As such research into mobile shopping on shopping apps should provide a thorough understanding of the various factors influencing their adoption and use. Considering the above, a comprehensive model assessing the factors affecting the adoption and use of m-shopping apps and how the cultural setting might affect their use is important as it can inform both researchers and practitioners on understanding consumer behavior of m-shoppers. Based on the extant literature, this paper develops and empirically validates a research framework to predict consumer's behavioral intention and use of m-shopping apps using the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) from Venkatesh et al., (2012) for studying the various drivers affecting m-shopping acceptance through mobile apps.

UTAUT 2 is suitable for our study due to the integration of three additional constructs, namely: *hedonic motivation*, *price value*, and *habit*, which are highly related to mobile shopping adoption and were not available on its initial conceptualization (Venkatesh et al., 2003, 2012). So far it has been used for explaining adoption behavior in many recent studies on various contexts of mobile commerce (Baptista & Oliveira, 2015; Hew et al., 2015; Teo et al., 2015; Wong et al., 2014). However little or no attention, to our knowledge, has been given in the specific context of mobile shopping apps acceptance and use. In this study, we make three contributions in that direction. First, we use the UTAUT2 to study the acceptance and use of mobile shopping apps in the context of m-commerce. Second, we complement the baseline UTAUT2 with manifestations of perceived risk in order to explore the context of uncertainty in mobile shopping based on (a) privacy risks and (b) transaction security. Third, we posit the adoption and use of mobile shopping apps in a cross-country setting (India and USA) in order to see how cultural dimensions may impact their manifestations.

The perception of risks among consumers is inherent in online transactions because of spatial and temporal separation from the retailers and acts as a deterrent to the adoption and use of new technologies. Most of the studies in m-shopping focus on factors or drivers of acceptance than of barriers (Groß, 2015) and hence the influence of potential obstacles like trust, privacy and security issues on consumers m-shopping behavior needs to be explored further. With more individuals using their mobile devices for activities like online shopping, bill payments, and gaming, the mobile threat perceptions are on the ascendency. Moreover, Issues related to malware, mobile networks constraint, and content issues present serious privacy and security risks for mobile consumers. Perceived risk has been found to negatively influence the behavioral intention and use behavior of online consumers in numerous past studies. An increase in security risk perception can lead to users' resistance of mobile banking (Kuisma et al., 2007). Location based services also increase users' privacy concern and risk perception as reported by (T. Zhou, 2011).

Thus, to address the above issues identified in previous research, we have integrated privacy risk and security risk construct in conjunction with the UTAUT2 model to apprehend their impact on the behavioural intention and use of mobile shopping apps. Moreover, UTAUT2 exclusively deals with various drivers of consumers technology acceptance and use. Thus, we believe that incorporating perceived risk constructs in the study context will help in increasing the applicability and predictive power of the proposed model. To our knowledge, no study till date has investigated the impact of consumers privacy and security risk associated with mobile shopping apps in a cross-cultural context. Thus examining the effects of the two perceived risk constructs along with other predictors of UTAUT2 on consumers adoption and use of mobile shopping apps in two distinctive cultural settings is expected to engender actionable insights for both academia and industry.

The role of perceived risk, as a barrier of m-shopping apps use, is also explored by contrasting its influence in two consumer panels (India and USA) sourced from countries with a high difference in Computer-Based Media Support Index (CMSI) which was computed with the most recent values of the World Value Survey. The CMSI (D. Straub et al., 1997; Van Slyke et al., 2010) is a composite measure based on the most recent four core cultural dimensions defined by Hofstede et al. (2010) which allows the consideration of simultaneous effects of the cultural dimensions as an aggregate measure, rather than considering a factor by factor analysis on each dimension. For both panels, we control for gender, age, education and experience of mobile shopping. In addition to the contributions to the existing literature on m-shopping adoption, the results of our study provide rich insights to mobile app developers and stakeholders who face a localization challenge for introducing a mobile shopping app to consumers from different cultural backgrounds (and thus corresponding CMSI's).

When considering our cross-country evaluation for our study, we evaluated adoption stage of m-shopping technology between the two countries. Similar to other studies of technology acceptance of online shopping conducted in a cross cultural setting (Ashraf et al., 2014), the influence of adoption stage on technology acceptance is a significant factor affecting the interpretation of our results. Considering that India and the USA are in different parts of the adoption stage regarding smartphone and m-shopping use, we designed our study to consider sampling of respondents who are in a compatible adoption stage with more emphasis put on young respondents for our Indian sample. We provide a more thorough discussion of this on the methods section.

To this end this paper is structured as follows: First, it starts with the conceptual background of the study followed by reviews of relevant literature and the theoretical foundations of the research model. Subsequently, we formulate the research hypotheses building on the existing hypothesized paths of the UTAUT2. Next, we provide the research methodology and report the results from the two studies (India, USA) followed by a discussion of the results and implications. The last section discusses limitations and outlines the future research directions.

2. Conceptual Development

Figure 1 depicts the theoretical framework for our study and is based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) as defined by Venkatesh et al. (2003, 2012). Behavioral intention and use behavior of mobile shopping apps are posited as the primary constructs that their acceptance and use. Behavioral intention of m-shopping apps is driven by variables such as performance and effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habitual use, which are posited as key antecedents.

In this study, we extend the UTAUT 2 model by including two manifestations of perceived risks as first-order constructs, namely: security risk and privacy risk. These two constructs allow for the analysis and assessment of the influence that perceived risks exercise on the adoption of m-shopping apps when compared to the original UTAUT 2 (baseline model). All aforementioned constructs act as predictors. The relationships between the constructs are hypothesized based on an extensive literature review which justifies their integration into a parsimonious and coherent research model. We provide an overview of past research on m-shopping apps and the theoretical justification of the hypothesized relationships in the sections that follow.

***********INSERT FIGURE 1 AROUND HERE***********

2.1 Mobile Shopping acceptance and Mobile Shopping Apps

Mobile shopping (m-shopping) allows consumers to order goods and services using mobile devices without any time or space limitations (H.-P. Lu & Yu-Jen Su, 2009). Research on m-shopping is still in its infancy and primarily focused on various technology and user characteristics for predicting its adoption (S. Yang et al., 2012). A study by Ko et al. (2009) reported the role of perceived value as a mediator in determining the behavioral intention to adopt m-shopping for fashion products. In another study in Spain (Bigné et al., 2007) found that consumer demographics such as age, attitude, past experiences and relations with mobile device use to be the main predictors of m-commerce decision. A study of US consumers found performance expectancy, social influence and facilitating conditions as key drivers of intentions towards mobile shopping service (S. Yang et al., 2012).Wong et al. (2012) confirmed the role of perceived usefulness (PU), perceived ease of use (PEOU) and subjective norms (SN) on intention towards m-shopping. Table 1 provides an extensive review of the past literature on various areas of m-commerce adoption. For each study, we report the country context and the outcome variables.

Mobile shopping apps are applications designed to run natively on mobile devices like smartphones and tablets, sharing the same interface characteristics as the host operating system. In the two largest app repositories: *iTunes* (for iOS) and *Google Play* (for Android), there is a multitude of apps enabling mobile shopping such as discount and daily deal apps, price comparison apps, digital wallets and payment apps, branded apps from retailers, etc. Contextualizing our research inquiry to shopping app acceptance as the enabling factor driving m-shopping acceptance, academic research to date has focused on adoption and use of various types mobile apps, but little attention has been given explicitly to m-shopping apps and those factors influencing their acceptance. Taylor and Levin (2014) reported that the design elements of an app, affect user interest as well as the intention to purchase by using it. Zhao and Balagué (2015) propose that personalization and customization are critical to selling products in m-commerce apps. Previous studies on mobile interfaces have mostly focused on improving mobile app usability and visibility (Biel et al., 2010; Tarasewich, 2003), assessed the influence of demographic, psychological and behavioral factors on adoption of mobile apps (C. S. Lee et al., 2010; Verkasalo et al., 2010) as well as the influence of user reviews regarding their performance and acceptance (Huang & Korfiatis, 2015).

************INSERT TABLE 1 AROUND HERE************

2.2 Mobile Shopping Adoption stages and Mobile Shopping acceptance

Diffusion of innovation theory (Rogers, 2010) has provided solid theoretical and empirical evidence regarding the adoption of online shopping and several studies have examined this process in a national and cross-national setting (Ashraf et al., 2014). Mobile shopping as a spillover of online shopping is a global phenomenon, and several market research statistics suggest that the range of adoption is converging across the G20 countries, in-line with the reported economic progress[2]. From that perspective, the study of mobile (shopping) apps has an interesting dimension from the perspective that apps can be easily localized and thus simultaneously exposed across markets with their rate of adoption been dependent on the smartphone installed base and retailer specific policies when it comes to branded apps. This setting has an advantage over the adoption of other technological

[2] Market research mobile shopping Statista.

innovations such as the smartphone installed base, which with the rapid decrease in production costs has reached a late majority stage (per Roger's category) globally.

What is interesting for the positioning of our study is that cultural dimensions (such as those captured by Hofstede(Hofstede et al., 2010) can significantly alter adoption processes across a wide range of technological diffusions. Van den Bulte & Stremersch (2004) for example in a meta-analysis of Bass diffusion model parameters (Bass, 1969) examined the influence of cultural values and income on the shape of the diffusion process arguing that they significantly affect the social contagion aspect of the technological diffusion. Mahler & Rogers (1999) also examined this factor in the case of mobile banking services while Scaglione et al. (2015) discussed the influence of adoption externalities in mobile social network use across G7 countries. In the specific case of our study, the adoption of mobile shopping apps is dependent on the diffusion of devices and the platform availability. For the specific case of India which is in the late adoption stage India's e-commerce market which was worth about $3.8 billion in 2009, is expected to touch whopping $38 billion marks by 2016 and "m" is increasingly replacing the "e" in E-commerce[3]. The number of smartphone users in India who use shopping apps has jumped to 54% in May 2015, from just 21% in the year 2014[4]. As regards to age category segments, the adoption stage of 18-25 year old has been the fastest growing age segment of online buyers in India bringing the adoption stage in this segment on par with that in developed economies (USA).

2.3 The Unified Theory of Acceptance and Use of Technology: UTAUT and UTAUT2

Adoption theory examines the individual and the choices an individual makes to accept or reject a technological innovation (E. T. Straub, 2009; Van Slyke et al., 2010). Past research

[3] Assocham India "*E-Commerce Industry will cross $38 bln mark by 2016*" available at: www.assocham.org/newsdetail.php?id=5427 (accessed 06 May 2017).
[4]Nielsen Informate "Mobile shoppers turn app happy", available at: www.nielsen.com/in/en/insights/reports/2015/mobile-shoppers-turn-app-happy.html (accessed 18 June 2017).

has proposed several theoretical models in the area of user acceptance of new technology with the technology acceptance model (TAM) been the dominant framework in the literature (Venkatesh et al., 2003). From a consumer behavior point of view, studies utilizing TAM have been performed in various contexts in e-commerce, online banking, and m-commerce. However, shortcomings of TAM are also reported when considering consumer behavior characteristics. Lu and Su (2009) reported that studies using the technology acceptance model (TAM) have failed to consider negative emotions, beliefs in the level of ability, and intrinsic motivations. Benbasat & Barki (2007) have also recommended researchers to explore different constructs and models beyond TAM.

Following these developments, UTAUT was developed by Venkatesh et al. (2003) by combining eight well-known IT acceptance and usage models. The four core constructs which significantly determines the behavioral intention (BI) and subsequently, use behavior (UB) are Performance Expectancy (PE), Effort Expectancy (EE), Facilitating Conditions (FC), and Social influence (SI). Venkatesh, Thong, & Xu (2012) extended UTAUT to UTAUT2 by adding consumer behavior-specific factors namely: Habit (HA), Hedonic Motivation (HM), and Price Value (PV) thereby extending its generalizability from an organizational to a consumer context. The UTAUT2 explains more variance in both BI and technology use as compared to UTAUT. Venkatesh, Thong, & Xu (2012) further suggest that future research should increase the applicability of UTAUT to a wide range of consumer technology use contexts. Therefore, we have adapted the UTAUT 2 model as it is more comprehensive and suitable for explaining user behavior of mobile shopping apps. As in the original specification of UTAUT 2 we have included gender and experience as controls in our research framework to account for demographic influences on different app user segments.

2.4 UTAUT2 in the context of Mobile Shopping App use.

Performance Expectancy

Performance expectancy (PE) in communication technology implies that users consider the mobile app to be beneficial because it enables them to accomplish their goal-oriented tasks (Venkatesh et al., 2003). From a measurement point of view, PE extends the concept of perceived usefulness (PU) from the original specification of the Technology Acceptance Model (TAM). Adapting PE to the context of mobile shopping apps considers how users perceive the benefits they receive by the app enabling them to perform various online shopping activities. In the TAM context involving transactions, perceived usefulness (PU) was a significant antecedent of m-shopping intention (Aldas-Manzano et al., 2009) and the usage intention towards mobile financial services (Y.-K. Lee et al., 2012). In various cultural contexts, Performance Expectancy has been found to exhibit a significant positive relationship with the Behavioral Intention to adopt m-commerce (Chong, 2013; Lai & Lai, 2014). In a study in China, Lu and Su (2009) observed that Performance Expectancy significantly influenced individuals mobile services use. Following this reasoning, we hypothesize that the provisions that m-shopping apps provide to consumers such as convenience and fast checkout (e.g., through mobile payment integration and/or fast login through the mobile device) would increase their intention to use m-shopping apps. Thus, we have:

H1. Performance Expectancy has a positive effect on the Behavioral Intention to use mobile shopping apps.

Effort Expectancy

Effort expectancy (EE) is described as "*the degree of ease associated with consumers' use of technology*" (Venkatesh et al., 2012, p. 159). It is measured by extending the perceived ease of use (PEOU) from the Technology Acceptance Model with items capturing usage complexity and general ease of use. Many past studies have confirmed the positive impact of PEOU on the adoption of m-commerce (Khalifa & Ning Shen, 2008; Tsu Wei et al., 2009). Perceived ease of use (PEOU) is vital in the early stages of adoption of new technology and is empirically shown to have a significant influence on the intention to use mobile payments (S. C. Kim et al., 2014). EE has been found to have a significant positive relationship with BI to use mobile apps (Hew et al., 2015). In a study by Chan and Chong (2013), perceived ease of use (PEOU) exerts a significant positive effect on various m-commerce activities. In a study on user acceptance of mobile internet services, effort expectancy (EE) was shown to have a significant effect on behavioral intention to use (Wang & Wang, 2010). Teo et al. (2015) also reaffirmed this finding in the context of m-payments. Considering the checkout process as the major driver of effort in the shopping context we hypothesize that from a user perspective, m-shopping apps are easy to use and require less effort from her side, this would result in a higher intention to adopt and use them. Thus, we have:

H2. Effort Expectancy has a positive effect on the Behavioral Intention to use mobile shopping apps.

Social Influence and Facilitating Conditions

Social Influence has been studied under several contexts and can be classified into two categories: influence exercised from the media (both printed and digital) and interpersonal influence derived from the users' social network (Rogers, 2010). A study by Lu et al. (2005) found that subjective norm and image exercise a positive effect on perceived usefulness (or relative advantage). The significant role played by the subjective norm in influencing the behavioral intention to adopt mobile commerce has also been shown empirically by Bhatti (2007). In another study in China, Yang et al., (2012) observed a positive effect of SI on adoption intention of mobile payment service. Social Influence (SI) was found to be significantly and positively correlated to the intention to use m-commerce in a study in Malaysia (Tsu Wei et al., 2009). We hypothesize that the behavioral intention to use m-shopping apps of users is likely to be influenced by colleagues, friends, family members, other experienced users, and celebrities. Thus, we have:

H3. Social Influence has a positive effect on Behavioral Intention to use mobile shopping apps.

On the other hand, Facilitating conditions (FC) refer to consumers' perceptions of the resources and support available to perform a behavior (Brown & Venkatesh, 2005; Venkatesh et al., 2003). Using mobile shopping apps requires some resources and skills such as using a mobile phone or a tablet, connecting to the Internet, installing various applications, as well as knowledge of mobile service carriers and security. A favorable set of facilitating conditions will lead to greater intention to use shopping apps. Based on their empirical work Oliveira et al. (2014) found that facilitating conditions have a significant positive effect on m-banking adoption. FC has also been reported to positively influences the behavioral intention to use mobile apps (Hew et al., 2015). We hypothesize that favorable perceptions of users on facilitating conditions like support and/or getting help from others will result in high level of behavioral intention to adopt and use m-shopping apps. Thus we have:

H4a.Facilitating Conditions have a positive effect on behavioral intention to use mobile shopping apps.

H4b. Facilitating Conditions have a positive effect on the use of mobile shopping apps.

UTAUT2: Hedonic Motivation

Babin et al. (1994) suggest that Consumer's online shopping considers two types of motivations: Hedonic and utilitarian. Hedonic motivation (HM) refers to the enjoyment or pleasure derived from technology use, and it has been found to play a significant role in determining technology acceptance and use (Brown & Venkatesh, 2005). In technology acceptance research, hedonic motivation is conceptualized as perceived enjoyment (Venkatesh et al., 2012). Enjoyment is a kind of intrinsic motivation derived from performing an activity, and it strongly predicted the attitude towards online shopping as reported by Childers et al., (2002). Arnold and Reynolds (2003) provide six types of hedonic shopping motivations in online shopping, namely: value, role, adventure, social, gratification and idea motivation. Users who experienced enjoyment from using various mobile applications are more likely to adopt them (S. C. Kim et al., 2014). Yang and Kim (2012) suggest that m-shoppers usually get stimulated by hedonic rather than utilitarian shopping values. Various shopping apps are trying to bring an element of fun and enjoyment by adding features like voice search, personalization and social sharing to satisfy one of the dimensions proposed by Arnold and Reynolds, (2003). In our study, we hypothesize that the higher the perceived enjoyment of a mobile app user, the higher will be the behavioral intention to use the app. Thus, we have:

H5. Hedonic Motivation has a positive effect on Behavioral Intention to use mobile shopping apps.

UTAUT2: Price Value

In the context of UTAUT 2, Price value (PV) is defined as "*consumers' cognitive trade-offs between the perceived benefits and cost of using various applications*" (Venkatesh et al., 2012, p. 161). It may include the device and data costs, and other types of service charges where applicable. As such, the price value has a positive effect on use behavior when the benefits derived from using technology are perceived to be greater than the cost. From a theoretical viewpoint, PV follows from the concept of perceived value (Zeithaml, 1988). In a study in China, Liu et al. (2015) found that perceived value significantly influences behavioral intention towards mobile coupon applications. In generic mobile commerce contexts, perceived value has also been reported to have a significant positive effect on customer satisfaction and loyalty (Lin & Wang, 2006). In our study, we hypothesize that if the perception of PV when using m-shopping apps has greater benefits compared to the monetary cost (e.g., device cost or mobile internet charges), users are more likely to download and use m-shopping apps. Thus, we have:

H6. Price Value (PV) has a positive effect on the Behavioral Intention (BI) to use mobile shopping apps.

UTAUT2: Habit

Habit (HA) has been defined as the extent to which people tend to perform actions automatically because of learning (Limayem et al., 2007). In that context Habit or Habitual use reflects the multiple results of past experiences (Venkatesh et al., 2012) and the regularity of past behavior is considered to be one of the principal determinants of present behavior (Ajzen, 2002). Several studies have examined habitual use in a cross-national context. Baptista and Oliveira (2015) in a study of mobile banking in Mozambique reported that habit was found to influence behavioral intention and use behavior significantly and it was found as the most important antecedent of use behavior. In another study conducted in Malaysia, Hew et al. (2015) found habit to be the strongest predictor of behavioral intention to use mobile apps. Kim (2012) suggested that habit significantly influenced the actual usage of mobile data services and applications. As mobile shopping apps are also integrated into the loyalty strategy of the retailer by using it to track rewards and provide incentives, we hypothesize that this will lead to continuous use and habit formation which in turn will lead to higher behavioral intention and use behavior. Thus, we have:

H7a. Habit has a positive effect on the behavioral intention to use mobile shopping apps.

H7b. Habit has a positive effect on use behavior of mobile shopping apps.

Focal Constructs: Use Behavior (UB) and Behavioral Intention (BI)

Use behavior (UB) as a construct has been treated in the literature as the main construct describing the determinants of computer use behavior as a special case (Davis et al., 1989). Use behavior is not explicitly defined in UTAUT2 per se, and in the original specification, it was measured through the items available in the system register (Venkatesh et al., 2003). In the current study, we have adapted a multi-item scale from previous studies for measuring UB of m-shopping apps. We seek to explore the influence of various constructs related to UTAUT2 outlined below as well as the effect of manifestations of perceived risk on the use behavior of mobile shopping apps.

The main antecedent of UB in the UTAUT model is framed as the behavioral intention (BI) and has a single direct effect on individuals' actual use of a given technology. This construct is derived from the theory of Reasoned Action and is defined as 'a measure of the strength of one's intention to perform a specified behavior' (Davis et al., 1989, p. 984). The theory of planned behavior (TPB) also describes the strong correlation between behavioral intention and actual behavior (Ajzen, 2002). Several studies in the past have confirmed the powerful correlation between intention to perform a behavior and actual behavior (Dabholkar & Bagozzi, 2002; Lucas & Spitler, 1999; Vijayasarathy, 2004). Gro ß (2015) in an empirical study, suggested that consumers' m-shopping behavior is significantly determined by their behavioral intention to use m-shopping also confirming previous empirical findings (Aldas-Manzano et al., 2009; Yu, 2012). Following the theoretical and empirical evidence, we expect a positive direct link between Behavioral intention and actual use/use behavior for m-shopping apps. Thus, we have:

H8. BI has a positive effect on use behavior of mobile shopping apps.

2.5 Manifestations of Perceived Risks in UTAUT 2

Privacy and Security Risk

In the context of user acceptance of electronic commerce, perceived risk (PR) is conceptualized as ''*the user's subjective expectation of suffering a loss in pursuit of a desired outcome*'' (Pavlou, 2003). This study considers the role of perceived risk as it may act as a barrier to mobile shopping apps adoption and use. Several researchers agree that perceived risk is a multidimensional construct. Bhatnagar et al., (2000) proposed three types of risk: financial risk, product risk, and information risk (security and privacy) in the context of web shopping. We consider the last dimension as the focal point for the manifestations of perceived risks in our study. On that direction Tsu Wei et al., (2009), observed that both security and privacy influences consumers' decisions to use m-commerce. As mentioned by Siau and Shen (2003), security and privacy risk are some of the key unfavorable factors contributing to the slow growth rate of user acceptance of m-commerce. Thakur and Srivastava (2014), in an empirical study related to consumer adoption intention of financial-technology innovation for Indian consumers, found security risk and privacy risk as significant sub-dimensions of PR. Following the literature, perceived risk (PR) has been manifested through two independent constructs: security risk (SECR) and privacy risk (PRVR) in our study. Security risk refers to the perceptions of security regarding the means of payment and the mechanism for storing and transferring of information (Kolsaker & Payne, 2002). Whereas, Flavián and Guinalíu (2006) propose security risk is about ensuring the integrity, confidentiality, authentication, and non-recognition of relationships. Privacy risk is the potential loss of control over one's personal information (Chiu et al., 2014). We hypothesize that by reducing the risk perception among users, this would lead to a greater willingness to shop on m-devices. It is expected to affect both the behavioral intention and the use behavior of mobile shopping apps. Thus, we hypothesize:

H9a. Privacy Risk has a negative influence on the Behavioral Intention to use mobile shopping apps.

H9b. Privacy Risk has a negative influence on the use behavior of mobile shopping apps.

H10a. Security risk has a negative influence on the Behavioral Intention to use mobile shopping apps.

H10b. Security risk has a negative influence on the use behavior of mobile shopping apps.

The moderating effect of culture on Perceived Risks: India and USA

Cultural dimensions are known influencers of consumer behaviour (Hofstede et al., 2010). Straub et al., (1997) constructed a "computer-based media support index" (CMSI) by connecting Hofstede's cultural dimensions (*power distance, individualism, masculinity and uncertainty avoidance*). It expresses the simultaneous effects of all four cultural dimensions on technology acceptance rather than factor by factor (Van Slyke et al., 2010). The CMSI index for Hofstede's indicators for the countries India and USA were 225 and 157 respectively which clearly indicates contrasting cultures of the two countries.

*********INSERT FIGURE 2 around here*********

In a previous study Ashraf et al. (2014) employed CMSI score to explain and predict online shopping adoption in Pakistan and Canada using the Technology Acceptance Model. Another study confirms the impact of uncertainty avoidance as a barrier to new IT innovations (Leidner & Kayworth, 2006). Other empirical findings also validate the impact of CMSI on the relationships among various predictor variables and e-mail use intention. (D. Straub et al., 1997).

In terms of the differential impact of Hofstede dimensions, high uncertainty avoidance causes high perceived risk in the context of online shopping. A study by Van Slyke et al. (2005) on the specific country pair that is the focus of our study reports that American users with high masculinity have a higher tendency to accept e-commerce compared to Indian users with low masculinity. Individuals high on power distance were found to display a significantly less favorable view towards experimenting with innovative IT solutions (Thatcher et al., 2003). Furthermore, a greater perception of risk is exhibited in a society high on power distance (Leng & Botelho, 2010). In line with above findings, Tong (2010) observed higher perception of risk about online shopping in high power distance culture like China compared to low power distance society like the USA that consequently acts as a barrier to online shopping adoption. Zhou et al. (2007) contend that collectivist cultures may not accept online shopping readily. In a cross-cultural study, Park & Jun (2003) substantiated the higher risk perception prevalent in a collectivist culture like Korea vis-à-vis society high on individualism in USA with low risk perception towards online transactions.

As the various cultural dimensions discussed above are not independent of each other, its advantageous to take a composite view by using CMSI index that expresses the simultaneous effects of all four cultural dimensions on technology adoption and use rather than examine them in isolation (Van Slyke et al., 2010). CMSI had a significant negative influence on user's intention to engage in e-commerce thereby validating the assumption that people with high CMSI are more averse to shop online (Van Slyke et al., 2010). Moreover, it has been established that regardless of increasing globalization cultural values remain consistent over time (Beugelsdijk et al., 2015). As there is a noticeable difference between India and US on various cultural dimensions mentioned earlier and thus on CMSI, we believe it may result in a significant differential impact on the various predictors of UTAUT2 and perceived risk across the two cultures.

H11: *Privacy risk and security risk has a stronger effect on behavioral intention and use behavior of mobile shopping apps for the country with a significant higher CMSI score than a country with low CMSI score.*

3. Data and Methods

3.1 Instrument development

Active users of mobile shopping apps were chosen the target population for our study. Primary data for the study was collected using structured questionnaires (see Appendix A) administered to respondents electronically through a market research consumer panel. The instrument was pre-tested with two university professors in the field of information systems and marketing and ten doctoral research scholars. Minor adjustments were made to make it more understandable, consistent, and relevant. A pretest was administered to students undergoing graduation and post-graduate studies in marketing management in a major UK university using a paper-based version which took place during their classrooms with prior permissions of the course organizer the 2nd week of November 2016.

3.2 Sampling and data collection

The survey was administered online, and participants were motivated with a payout for a complete response. Subject recruitment was performed from two consumer panels for India and US which were sourced from a market research company. For both the US and Indian sample the minimum wage was used as a baseline calculation of the allocated time that each participant had at her disposal to answer the survey (30 mins). The items for each construct of the model were measured on a seven-point Likert scale (*Strongly Disagree – Strongly Agree*) and each construct was presented on a separate page to avoid confusion. Two-level randomization was used (order of constructs, order of items) to avoid endogeneity and impulsive responses. The complete questionnaire with the respective sources of items is shown in Appendix A. As suggested by Hew et al. (2015) we included more items from the original items specified by (Venkatesh et al., 2003, 2012) in order to have a complete measurement procedure. As aforementioned mobile shopping is an activity that has a high penetration on younger participants and as such, we didn't impose age quotas on the age sampling since we wanted to ensure that respondents had experience on the use of mobile shopping apps.

Furthermore, all the methodological remedies suggested by MacKenzie & Podsakoff (2012) were followed such as explaining the importance of questions and clarifying doubts as well as ensuring anonymity and confidentiality in all stages of the survey.

3.3 Method of Analysis: PLS-SEM

This study applied the variance based partial least squares structural equation modeling (PLS-SEM) approach (Chin, 1998) for analyzing the research model using Smart-PLS (Ringle et al., 2005). The PLS-SEM approach is advantageous under conditions of small sample sizes (Reinartz et al., 2009) as it requires very few assumptions about the distribution of the variables. Furthermore, this approach suits research contexts that are in the early stage of development and have not been studied extensively (Hair et al., 2012).

The analysis was performed by following the two-step approach as recommended by Anderson & Gerbing (1988). The reliability and validity of the measurement model were assessed first using the recommended procedural remedies, followed by the structural model assessment and hypotheses testing using a bootstrapping approach. The settings recommended by Hair et al. (2012) were used in running the PLS-algorithm and as such the path-weighting scheme was selected to follow a standardized data metric. In addition, the value of the maximum number of iterations was 300, the initial value for all outer weights was set equal to one, and the stopping criteria value was $<10^{-6}$.

4. Analysis and Results

Two independent studies with participants from two consumer panels (India and USA) were performed to validate UTAUT 2 on predicting mobile shopping app behavioral intention and use behavior. All studies were conducted using an online questionnaire with two attention checks in random sections of the questionnaire to ensure participant attention. Those who failed the attention check were automatically excluded from the system, and their responses were discarded. For both studies, multicollinearity and common method bias were assessed and found to be not of a problem. Correlations between items and the square root of the AVE are reported Table 4. CMB was assessed both with the common latent factor and Harman's single factor test, following Podsakoff et al. (2003) and was not an issue. For the India Study, the questionnaire was distributed in English considering that the participants in the consumer panel have participated in other English-speaking market research studies, language proficiency was not considered an issue.

We report the results of each study separately on the sections that follow.

4.1 Study 1: India

Responder Demographics

Table 2 below shows the demographic profiles of respondents surveyed for the India Study. The percentage of male and female was 59.7 % and 40.3% respectively. The minimum and maximum age of subjects was 18 and 30 respectively with the median age of 22. Current educational qualifications show that 72.8% were pursuing graduation and the rest 27.2% pursued post-graduate studies. The minimum and maximum experience level of using mobile shopping apps was 1 month and 24 months respectively with the median experience level of 12 months. 9.0% of respondents were the most frequent users of shopping apps compared to 24.8% of users who used it rarely (once or twice) in the last six months.

*********INSERT TABLE 2 HERE *********

Measurement model evaluation

Convergent and discriminant validity tests were performed to evaluate the measurement model. Factor loadings for all items exceeded the recommended threshold of 0.70 (Fornell & Larcker, 1981). The composite reliability (CR) for all constructs exceeded the recommended value of 0.60 (Bagozzi & Yi, 1988). Furthermore, the average variance extracted (AVE) values exceeded 0.50 (Kline, 2015) and Cronbach's alpha values for all constructs were greater than the prescribed value 0.70 by Nunnally and Bernstein (1994).

As can be noted from Table 3 below all the criteria for achieving convergent validity are satisfied. The discriminant validity of each construct was also assessed, with the average variance extracted (AVE) to be greater than the variance shared between the constructs and other constructs in the model (Fornell & Larcker, 1981). As demonstrated in Table 4 the square root of AVEs is significantly greater than their corresponding intercorrelations.

*********INSERT TABLE 3 around here*********

*********INSERT TABLE 4 around here*********

Analysis of the structural model.

The adequacy of the structural model in PLS-SEM was evaluated on the basis of various criteria namely: (a) the level of significance of path coefficients, (b) the coefficient of determination (R^2), and (c) predictive relevance Q^2 value of the path model (Hair et al., 2012). The bootstrap re-sampling procedure with 5000 samples for the N_{india}=221 cases with no sign changes was applied to evaluate the statistical significance of path coefficients. The PLS algorithm was used to obtain coefficient size. Table 5 shows the findings from the hypotheses testing. The results suggest that behavioral intention to use mobile shopping apps was significantly influenced by the UTAUT 2 exogenous constructs. Performance expectancy (β=0.331, $p<0.001$), effort expectancy (β=0.191, $p<0.01$), facilitating conditions (β=0.173, $p<0.01$), hedonic motivation (β=0.111, $p<0.05$), price value (β=0.111, $p<0.05$), habit (β=0.104, $p<0.05$) and privacy risk (β=-0.118, $p<0.05$) have been reported to have a significant influence on behavioral intention to use mobile shopping apps. On the contrary, social influence (β=-0.014, $p>0.05$) and security risk (β=0.059, $p>0.05$) were not significant in affecting behavioral intention to use mobile shopping apps. As predicted, use behavior (UB) of mobile shopping apps was significantly affected by behavioral intention (β=0.488, $p<0.001$). Direct effects of habit (β=0.276, $p<0.001$), privacy risk (β=-0.149, $p<0.01$) and security risk (β=-0.107, $p<0.05$) were all significant except for facilitating conditions (β=-0.050, $p>0.05$) which did not influence use behavior significantly.

*********INSERT TABLE 5 around here*********

Variance explained, Predictive relevance and effect size

The results reveal that 63.76 percent of the variation in behavioral intention to use mobile shopping apps is explained by the constructs effort expectancy, facilitating conditions, hedonic motivation, habit, performance expectancy, price value, social influence, privacy risk and security risk. Furthermore, 61.80 percent of the variation in use behavior of mobile shopping apps is explained by the various constructs behavioral intention, facilitating conditions, habit, privacy risk and security risk. Therefore, we can confirm that UTAUT2 is applicable in mobile shopping apps context. For assessing the predictive power of the model, literature prescribes R^2-values of 0.67, 0.33 and 0.19 as substantial, moderate and weak, respectively (Chin, 1998; Henseler et al., 2015). Based on the above assumption the research model moderately explains variations in behavioral intention and use behavior of mobile shopping apps.

For evaluating the predictive power of our model, we applied the cross-validated redundancy measures of Q^2 (Hair et al., 2012). Behavioral intention and use behavior were found to have adequate predictive relevance. As can be seen in Table 5 the reported Q^2 values are greater than 0.35 for both suggesting high predictive relevance as with the prescribed cutoff (Hair et al., 2012). Therefore, the research model has substantial predictive power in explaining behavioral intention to use mobile shopping apps and the use behavior.

4.2 Study 2: USA

For evaluating the effect of culture in the manifestation of perceived risks, we conducted a second study using the same instrument in a panel of US consumers. We outline the results of this analysis below.

Responder Demographics

The demographic profiles of respondents surveyed for the USA Study is depicted in Table 2. The percentage of male and female are 39.3 % and 60.7% respectively. The minimum and maximum age of subjects is 18 and 40 respectively with the median age of 30. Current educational qualifications show that majority 40.7% are pursuing graduation followed by 31.0 % diploma holders and rest belong to post-graduation study and others. The minimum and maximum experience level of using mobile shopping apps was one month and 60 months respectively with the median experience level of 12. 13.3 % of respondents are the most frequent users of shopping apps compared to 11.0 % of users who use it rarely (once or twice) in last six months.

Measurement model evaluation.

We performed the convergent and discriminant validity tests to assess the measurement model for this study as we did for Study 1. As presented in Table 3, for all constructs, factor loadings, composite reliability (CR), average variance extracted (AVE), and Cronbach's α values were greater than their prescribed values, thus confirming convergent validity. Discriminant validity was also established as shown in Table 4.

Analysis of the structural model.

As with Study 1, the structural model was evaluated using the same criteria and procedural remedies. Table 6 shows the findings from the hypotheses testing. The results show that behavioral intention to use mobile shopping apps was significantly influenced by Performance Expectancy (β=0.457, $p<0.001$), Facilitating Conditions (β =0.372, $p<0.001$) and Hedonic Motivation (β=0.216, $p<0.05$). Performance expectancy has been reported to have the strongest influence on behavioral intention to use mobile shopping apps. Whereas effort expectancy (β=0.027, $p>0.05$) Social Influence (β=-0.072, $p>0.05$); price value (β=0.033, $p>0.05$), habit (β=-0.078, $p>0.05$), privacy risk (β=-0.007, $p>0.05$) and security risk (β=-0.042, $p>0.05$) did not play a significant role in affecting behavioral intention to use mobile shopping apps. Furthermore, use behavior (UB) of mobile shopping apps was significantly influenced by behavioral intention (β=0.672, $p<0.001$) and habit (β=0.237, $p<0.001$). On the contrary facilitating conditions (β=-0.045, $p>0.05$), privacy risk (β=0.002, $p>0.05$) and security risk (β=0.017, $p>0.05$) were not significant in influencing use behavior.

*********INSERT TABLE 6 around here*********

Variance explained, Predictive relevance and effect size

The results suggest that ~70% of the variation in behavioral intention to use mobile shopping apps is explained in our research framework. Furthermore, 58.5% of the variation in use behavior of mobile shopping apps is explained by the various exogenous constructs. Hence based on the result, we can confirm that UTAUT2 is applicable in mobile shopping apps context and substantially explains variations in behavioral intention and use behavior of mobile shopping apps. As can be seen in Table 6, the endogenous latent constructs (Behavioral intention and Use Behavior) were both found to have adequate predictive relevance, as observed from the Q^2 values.

Analysing the moderating role of CMSI

We proceed to analyze the moderating impact of culture represented by the Computer-based Media Support Index (CMSI) by relying on the partial least square multi-group analysis (PLS-MGA) approach. It does not depend on distributional assumptions and is the preferred method in the context of our study (Henseler, 2012). In particular, we checked for the differential impact of CMSI on the relationships between both the risk constructs (privacy/security) and consumers' behavioral intention and use of mobile shopping apps hypothesized in our model. The results of PLS-MGA comparing all the paths in the model are presented in Table 7. The full set of data was divided into two groups viz. Indian sample (High CMSI) with 221 cases and US sample (Low CMSI) with 145 cases. As our study is cross-cultural in nature, firstly we performed an invariance test to make sure that the constructs under study are measured identically and is interpreted similarly by respondents from both the country. We followed the three-step measurement invariance of composite models (MICOM) procedure to check for configural invariance, compositional invariance, and equality of composite mean values and variances proposed by Henseler et al. (2016). The results presented in Appendix C illustrate partial measurement invariance for our model, thereby allowing multi-group comparison between both countries. Significant moderating influence can be noted between behavioural intention and use behaviour, habit and behavioural intention, and privacy risk and use behaviour at confidence level of 95%. Moreover cross-cultural differences were observed between privacy risk and behavioural intention, security risk and use behaviour, and facilitating conditions and behavioural intention at 90% CL. The effect of privacy risk on both the behavioural intention and use behaviour was found to be stronger for the Indian sample compared to the US sample. Consumers' perceived security risk also exerted stronger adverse influence on the use of shopping apps for respondents in India vis-à-vis their American counterparts. But no significant moderating influence was reported between security risk and behavioural intention. Thus, H11 was partially supported from the findings of our study.

*********INSERT TABLE 7 around here*********

5. Discussion and Implications

The purpose of this study was to investigate various factors influencing consumer's behavioral intention and use of mobile shopping apps. The UTAUT 2 model was used and extended with the addition of constructs for privacy and security risk to explore adoption and use of mobile shopping apps in India and USA. Based on the results of the hypothesis testing our study provides theoretical and managerial insights into m-shopping apps adoption and use. We outline these findings in the sections that follow.

5.1 Findings for India

The results reveal that the UTAUT2 model holds a good predictive power for India (High CMSI score). With the inclusion of the risk constructs, it explains 63.76% of variance in behavioral intention and 61.80% of variance of Use Behavior regarding mobile shopping apps. Apart from social influence, all the constructs related to UTAUT2 were found to be significant drivers of behavioral intention. Performance Expectancy had the strongest influence on behavioral intention to use m-shopping apps reconfirming the results of Lai & Lai (2014). The insignificant impact of Social Influence (SI) on behavioral intention, also observed in the study of Hew et al. (2015), suggests that shopping app users' social network could not influence their beliefs and behavior. Hence, retailers and shopping apps developers may ignore this construct while devising their strategies.

Behavioral intention was reported to have the strongest correlation with use behavior of shopping apps followed by habit. However, inconsistent with the findings of Venkatesh et al. (2012), the influence of facilitating conditions on use behavior is insignificant. Nevertheless, this finding is in line with the study of Baptista & Oliveira (2015). A possible explanation for this might be that the young generation is accustomed to new technologies and don't give much importance to various supporting factors and feel they are self- sufficient in using m-shopping apps. As for risk perception of users in India, privacy risk is found to be a significant barrier towards behavioral intention and use of m-shopping apps. Privacy risk negatively affects the adoption intention and actual usage of apps. Likewise, security risk was found to have direct negative impact on use behavior of shopping apps. However, the impact of security risk on behavioral intention was found to be insignificant. Hence hypothesis H9a, H9b, and H10b are supported whereas H10a was not supported.

5.2 Findings for the USA

For the USA sample, our research framework explained 69.70 % variance in behavioral intention and 58.54 % variance in use behavior. Performance expectancy was found to be the strongest predictor of behavioral intention. Apart from this facilitating conditions and hedonic motivation had significant direct positive effect on user's intention. The influence of other constructs on behavioral intention was statistically insignificant. Further, similar to the Indian panel behavioral intention and habit was observed as significant driver of use behavior for the American study. The relationship between FC and UB was found insignificant. Interestingly our study confirmed that privacy risk and security risk does not influence the behavioral intention and actual use of mobile shopping apps in a significant manner.

5.3 Comparison between India and USA

For both studies, performance expectancy was found to be the strongest driver of behavioral intention. It supports the proposed hypothesis that consumers would have higher intention to use m-shopping apps when it provides various useful functions like convenience and fast shopping. The influence of effort expectancy on behavioral intention was significant for the India study whereas for the USA sample no significant relationship existed. It can be justified as compared to Indian consumers Americans are more experienced users of mobile shopping and proficient to use complex systems. For both studies, social influence was not found to impact behavioral intention of consumers significantly, and this was confirmed also with a pooled sample analysis (Appendix B). Past literature posits that collectivist cultures are socially oriented and value the opinions of the group more than themselves (Hofstede et al., 2010). However, mobile shopping being perceived as a highly personal activity, people around the consumers could not influence their beliefs and behavior for both the countries. The results are consistent with the findings of Hew et al. (2015).

Another interesting similarity that was observed in both samples is the insignificant impact of facilitating conditions on the use behavior. A possible explanation for this might be that the young generation is accustomed to new technologies and don’t give much importance to various supporting factors and feel they are self- sufficient in using m-shopping apps. The result from India shows that PV has a significant impact on BI to use m-shopping apps which is consistent with existing findings in the literature (Deng et al., 2014; Liu et al., 2015; Venkatesh et al., 2012). But PV had insignificant impact for the US sample considering the possible difference in data access costs (higher in India compared to the USA) while for India was significant suggesting that users higher value for money.

As expected, significant differences were found from the MGA results pertaining to the role of privacy risk and security risk between Indian and American sample. Both privacy risk and security risk were found to be a significant inhibitor to the adoption and use of mobile shopping apps in India. The results justified our assumption that privacy risk and security risk have a stronger negative influence on consumers behavioral intention and use of mobile shopping apps for consumers with a high CMSI score than for consumers with a low CMSI. Building on the previous works of Straub et al. (1997), Ashraf et al. (2014), and Van Slyke et al. (2010), our findings validates the moderating role of CMSI by extending it to explain the adoption and use of mobile shopping apps in a cross-cultural setting. Indian consumers are found to be wary of the privacy and security threats related to the m-shopping environment. It's similar to the risk aversion of Malaysian and Chinese consumers to m-commerce (Chan & Yee-Loong Chong, 2013). Compared with this, the study results from USA sample showed the lack of significant influence of privacy risk and security risk on consumer's adoption and use of mobile shopping apps. It confirms that American mobile shoppers are less risk-averse than their Indian counterparts. These findings are consistent with the assumptions of Hofstede (2001) that Indians are less likely to take risk compared to their western counterparts. The contrasting results, related to the risk perception clearly demonstrates the cultural differences between the two countries as manifested through the CMSI score. As inferred from Figure 2, a major difference between India and USA exists regarding the cultural dimension of power distance and individualism/collectivism. Thus, the higher risk aversion of Indian consumers towards adoption and use of mobile shopping applications, compared to their American counterparts may be a result of the substantial difference in those two cultural dimensions. Our finding implies that individuals belonging to a higher power distance culture (India) may perceive a higher degree of risks with mobile shopping apps in contrast to those from lower power distance culture (USA). Hence, our result substantiates prior findings of Leng and Botelho (2010) and Tong (2010). Moreover, higher power distance society foster distrust among individuals that consequently increases their risk perception (Ji et al., 2015). Concurrently, the effect of the dimension, individualism/collectivism on the findings of this study cannot be dismissed. Triandis (1995) reported that collectivist societies are less inclined to new innovations and tend to focus on potential negative outcomes of their behavior. Whereas, individualistic culture emphasizes convenience and variety seeking behavior (Joines et al., 2003). Thus, India being a collectivist society exhibits greater risk that acts as a significant deterrent to the adoption and use of mobile shopping applications. Whereas, Individualistic consumers in the USA are more inclined to use mobile shopping apps due to their inherent advantages of convenience and connectivity. This validates the findings of Park and Jun (2003) and further extend it to the adoption and use of mobile shopping apps in a cross-cultural context. At the same time, the results may also be attributed to the regulatory framework and consumer protection laws which are more stringent in USA to safeguard the interest of consumers as compared to India and as such the consequences of risk are not that strong in the USA compared to India.

5.4 Implications

Our study has theoretical implications from the perspective that it suggests that UTAUT 2 can adequately explain the behavioral intention and use of m-shopping apps in cross-cultural settings. Considering that UTAUT 2 is a measure that has been validated in a mature economy like the USA, the fact that it shows consistency in an emerging market context as that of India, helps to advance our understanding of consumer behavior research in a cross-cultural setting using instruments developed in different contexts (Hoppner & Griffith, 2015). While past research has addressed m-shopping acceptance and use in general, this has not explicitly done in the context of m-shopping apps in a cross-country panel. Our study extends the applicability of UTAUT 2 to that direction and is robust by applying the UTAUT2 in two cultural contexts. Hence this study advances our understanding of the antecedents of mobile shopping apps use behavior. By integrating manifestations of perceived risk into the baseline model, we observed their effect on the intention and use of m-shopping apps in a cross-country context where CMSI is significantly different. We have employed the Hofstede measures to find two countries with distinctive national cultural dimension to test the efficacy of our model as it was shown in Figure 2. The predictive power of the baseline UTAUT2 model is strong and holds good for both India (high CMSI) and USA (low CMSI) providing that is suitable for cross-country studies which can enhance our understanding of how consumers from different background use apps for shopping.

Our study also provides insights for app developers and retailers active both in India and USA. As suggested by the results, performance expectancy has the strongest influence on the intention to use m-shopping apps. Hence, online marketers and app developers should emphasize on providing newer and better functionalities on their shopping apps making it more convenient, fast and useful for consumers. For Indian consumers, effort expectancy had a significant impact on the behavioral intention to use shopping apps. Thus, app developers are encouraged to design the user interface to be convenient and easy to navigate. They should make the shopping apps simple and easy to use so that users can find and order goods and services with a minimum of physical and mental effort. Use of local language in designing the user interface may also increase the usability of the app and its adoption by users. Since hedonic motivation significantly influences behavioral intention to use for both the sample, shopping app developers should make shopping with apps enjoyable for users with interactive features to engage consumers and enhance the overall shopping experience. Higher levels of engagement and enjoyment will lead to higher intention to use apps. Even if shopping using m-devices and apps is perceived as a personal activity by its users and not as a social activity, interface designers should not ignore social influence and promote social interaction among users integrating social media platforms with apps like integrating with YouTube videos to increase social sharing and Word-of-mouth. Since mobile shopping is in an early stage of adoption in India, consumers risk perception is higher and significantly impacts their intention to adopt. To reduce the barriers exercised by perceived risk, retailers and other stakeholders should provide better security in transaction and privacy protection which will result in an increase in the use of m-shopping apps. The findings of this study validate our research framework based on UTAUT 2 and provide several guidelines for practitioners in India and the USA to develop successful marketing strategies to enhance adoption and use of mobile shopping apps.

6. Conclusions Limitations and future research

The current study has effectively utilized the UTAUT2 as a base model to examine the various factors influencing behavioral intention and use of m-shopping apps. The role of perceived risk as a barrier to use of m-shopping apps has been explored along with the other constructs thereby providing more predictive power to the model. Overall the findings from the research model will provide valuable insight to all stakeholders in m-shopping apps industry especially for those tasked with app localization which is known to be influenced by cultural issues.

This study has certain limitations which could be addressed in future research. Since both panels were sampled with respondents from a relatively young age group (millennials), the findings of the study are limited to that particular age group. Future research should target a more general population with respondents from a diverse group of age, income, education, and occupation to fully understand m-shopping apps use behavior also considering the case of supply data. More specifically the consideration market size (e.g., number of downloads from the App stores) and retailer readiness is something that can provide further insights into the consumer adoption and diffusion of technological innovations. Furthermore, as this study employs a cross-sectional design, future studies should consider longitudinal approaches as explicated with latent growth models. This will allow capturing the change in consumer's perception and behavior over time, thus yielding useful insight on the topic. Whether the drivers and barriers to different types of shopping apps are different is another research area which will be appealing for future studies.

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Table 1: Overview of related studies on m-commerce/m-shopping adoption

Study	Data source	Context	Base Model	Method / Sample	Antecedents	Outcome Variable(s)
Kim et al.(2014)	257 US undergraduate students	Mobile app usage	TAM	Online survey	Perceived informative Usefulness, Perceived Entertaining usefulness, Perceived social useful Ness, Perceived ease of Use, User review	Attitude toward App usage, Behavioural intention to use mobile app
Baptista and Oliveira (2015)	252 respondent's in Mozambique	Mobile banking	UTAUT2	Online survey	Performance expectancy, Effort expectancy, Social influence, Facilitating conditions, Hedonic motivation, Price value, Habit	Behavioral intention, Use behavior
Hew et al. (2015)	288 students in Malaysia	Mobile apps	UTAUT2	Self-administered questionnaire	Performance expectancy, Effort expectancy, Social influence, Facilitating conditions, Hedonic motivation, Price value, Habit	Behavioural intention
Lai and Lai(2014)	219 responses in Macau	M-commerce	UTAUT	Field survey	Performance expectancy, Effort expectancy, social Influence , facilitating conditions and privacy concern	Behavioural intention
Oliveira et al. (2014)	194 mobile phone users in Portugal	Mobile banking	UTAUT, TTF, ITM	Online survey	Performance expectancy, effort Expectancy, social influence, Facilitating conditions, task Characteristics, technology characteristics, task-technology fit , structural assurances , personal propensity to trust and firm reputation	Initial trust , Behavioral Intention and adoption
Yang and Kim (2012)	400 mobile service users in USA	Mobile shopping	-	Online survey	Hedonic shopping motivation, utilitarian shopping motivation	Mobile shopping use
Liu et al. (2015)	271 m-coupon users in China	Mobile coupon applications	-	Online survey	Perceived value having perceived Money savings, perceived Convenience, perceived Enjoyment, perceived fee, Perceived privacy risk dimensions, personal Innovativeness and coupon proneness	Behavioural intention
Lin and Wang (2006)	255 users in Taiwan	Mobile commerce	-	Field survey	Perceived value , trust and habit	Satisfaction and customer loyalty
Gro ß (2015)	128 users in Germany	Mobile shopping	TAM	Survey questionnaire	Perceived usefulness, perceived Ease of use , perceived Enjoyment and trust	Attitude, behavioral Intention and usage behavior

Yu (2012)	441 respondents in Taiwan	Mobile banking	UTAUT	Shopping mall intercept	Performance expectancy, effort expectancy , social influence, facilitating conditions, perceived credibility, perceived financial cost and perceived self-efficacy	Intention and behavior
Thakur and Srivastava (2014)	774 respondents in India	Mobile payment services	TAM, UTAUT	Structured questionnaire	Perceived usefulness, perceived Ease of use , facilitating conditions, social influence, personal innovativeness, security risk, privacy risk and monetary risk	Behavioural intention
Luo et al.(2010)	122 students in USA	Mobile banking services		Survey	Performance expectancy, trust belief , perceived risk, self-efficacy, disposition to trust and structural assurance	Behavioural intention
Verkasalo et al.(2010)	490 respondents in Finland	Mobile applications	-	Consumer panel	Technical barriers, social norm, Behavioural control, perceived enjoyment and perceived usefulness	Intention to use
Lee et al.(2012)	240 internet banking users in Korea	Mobile financial services	TAM, TTF	Online survey	Task fit, monetary value, connectivity, personal innovativeness, absorptive capacity, perceived usefulness and perceived ease of use	Usage intention
Khalifa and Shen (2008)	202 mobile phone users in Hong Kong	Mobile commerce	TAM, TPB	Survey	Perceived usefulness, ease of use, self-efficacy, cost , convenience, privacy, security, efficiency and subjective norm	Intention to adopt

Table 2: Participant Demographics for both studies

	India		USA	
	Frequency	Percentage	Frequency	Percentage
Gender				
Male	132	59.7	57	39.3
Female	89	40.3	88	60.7
Age (in Years)				
<25	194	87.7	29	20.0
25-35	27	12.3	92	63.4
>35	-	-	24	16.6
Educational Qualification				
Graduation	161	72.8	59	40.7
Post -Graduation	60	27.2	12	8.3
Diploma	-	-	45	31.0
Others	-	-	29	20.0
Experience of using m-shopping apps (in months)				
<6	31	14.0	48	33.1
6-12	103	46.6	48	33.1
>12	87	39.3	49	33.8
Usage intensity				
Rarely or Hardly at all (only once or twice)	55	24.8	16	11.0
Approximately once every two months	52	23.5	22	15.1
Approximately once a month	53	23.9	38	26.2
Several times a month	41	18.5	50	34.4
Several times a week	20	9.0	19	13.3

Table 3: Cross-country Factor loadings and reliability assessments for the India and USA sample

	Factor Loadings	
	India	USA
Performance Expectancy (India: AVE = .68, CR = .89; USA: AVE = .71, CR = .90)		
I find mobile shopping apps useful in my daily life.	.84	.82
Using mobile shopping apps help me do shopping more quickly.	.81	.89
Using mobile shopping apps increase my productivity.	.83	.86
Using mobile shopping apps increase my chances of achieving things that are important to me.	.80	.78
EE (India: AVE = .73, CR = .91; USA: AVE = .78, CR = .93)		
Learning how to use mobile shopping apps is easy for me.	.84	.90
My interaction with mobile shopping apps is clear and understandable.	.88	.84
I find mobile shopping apps easy to use.	.87	.91
It is easy for me to become skillful at using mobile shopping apps.	.83	.88
SI (India: AVE = .73, CR = .91; USA: AVE = .77, CR = .93)		
People who are important to me think that I should use mobile shopping apps.	.84	.88
People who influence my behavior think that I should use mobile shopping apps.	.89	.90
People whose opinions that I value prefer that I use mobile shopping apps.	.88	.88
People around me consider it is appropriate to use mobile shopping apps.	.79	.83
FC (India: AVE = .76, CR = .90; USA: AVE = .75, CR = .90)		
I have the resources necessary to use mobile shopping apps.	.89	.86
I have the knowledge necessary to use mobile shopping apps.	.89	.86
Mobile shopping apps are compatible with other technologies I use.	.83	.86
HM (India: AVE = .82, CR = .93; USA: AVE = .86, CR = .94)		
Using mobile shopping apps is fun.	.91	.94
Using mobile shopping apps is enjoyable.	.95	.94
Using mobile shopping apps is very entertaining	.86	.89
PV (India: AVE = .75, CR = .90; USA: AVE = .88, CR = .95)		
Mobile shopping apps are reasonably priced.	.84	.92
Mobile shopping apps are a good value for the money.	.93	.94
At the current price, mobile shopping apps provide a good value	.83	.94
HA (India: AVE = .71, CR = .91; USA: AVE = .69, CR = .90)		
The use of mobile shopping apps has become a habit for me.	.85	.86
I am addicted to using mobile shopping apps.	.82	.84
I must use mobile shopping apps.	.83	.80
Using mobile shopping apps has become natural to me.	.86	.83
SECR (India: AVE = .68, CR = .86; USA: AVE = .69, CR = .87)		
I fear that while I am paying a bill by mobile shopping apps, I might make mistakes since the correctness of the inputted information is difficult to check from the screen.	.79	.87
I fear that while I am using mobile shopping apps, the battery of the mobile phone will run	.83	.75

out or the connection will otherwise be lost.		
I fear that while I am using mobile shopping apps the list of PIN codes may be lost and end up in the wrong hands.	.85	.86
PRVR (India: AVE = .80, CR = .92; USA: AVE = .70, CR = .87)		
I think mobile shopping apps service providers could provide my personal information to other companies without my consent.	.89	.82
I think subscribing to mobile shopping apps services increases the likelihood of receiving spam/spam SMS.	.89	.82
I think mobile shopping apps services endanger my privacy by using my personal information without my permission.	.89	.86
BI (India: AVE = .78, CR = .91; USA: AVE = .86, CR = .95)		
Assuming I had access to mobile shopping apps, I intend to use it.	.89	.94
Given that I had access to mobile shopping apps, I predict that I would use it.	.90	.92
I intend to continue using mobile shopping apps in the future.	.85	.92
UB (India: AVE = .85, CR = .95; USA: AVE = .64, CR = .87)		
In the past six months, I have used mobile shopping apps in order to purchase online products.	.94	.86
In the past six months, I have used mobile shopping apps in order to shop for products from different online retailers.	.91	.73
In the past six months, I have used mobile shopping apps to make personal purchases.	.93	.87
I have used different kinds of mobile shopping apps in the last six months.	.90	.71

Table 4: Discriminant Validity and Tests of Differences between Correlations

Study 1: India

Constructs	*M*	*SD*	*BI*	*EE*	*FC*	*HA*	*HM*	*PE*	*PRVR*	*PV*	*SECR*	*SI*	*UB*
BI	5.13	1.49	**0.885**										
EE	5.60	1.21	0.610	**0.859**									
FC	5.41	1.23	0.555	0.679	**0.877**								
HA	3.61	1.58	0.550	0.343	0.303	**0.847**							
HM	4.46	1.50	0.512	0.423	0.423	0.424	**0.908**						
PE	4.83	1.42	0.701	0.544	0.423	0.622	0.472	**0.824**					
PRVR	4.11	1.69	-0.413	-0.231	-0.182	-0.435	-0.222	-0.429	**0.895**				
PV	4.88	1.29	0.472	0.309	0.274	0.403	0.327	0.462	-0.364	**0.871**			
SECR	3.74	1.58	-0.301	-0.348	-0.264	-0.258	-0.198	-0.334	0.528	-0.251	**0.824**		
SI	4.08	1.44	0.360	0.184	0.231	0.451	0.335	0.492	-0.152	0.375	-0.136	**0.857**	
UB	4.55	1.69	0.706	0.431	0.360	0.622	0.392	0.549	-0.519	0.429	-0.391	0.321	**0.925**

Study 2: USA

Constructs	*M*	*SD*	*BI*	*EE*	*FC*	*HA*	*HM*	*PE*	*PRVR*	*PV*	*SECR*	*SI*	*UB*
BI	6.05	1.11	**0.929**										
EE	6.23	1.02	0.625	**0.886**									
FC	6.26	0.89	0.676	0.741	**0.867**								
HA	3.96	1.84	0.400	0.318	0.244	**0.835**							
HM	5.67	1.22	0.624	0.527	0.460	0.606	**0.927**						
PE	5.47	1.44	0.702	0.496	0.418	0.596	0.630	**0.844**					
PRVR	4.26	1.65	-0.187	-0.093	-0.176	-0.241	-0.121	-0.241	**0.838**				
PV	5.52	1.19	0.416	0.333	0.382	0.319	0.440	0.389	-0.147	**0.940**			
SECR	3.55	1.74	-0.215	-0.232	-0.262	-0.063	-0.054	-0.130	0.429	-0.071	**0.832**		
SI	4.36	1.54	0.245	0.193	0.136	0.510	0.485	0.419	-0.205	0.244	0.047	**0.878**	
UB	5.75	1.54	0.732	0.465	0.462	0.493	0.603	0.650	-0.165	0.346	-0.129	0.234	**0.802**

Notes: PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating conditions; HA: habit; HM: hedonic motivation; PV: price value; PRVR: privacy risk; SECR: security risk; BI: behavioral intention; UB: use behavior. Diagonal elements (bold) are the square root of the AVE for each construct; Off-diagonal factors correspond to construct intercorrelations.

Table 5: Results of UTAUT 2 on the India Sample (Study 1)

	UTAUT 2		UTAUT 2 with Privacy risk, Security risk	
Directional Paths	***β***	***t-value***	***β***	***t- value***
Behavioral Intention → Use of Mobile shopping apps	0.546***	8.755	0.488***	8.049
Effort Expectancy → Behavioral Intention	0.175*	2.357	0.191**	2.581
Facilitating Conditions → Behavioral Intention	0.171**	2.698	0.173**	2.749
Facilitating Conditions → Use of Mobile shopping apps	-0.044	0.729	-0.050	0.870
Habit→ Behavioral Intention	0.133*	2.509	0.104*	1.993
Habit→ Use of Mobile shopping apps	0.335***	6.093	0.276***	5.079
Hedonic Motivation→ Behavioral Intention	0.110*	2.203	0.111*	2.191
Performance Expectancy → Behavioral Intention	0.355***	5.346	0.331***	4.569
Price Value → Behavioral Intention	0.129*	2.549	0.111*	2.162
Social Influence→ Behavioral Intention	-0.032	0.582	-0.014	0.254
Manifestation and Impact of Perceived Risks				
Privacy Risks → Behavioral Intention			-0.118*	2.017
Privacy Risks → Use of Mobile shopping apps			-0.149**	3.012
Security Risks → Behavioral Intention			0.059	1.067
Security Risks → Use of Mobile shopping apps			-0.107*	2.058
	R^2 on BI		*R^2 on UB*	
Base Model	0.63		0.58	
With Perceived risk	0.64		0.62	
	Q^2 on BI		*Q^2 on UB*	
Predictive Relevance of the endogenous latent Construct.	0.45		0.48	

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, N=221(India)

Table 6: Results of UTAUT 2 on the USA Sample (Study 2)

	UTAUT 2		UTAUT 2 with Privacy risk, Security risk	
Directional Paths	***β***	***t-value***	***β***	***t- value***
Behavioral Intention → Use of Mobile shopping apps	0.671***	8.007	0.672***	8.064
Effort Expectancy → Behavioral Intention	0.033	0.243	0.027	0.205
Facilitating Conditions → Behavioral Intention	0.380***	3.547	0.372***	3.491
Facilitating Conditions → Use of Mobile shopping apps	-0.049	0.580	-0.045	0.528
Habit → Behavioral Intention	-0.076	1.191	-0.078	1.219
Habit → Use of Mobile shopping apps	0.237***	3.727	0.237***	3.731
Hedonic Motivation→ Behavioral Intention	0.212*	2.248	0.216*	2.290
Performance Expectancy → Behavioral Intention	0.459***	5.103	0.457***	5.005
Price Value → Behavioral Intention	0.032	0.553	0.033	0.537
Social Influence → Behavioral Intention	-0.076	0.985	-0.072	0.935
Manifestation and Impact of Perceived Risks				
Privacy Risks → Behavioral Intention			0.007	0.128
Privacy Risks → Use of Mobile shopping apps			0.002	0.028
Security Risks → Behavioral Intention			-0.042	0.716
Security Risks → Use of Mobile shopping apps			0.017	0.276
	R^2 on BI		*R^2 on UB*	
Base model	0.70		0.59	
With Perceived risk	0.70		0.59	
	Q^2 on BI		*Q^2 on UB*	
Predictive Relevance of the endogenous latent Construct.	0.531		0.340	

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, N=145(USA)

Table 7: Results of PLS-MGA

Path	Path coefficient India	Path coefficient US	Path coefficient difference (∣India-US∣)	p-values
BI → UB	0.488	0.672	0.184*	0.966
EE → BI	0.191	0.027	0.164	0.137
FC → BI	0.173	0.372	0.199†	0.949
FC → UB	-0.050	-0.045	0.004	0.519
HA → BI	0.104	-0.078	0.182*	0.014
HA → UB	0.276	0.237	0.039	0.316
HM → BI	0.111	0.216	0.105	0.836
PE → BI	0.331	0.457	0.126	0.859
PRVR → BI	-0.118	0.007	0.125†	0.942
PRVR →UB	-0.149	0.002	0.151*	0.978
PV → BI	0.111	0.033	0.079	0.158
SECR → BI	0.059	-0.042	0.102	0.085
SECR → UB	-0.107	0.017	0.125†	0.943
SI → BI	-0.014	-0.072	0.057	0.240

Notes: PE: performance expectancy; EE: effort expectancy; SI: social influence; FC: facilitating conditions; HA: habit; HM: hedonic motivation; PV: price value; PRVR: privacy risk; SECR: security risk; BI: behavioral intention; UB: use behavior.*p-value < 0.05 or > 0.95, † p-value < 0.1 or > 0.90

Table 8: Control paths for UTAUT 2 on the India and USA Sample

	India		US	
Directional paths	***β***	***t-value***	***β***	***t-value***
Age → Behavioral Intention	-0.006	0.111	0.035	0.774
Age → Use of Mobile shopping apps	0.082*	2.250	0.001	0.016
Gender→ Behavioural Intention	-0.009	0.183	0.000	0.006
Gender→ Use of Mobile shopping apps	-0.055	1.190	-0.038	0.629
Experience→ Behavioural Intention	0.093	1.703	0.061	1.498
Experience→ Use of Mobile shopping apps	0.005	0.104	-0.018	0.329

Notes: * $p < 0.05$, N=221(India), N=145(USA)

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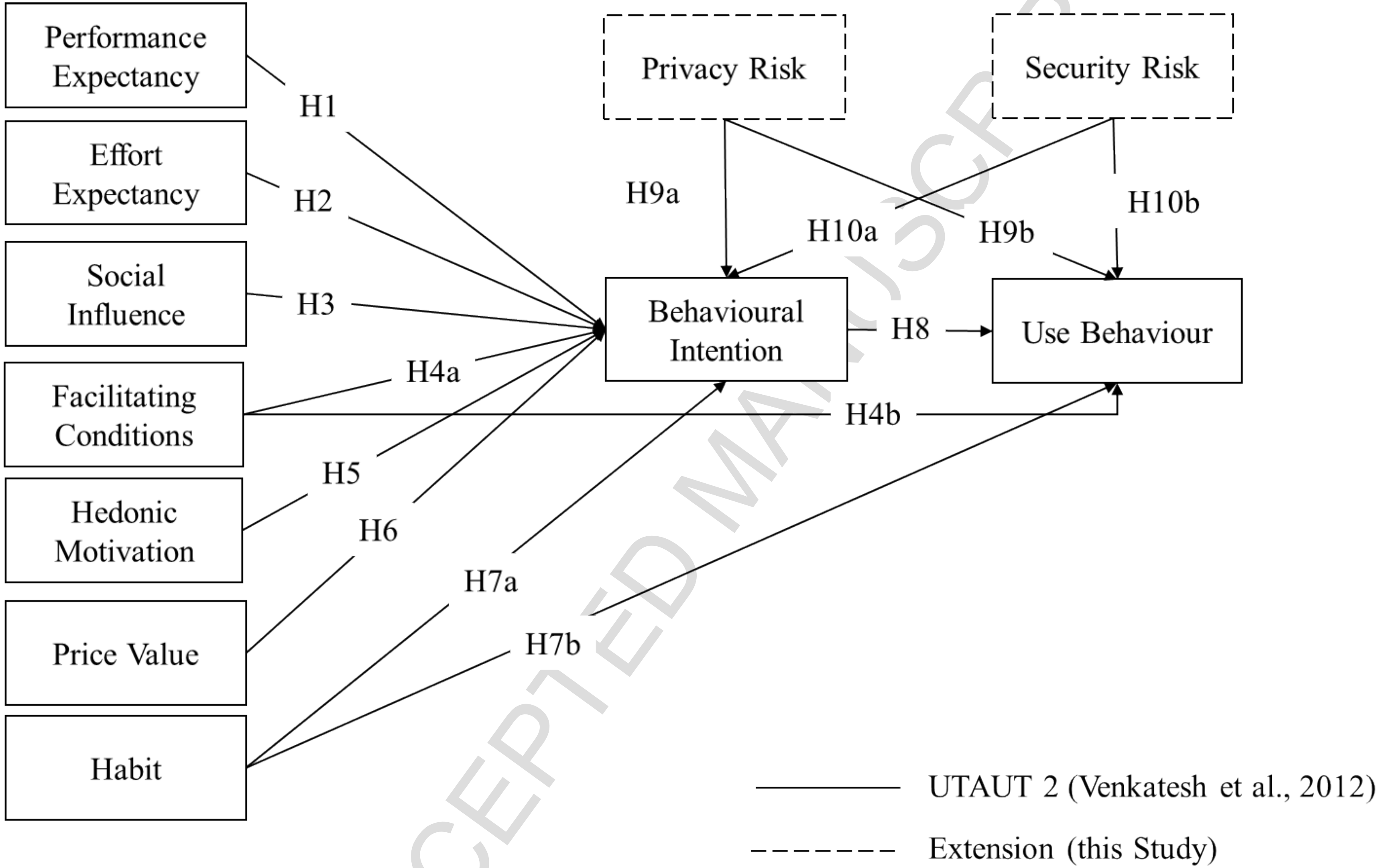

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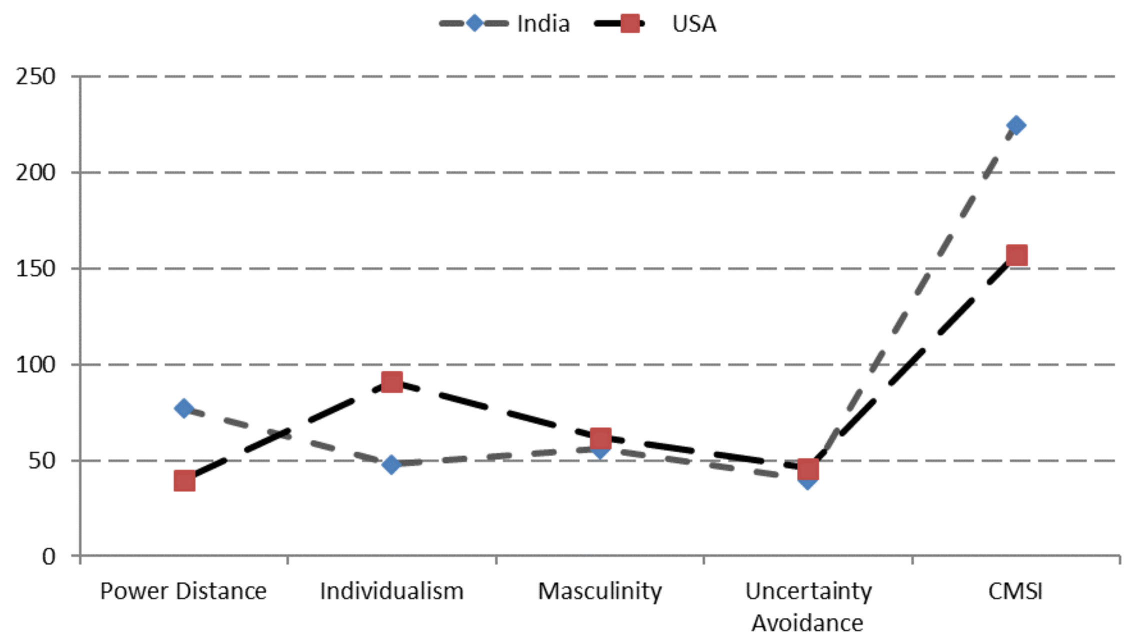
2 Figure 1: UTAUT 2 with Perceived risks.



Countries	Power Distance	Individualism	Masculinity	Uncertainty Avoidance	**CMSI**
India	77	48	56	40	225
USA	40	91	62	46	157

Note: CMSI corresponds to the Computer-Based Media Support Index

Figure 2: Hofstede Cultural Dimensions and CMSI values for India and the USA

Appendix A: Questionnaire items and sources

Construct	Items	Scale based on
Performance Expectancy(PE)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* I find mobile shopping apps useful in my daily life. Using mobile shopping apps help me do shopping more quickly. Using mobile shopping apps increase my productivity. Using mobile shopping apps increase my chances of achieving things that are important to me.	Venkatesh et al. (2003,2012)
Effort Expectancy(EE)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* Learning how to use mobile shopping apps is easy for me. My interaction with mobile shopping apps is clear and understandable. I find mobile shopping apps easy to use. It is easy for me to become skilful at using mobile shopping apps.	Venkatesh et al.(2012)
Social Influence(SI)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* People who are important to me think that I should use mobile shopping apps. People who influence my behaviour think that I should use mobile shopping apps People whose opinions that I value prefer that I use mobile shopping apps. People around me consider it is appropriate to use mobile shopping apps.	Venkatesh et al. (2012) and San Martin and Herrero (2012)
Facilitating Conditions(FC)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* I have the resources necessary to use mobile shopping apps. I have the knowledge necessary to use mobile shopping apps. Mobile shopping apps are compatible with other technologies I use.	Venkatesh et al. (2003,2012)
Hedonic Motivation(HM)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* Using mobile shopping apps is fun. Using mobile shopping apps is enjoyable. Using mobile shopping apps is very entertaining.	Venkatesh et al. (2012)
Price Value(PV)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* Mobile shopping apps are reasonably priced. Mobile shopping apps are a good value for the money. At the current price, mobile shopping apps provide a good value.	Venkatesh et al. (2012)
Habit(HA)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* The use of mobile shopping apps has become a habit for me. I am addicted to using mobile shopping apps. I must use mobile shopping apps.	Venkatesh et al. (2012), Hew et al.(2015) and Tomas and Elena (2013)

	Using mobile shopping apps has become natural to me.	
Security Risk(SECR)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* I fear that while I am paying a bill by mobile shopping apps, I might make mistakes since the correctness of the inputted information is difficult to check from the screen. I fear that while I am using mobile shopping apps, the battery of the mobile phone will run out or the connection will otherwise be lost. I fear that while I am using mobile shopping apps the list of PIN codes may be lost and end up in the wrong hands.	Kuisma et al. (2007), Laukkanen and Lauronen (2005), Jo Black et al. (2001) and Thakur and Srivastava(2014)
Privacy Risk(PRVR)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* I think mobile shopping apps service providers could provide my personal information to other companies without my consent. I think subscribing to mobile shopping apps services increases the likelihood of receiving spam/spam SMS. I think mobile shopping apps services endanger my privacy by using my personal information without my permission.	Flavian and Guinaliu (2006) ,Cheung and Lee (2001) and Thakur and Srivastava(2014)
Behavioural Intention(BI)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* Assuming I had access to mobile shopping apps, I intend to use it. Given that I had access to mobile shopping apps, I predict that I would use it. I intend to continue using mobile shopping apps in the future.	Venkatesh and Bala(2008),Venkatesh et al.(2012)
Use Behaviour(UB)	*Please indicate to what extent you agree with the statements (1=strongly disagree, 7=strongly agree).* In the past six months, I have used mobile shopping apps in order to purchase online products. In the past six months, I have used mobile shopping apps in order to shop for products from different online retailers. In the past six months, I have used mobile shopping apps to make personal purchases. I have used different kinds of mobile shopping apps in the last six months.	Klopping and McKinney (2004), Lai, Debbarma, and Ulhas (2012), Porter and Donthu (2006) and Gro ß (2015)

Appendix B: Results of the model with pooled samples (India and USA).

	UTAUT 2		UTAUT 2 with Privacy risk, Security risk	
Directional Paths	***β***	***t-value***	***β***	***t- value***
Behavioral Intention → Use of Mobile shopping apps	0.629***	14.042	0.605***	13.052
Effort Expectancy → Behavioral Intention	0.149*	2.413	0.152*	2.499
Facilitating Conditions → Behavioral Intention	0.227***	4.099	0.228***	4.115
Facilitating Conditions → Use of Mobile shopping apps	-0.036	0.738	-0.039	0.805
Habit→ Behavioral Intention	0.059	1.481	0.041	1.096
Habit→ Use of Mobile shopping apps	0.270***	7.246	0.252***	6.797
Hedonic Motivation→ Behavioral Intention	0.134**	3.283	0.143***	3.369
Performance Expectancy → Behavioral Intention	0.391***	7.045	0.376***	6.516
Price Value → Behavioral Intention	0.110**	2.810	0.101*	2.530
Social Influence→ Behavioral Intention	-0.057	1.535	-0.054	1.421
Manifestation and Impact of Perceived Risks				
Privacy Risks → Behavioral Intention			-0.074*	1.966
Privacy Risks → Use of Mobile shopping apps			-0.057	1.593
Security Risks → Behavioral Intention			0.007	0.186
Security Risks → Use of Mobile shopping apps			-0.064	1.732
	R^2 on BI		*R^2 on UB*	
Base Model	0.67		0.61	
With Perceived risk	0.68		0.62	
	Q^2 on BI		*Q^2 on UB*	
Predictive Relevance of the endogenous latent Construct.	0.51		0.46	

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, N=366(India,221+USA,145). Controls for Age, Gender, Experience of Use

Appendix C: Measurement Invariance between the Indian and the USA sample.

BASE MODEL(UTAUT)

Step 1- Configural invariance is established automatically

Step 2-Compositional invariance

	Original Correlation	*Correlation Permutation Mean*	*5.0%*	*Permutation p-Values*
BI	1.000	1.000	1.000	0.438
EE	0.999	1.000	0.999	0.268
FC	1.000	1.000	0.998	0.556
HA	0.997	0.999	0.996	0.073
HM	1.000	1.000	0.999	0.850
PE	1.000	0.999	0.998	0.624
PV	0.997	0.999	0.998	**0.016**
SI	0.999	0.924	0.985	0.659
UB	0.999	1.000	1.000	**0.000**

As can be seen from the table above invariance is achieved apart from 2 constructs price value(PV) and use behaviour(UB).

Step 3 Checking composite mean and variance

	Mean - Original Difference (India - USA)	*Mean - Permutation Mean Difference (India - USA)*	*Permutation p-Values*	*Variance - Original Difference (India - USA)*	*Variance - Permutation Mean Difference (India - USA)*	*Permutation p-Values*
BI	-0.707	-0.001		0.500	0.008	0.002
EE	-0.604	0.000		0.291	0.002	0.092
FC	-0.803	0.000		0.685	0.005	0.000
HA	-0.325	0.001	0.004	-0.205	0.003	0.107
HM	-0.860	0.001		0.369	0.003	0.010
PE	-0.532	0.001		-0.071	0.005	0.649
PV	-0.549	0.001		0.006	0.007	1.000
SI	-0.216	0.002	0.046	-0.175	0.004	0.234
UB	-0.775	-0.001		0.498	0.007	0.001

HA and SI are significantly different in terms of mean and BI,FC,HM and UB are significantly different in variances.

BASE MODEL+PRIVACY RISK+SECURITY RISK

Step 2-Compositional invariance

	Original Correlation	Correlation Permutation Mean	5.0%	Permutation p-Values
BI	1.000	1.000	1.000	0.452
EE	0.999	1.000	0.999	0.271
FC	1.000	1.000	0.998	0.567
HA	0.997	0.999	0.997	0.071
HM	1.000	1.000	0.999	0.838
PE	1.000	0.999	0.998	0.613
PRVR	0.999	0.997	0.992	0.824
PV	0.997	0.999	0.998	0.018
SECR	0.996	0.968	0.976	0.623
SI	0.999	0.924	0.985	0.657
UB	0.998	1.000	0.999	0.000

PV and UB are significantly different

Step 3 Checking composite mean and variance

	Mean - Original Difference (India - USA)	***Mean - Permutation Mean Difference (India - USA)***	***Permutation p-Values***	***Variance - Original Difference (India - USA)***	***Variance - Permutation Mean Difference (India - USA)***	***Permutation p-Values***
BI	-0.706	0.000		0.499	0.007	0.002
EE	-0.604	0.002		0.291	0.003	0.081
FC	-0.803	0.001		0.685	0.003	
HA	-0.325	0.000	0.002	-0.205	0.005	0.109
HM	-0.860	-0.002		0.369	0.003	0.008
PE	-0.532	0.001		-0.071	0.006	0.643
PRVR	-0.098	0.001	0.353	0.189	0.006	0.174
PV	-0.549	0.000		0.006	0.005	1.000
SECR	0.146	-0.001	0.173	-0.209	0.002	0.102
SI	-0.216	0.001	0.042	-0.175	0.003	0.242
UB	-0.774	0.000		0.497	0.006	0.002

HA and SI significantly different on mean diff and BI, HM and UB significantly different on variances.

Appendix D: F- statistic for regression

	F-value		Significance	
DV / Sample	BI	UB	BI	UB
Pooled data	77.955	121.691	0.000***	0.000***
India	39.983	72.454	0.000***	0.000***
US	29.710	35.732	0.000***	0.000***

Note: DV: dependent variable; BI: behavioral intention; UB: use behavior

Appendix E: Results of the parametric test and Welch-Satterthwait test on change in R^2

Parametric Test				Welch-Satterthwait Tet	
	R^2 difference (∣India-US∣)	t-Value	p-Value	t-Value	p-Value
Behavioural intention	0.059	0.894	0.372	0.944	0.347
Use behaviour	0.033	0.472	0.637	0.464	0.643

- The suitability of UTAUT2 on explaining adoption of m-shopping apps is examined
- Perceived Privacy and Security risks are added to UTAUT2
- We conduct two studies in India and USA using consumer panels
- We find that perceived risks are affecting m-shopping app adoption in USA
- Results add to the discussion of adoption stages for developed vs emerging markets