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Exploring Factors Affecting Consumers' Behavioral Intention to Adopt Mobile Payment Services: A Case Study in the Kathmandu Valley, Nepal

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Abstract

Mobile payments will become increasingly common in the future since they reduce transaction time, and they have already replaced interactions with physical money in some markets. Yet in Nepal, consumers' adoption of mobile payment services remains very low as compared to other traditional forms of payments, such as cash and credit cards. Thus, this study aimed to investigate the factors influencing consumers' behavioral intention to adopt Mobile Payment Services in Kathmandu Valley, the area surrounding the capital of Nepal. The Unified Theory of Acceptance and Use of Technology was integrated with Privacy Calculus Theory and used in this study. Structural equation modeling results from 455 respondents revealed that facilitating conditions such as necessary knowledge and other technologies had a positive and the strongest influence on consumers' actual use of such payments. Effort expectancy had a high and positive influence on consumers' behavior intention towards mobile payment services. Consumers' behavior intention was also positively influenced by performance expectancy and social influence. Mobile payment service providers could use these factors to effectively address consumers' needs and try to exceed the expectations of their target consumers.

Keywords: *Mobile payment, services, adoption, consumers' behavioral intention*

Introduction

Technological advancements have made our lives more convenient in recent years. We have come a long way since the days of radio, television, computers, and mobile phones. However, the Internet is one of the most revolutionary inventions, as its integration with smartphone has changed so many things. Initially mobile phones were used only for voice communications and then text messages, but now they do most everything. Smartphones are small computers that enhance our entertainment, communication, work, commerce, and learning. According to Statista (2022), there are over six billion smartphone users worldwide, and this number is rapidly growing. Because of the near universal presence of mobile devices, it is not surprising that adoption of mobile payment solutions is increasing globally and driving growth in cashless transactions. Integrating digital payments into the economies of emerging and developing nations addresses crucial issues of wide-ranging economic growth and individual financial empowerment (World Bank, 2014).

The global usage of Mobile Payment Services (MPS) is increasing, but its growth is always reliant on customers' access to new technology, their changing lifestyle choices, and also on a variety of economic factors (Cabanillas et al., 2017). For a rapidly expanding and growing trend such as that of mobile payments, it is necessary to conduct additional, in-depth research on the adoption process of these tools, as well as to actively monitor the effects that different financial services have on consumers' opinions and their everyday routines. At the moment, China is the world leader in terms of proximity mobile payment adoption (Best, 2021). Also, China and India are among the top world leaders in terms of mobile payment adoption, whereas Nepal, a small mountainous nation squeezed in between these two giants, is still struggling towards mobile payment services on account of slow user adoption. Many people are accustomed to traditional methods of payments, such as cash and credit cards (Nepal Entrepreneurs' Hub, 2018). Though Nepal doubled the number of e-wallet companies in eight months, most of them face sustainability challenges (Acharya, 2021). There are also increasing numbers of data breach cases, exposing email addresses, phone numbers, passwords, and locations. These breaches are considered very sensitive, not only because of users' data privacy,

but also due to the risk to the potential security of the money which is held in their digital wallets (Myrepublica, 2020). Poor infrastructure and road conditions exist in most of these regions, affecting transportation and logistics. On top of that, only a few bank branches are available outside of the Kathmandu Valley (Khalti Digital Wallet, 2018; Maharjan, 2019; USAID, 2021). But at the same time, the majority of people in Nepal have access to mobile phones, and this could be a game changer in a country with little development in roads and logistics. The majority of Nepalese still lack easy access to financial institutions.

Mobile payment services facilitate commercial transactions and allow consumers to pay for goods and services using these payment methods wherever and whenever they wish. Even with these noticeable advantages, MPS cannot be maximized if users do not adopt them (Park et al., 2019). As a result, determining the factors that influence MPS adoption still remains a challenge. Therefore, many researchers have used various theories and models of technology acceptance and adoption to examine and predict the factors that can affect user's behavior intention and lead to the adoption of new technology. Theories and models adopted have included the Theory of Reasoned Action, Theory of Planned Behavior, Task Technology Fit, Unified Theory of Acceptance and Use of Technology (UTAUT), and Technology Acceptance Model (TAM). Among these, research has indicated that UTAUT provides a better understanding of the variance in behavioral intention to use a MPS (Venkatesh et al., 2003). Improvements in technology have made many things easier, whereas it has also increased many concerns over privacy, security, and other risks, as well as variables that might negatively influence the adoption intention of MPS. For research in mobile payment adoption, scholars have also extended UTAUT with various other factors. In this study, Privacy Calculus Theory (PCT) was integrated with UTAUT to assist in the understanding and examination of the cost/benefit trade-off of information disclosure. While most prior studies report a negative influence of privacy concerns on information disclosure, many individuals also tend to overvalue the benefits while undervaluing their privacy (Jiang et al., 2013).

Very few research studies have been conducted in lower-middle income economies, with the majority of residents living in rural areas, to better understand consumer intentions and perceptions of MPS. The main intent of this study was to bridge these gaps by using UTAUT, the most used theory in technology adoption, along with PCT, which examines the cost and benefit trade-off of information disclosure, and is one of the most prominent information privacy research frameworks.

The objectives of this study were to explore these relationships by addressing the following research questions:

1. What is the relationship between the variables posited by UTAUT and PCT with consumers' behaviour intention and adoption of MPS?
2. What are the most influential factors leading to actual use of MPS in Kathmandu Valley?
3. To what extent do perceived risk and perceived benefits affect consumers' behavior intention and actual use of MPS?

Literature Review

Advancement in the IT sector and research on the adoption of IT use is one of the mainstream research objectives on the global scale. Carlsson et al. (2006) have pointed out that it is important to make a distinction between the acceptance of mobile devices, the technology by itself, and mobile services. They considered that technology was not enough reason to use services, there should be value-adding to make the user change their everyday routine. Hence, the literature and theory adopted in this study is based on the behavior intention (BI) and adoption of use and this study includes two of the most prominent theories to examine the user's behavior intention to adopt mobile payment service.

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT was developed by Venkatesh et al. (2003) with the aim to predict user adoption of information technologies, and has approximately 70% explanatory power, which is 20% to 30% higher

than the Technology Acceptance Model (TAM) (Venkatesh et al., 2003). It incorporates eight theories, including the Theory of Reasoned Action, Theory of Planned Behavior, TAM, a model combining TAM and TPB (C-TAM-TPB), the Model of PC Utilization, Innovation Diffusion Theory, Motivation Model, and Social Cognitive Theory (Venkatesh et al., 2003). UTAUT has been used in numerous research studies and by many researchers to understand the factors that influence the use of technology. Venkatesh et al. (2003) also identified performance expectancy, effort expectancy, social influence, and facilitating conditions through empirical analysis as the main factors determining user adoption.

Performance Expectancy

Performance expectancy refers to the extent to which individuals believe that using the system or technology will assist them in improving their job performance. As Vankatesh et al. (2003) developed UTAUT using various previous models, performance expectancy was also developed using five factors from previous models. Many researchers have provided evidence of the significant influence of performance expectancy on user behavioral intention to adopt MPS (Lee et al., 2019; Abrahão et al., 2016). In the light of reported evidence, the following hypothesis was proposed:

H_1: Performance expectancy positively influences behavioral intention to adopt MPS.

Effort Expectancy

Effort expectancy is referred to as the degree of ease associated with use of the system or new technology (Vankatesh et al., 2003). It is projected that the higher the ease of MPS, the higher would be users' behavioral intention (Alalwana et al., 2017; Chong, 2013). Numerous researchers have shown that effort expectancy has a positive influence and is also one of the most effective factors on behavioral intention to adopt MPS (Alalwana et al., 2017; Chong, 2013). Oliveira et al. (2016) conducted a meta-analysis of 57 articles, and found that effort expectancy was positively correlated with mobile banking intention and adoption. Based on this evidence, the following hypothesis was proposed:

H_2: Effort expectancy positively influences behavioral intention to adopt MPS.

Social Influence

Social influence refers to the degree to which someone who is considered to be important to an individual thinks that they should use the new system or technology (Venkatesh et al., 2003). Social influence incorporates three similar constructs from other models—subjective norms (Theory of Reasoned Action, TAM2, Theory of Planned Behavior, and Decomposed Theory of Planned Behavior), social factors (using the Model of PC Utilization), and Image (using Innovation Diffusion Theory). Numerous studies in the mobile payment environment, including China (Guo et al., 2018), Qatar (Musa et al., 2015), and Portugal (Oliveira et al., 2016), have confirmed the significant impact of social influence on behavioral intentions. In the light of this reported evidence, the following hypothesis was proposed:

H_3: Social influence positively influences behavioral intention to adopt MPS.

Facilitating Conditions

Facilitating conditions refers to an individual's perception of the availability of technical and organizational infrastructure required to use the intended system. This definition covers constructs of perceived behavioral control (Planned Behavior Theory and Decomposed Planned Behavior Theory), facilitating conditions (PC Utilization Model), and adaptability (Innovation Diffusion Theory) (Davis et al., 1989; Venkatesh et al., 2003; Venkatesh et al., 2000). The facilitating conditions construct was derived from perceived behavioral control, and indicates that users, including banks and markets, require system availability at work. It is argued that the lack of technological infrastructure may discourage users from adopting technology. Numerous studies in the mobile payment environment have found facilitating conditions to significantly contribute to adoption of mobile payments

(Upadhyay et al., 2022; (Widyanto et al., 2021). Based on these arguments, the following hypothesis was proposed:

H_4: Facilitating conditions positively influence actual use of MPS.

Privacy Calculus Theory

The Privacy Calculus Theory, originally titled as "calculus of behavior," assumes that individuals are thinking about future consequences of their behavioral reactions (Laufer & Wolfe, 1977). PC Theory examines the cost and benefit trade-off of information disclosure (Culnan & Armstrong, 1999; Laufer & Wolfe, 1977). Individuals perform a subjective cost-benefit analysis, and disclosure occurs when the individual anticipates that the benefits will outweigh the risks of privacy loss (Smith et al., 2011).

Perceived Risk

Perceived risk is defined as a consumer's belief about the potential uncertain negative outcomes from online transactions (Kim et al., 2008). Risk has been studied for decades by researchers in other fields, but Jarvenpaa et al. (1999) were the first to apply it to online transactions. Unless given reasons to believe otherwise, consumers typically assume that transacting with a website is risky (Malhotra et al., 2004). In many studies of technology adoption, perceived risks have negatively influenced users' behavior intention and adoption of new technology (Nguyen & Huynh, 2018; Hwang & Choe, 2019; Yi et al., 2020). Based on these arguments, the following hypothesis was proposed:

H_5: Privacy risk negatively influences behavioral intention to adopt MPS.

Perceived Benefit

Perceived benefit is defined as the expectation that users will be better off compared to online transactions with specific websites (Kim et al., 2008). Users disclose personal information on social media in order to maintain or establish more interactive relationships, to gain a sense of belonging to an organization, and to obtain more services (Li & Chen, 2010). Many researchers have found perceived benefit to have a positive influence on behavioral intention (Geetha & Bindhu, 2019; Bhatti & Rehman, 2019; Huang, 2016) and many more. Based on these authors, the following hypothesis was proposed:

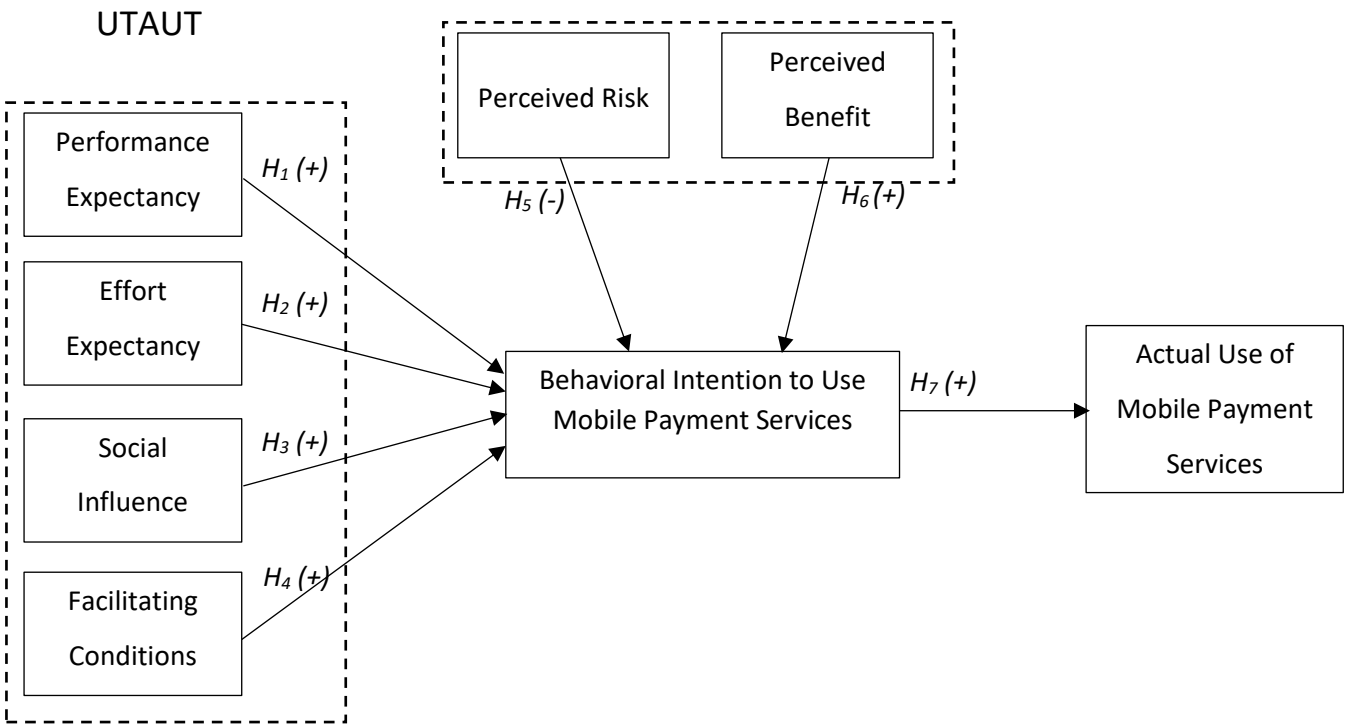
H_6: Perceived benefit positively influences behavioral intention to adopt MPS.

Behavioral Intention

Behavioral intention is defined as the subjective probability that individuals' will perform a specified behavior (Ajzen & Fishbein, 1980). Numerous research studies in different fields have been conducted, and various interpretations have been made of the concept of behavioral intention. Warshaw and Davis (1985) defined behavioral intention as "the extent to which a person has developed conscious plans to perform or refrain from performing some specified behavior." Most of the time, this has direct and positive impacts on its actual use (Venkatesh et al., 2003; Schukat & Heise, 2021). Based on these arguments, the following hypothesis was proposed:

H_7: Behavioral intention positively influences actual use of MPS.

Figure 1 *Conceptual Framework*



Methodology

This study used a quantitative technique with an online survey to collect data. The questionnaire was developed from earlier studies and adjusted based on the results of an Item Objective Congruence (IOC) test. The survey questions employed five-point Likert scales with responses ranging from *Strongly Disagree* to *Strongly Agree*. During the questionnaire development process, back-translation techniques from English to Nepalese were used. With the help of 40 sample respondents, a pilot study was undertaken. As a preliminary examination of the pilot study, Cronbach's alpha reliability analysis was used to test the measurement's internal consistency, and exploratory factor analysis (EFA) was used in pilot testing to verify measurement validity, identify item dimensionality, and remove items with low factor loadings–as well as redundant items–from the questionnaire to be used in the final study. After the survey questionnaire was refined, the final data was collected from 455 convenient respondents using a self-administered online questionnaire. Again, Cronbach's alpha analysis was used to analyze scale reliability from the final data, while confirmatory factor analysis (CFA) and structural equation modeling (SEM) were used to assess reliability, scale validity, and the links between the independent and dependent variables.

Data Analysis and Results

The data analysis was divided into three parts. To begin with, the Cronbach's alpha was used to ensure reliability of scale items to measure all variables. The output was between .76 and .99 for all the variables, which is higher than the threshold of 0.70, and hence assured the internal consistency of the scales (Hair et al., 2009). Second, the discriminant validity of the questionnaire was measured using CFA. Finally, SEM analysis was done to test the proposed conceptual model.

According to a descriptive analysis of the 455 respondents' characteristics living in the Kathmandu Valley, the majority were in the 25 to 40 years age group (52%). Males accounted for 53% and females 47%. Most respondents had a bachelor's degree, followed by a high school education and a master's degree. The majority of respondents, who studied and worked at the same time, did free lancing and were self-employed millennials. The majority of people working full time were respondents in the 41 to 56 years age group.

Twenty-nine scale items were modified from previous research studies to measure eight variables, six for UTAUT and two for PCT (adapted from Venkatesh et al., 2003; Kim et al., 2008; and Laufer & Wolfe, 1977). The structural model finally adopted is illustrated in Figure 2. Some scale items were removed to improve model fit indices, and 24 scale items remained. The CFA and SEM results are reported in the table which follows.

Figure 2 *Final Structural Equation Modeling with Standardized Beta Coefficients*

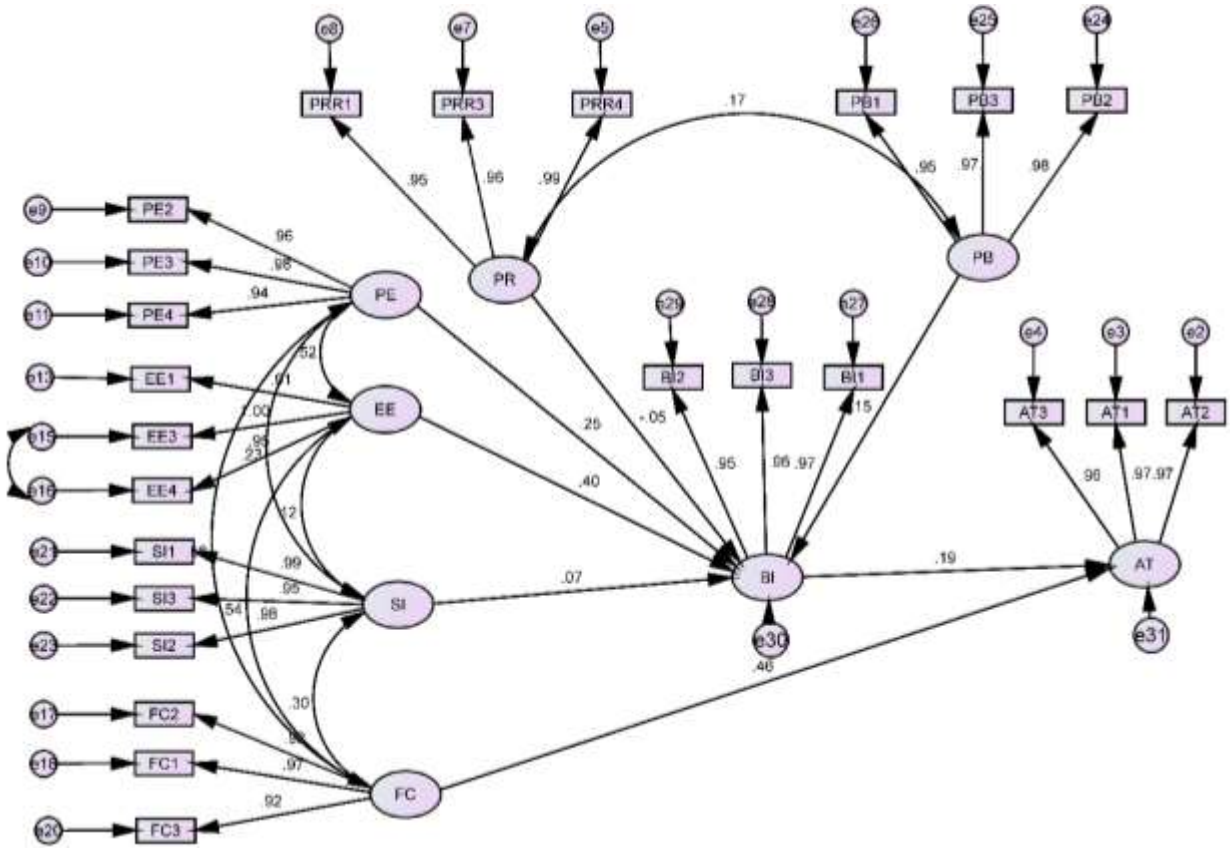


Table 1 provides the model fit measures from CFA analysis, which was applied to all variables—both UTAUT and PCT. Based on the overall CFA outcomes, the key criteria were met for the acceptance of the measurement model as shown in Table 1. The ratio produced by the proposed model ($\chi 2/df$ = 3.7) was still below the 5.0 threshold (p-value = .000, AGFI > 0.90, CFI > 0.90, NFI > 0.90, RMSEA ≤ 0.08). The results showed that all indexes in the CFA achieved the required levels to indicate goodness of fit to the model. SEM model evaluation was conducted since CFA is a part of SEM analysis. Most of the fit indices met the requirements in SEM analysis although the values for GFI and AGFI did not exceed .90 (the threshold value). However, they still met the requirements recommended by Baumgartner and Homburg (1996) and Doll et al. (1994). A value is tolerable if GFI is above .830. Therefore, the proposed structural model had a better goodness of fit as a result of overall fit statistical analysis.

Table 1 *Fit Index Results of Confirmatory Factor Analysis and Structural Equation Modeling*

Measure	CMIN/DF	GFI	NFI	CFI	AGFI	RMSEA	*p* Value
FIT Criteria	**< 5.00**	**≥ .90**	**≥ .90**	**≥ .90**	**≥ .90**	**< .08**	**≤ .05**
UTAUT	3.830	.905	.961	.971	.868	.079	.000
PC	2.338	.960	.986	.992	.938	.054	.000
SEM	3.724	.875	.947	.961	.842	.077	.000

Note. GFI = Goodness-of-Fit Index; AGFI = Adjusted Goodness-of-Fit Index; CFI = Comparative Fit Index; NFI = Normed Fit Index; RMSEA = Root Mean Square Error of Approximation.

Table 2 indicates that four out of seven hypothesized relationships were supported and significant in terms of standardized regression weights, whereas H_3, H_5, and H_6 were not. The results showed that facilitating conditions (β = 0.394, *t*-value=10.211, $p < .001$) and effort expectancy (β = 0.319, *t*-value = 8.942, $p < .001$) had the most significant influence on actual use and behavioral intention toward MPS. However, performance expectancy (β = 0.233, *t*-value = 5.455, $p < .001$) also had a positive relationship with behavioral intention. Therefore, H_1, H_2, and H_4 were accepted because all the relationships with behavioral intention and actual use were significant. Also the relationship between behavioral intention and actual use was positive and significant in this study, being supported by the following data (β = 0.174, *t*-value = 4.227, $p < .001$). Hence, the final hypothesis H_7 was also fully supported. Finally, we rejected the null hypothesis as the *p* value was not significant.

Table 2 *Summary of Hypothesis Testing*

Hypothesis	Path & Proposed effect	Estimate	*SE*	CR	*p*	Finding
H_1	Performance Expectancy → Behavior Intention +	.233	0.043	5.455	***	Accepted
H_2	Effort Expectancy → Behavior Intention +	.319	0.036	8.942	***	Accepted
H_3	Social Influence → Behavior Intention +	.050	0.027	1.884	.060	Rejected
H_4	Facilitating Condition → Actual Use +	.394	0.039	10.211	***	Accepted
H_5	Perceived Risk → Behavior Intention (-)	-.026	0.019	-1.359	.174	Rejected
H_6	Perceived Benefit → Behavior Intention +	-.086	0.022	-3.934	***	Rejected
H_7	Behavior Intention → Actual Use +	.174	0.041	4.227	***	Accepted

*Note. * $p < .05$; ** $p < .01$; *** $p < .001$*

Discussion

After analyzing the results, several interesting key findings emerged. H_4 (facilitating conditions) was the most significant factor in adoption of MPS. This means that the technical infrastructure to support MPS in Kathmandu Valley was highly correlated with consumers' mobile payment adoption. Numerous studies of the mobile payment environment have found the same outcome, that facilitating conditions had a significant influence on the adoption of mobile payments (Upadhyay et al., 2022; Widyanto et al., 2021). Effort expectancy was the second most important factor influencing consumers' behavioral intention towards MPS, and performance expectancy also positively impacted consumers' intention to adopt MPS. These outcomes are in line with the notion entrenched in previous research and theoretical literature suggesting that when individuals have all the necessary technology, when it is easy to understand and use, and when it functions to improve their outcomes, they are committed and become frequent users of new technology as a result (Widyanto et al., 2021; Oliveira et al., 2016; Khalilzadeh et al., 2017).

Theoretical Contributions

This research extends the application of UTAUT along with PC Theory to understand consumers' behavior. It showed that all factors of UTAUT had significance in behavioral intention to adopt MPS in the Kathmandu Valley, which supported the study of Venkatesh et al. (2003). Facilitating conditions and effort expectancy were found to be the most influential factors in adoption of MPS. However, it is noteworthy that perceived benefit from PC negatively affected behavioral intention. In fact, the negative estimates may be due to several factors: trust, security, or risk. As seen in one study, trust mediated a positive relationship between perceived benefit and behavioral intention, while a direct relationship was not supported in the same study (Park et al., 2018). These findings indicate that future research should be done, including factors like trust mediating perceived benefits, because trust

seems to be lacking in the Nepalese context, as another study revealed an insignificant relation between trust and intention to adopt digital payments (Giri & Ghimire, 2020).

Managerial Implications

From a managerial standpoint, the findings of this research have several implications that may serve as a foundation for marketers, managers, and relevant stakeholders in the MPS market to develop practical marketing strategies for their businesses. First, considering how facilitating conditions and effort expectancy had a stronger effect in intention and actual use of MPS, managers should aim to create an environment that facilitates availability of the technical and organizational infrastructure required to use MPS. Also, companies must invest in dependable technologies and enough network coverage. They should link up with companies that will help to improve their facilitating conditions. The significant impact of effort expectancy on behavioral intention indicates that developers should design user-friendly mobile applications to enhance consumers' belief in using MPS. Also, we see that most millennials in this study were inclined towards freelance activities, entrepreneurial enterprises, and multitasking, so similar kinds of services must be developed to grab future market share. The positive relationship between performance expectancy and behavioral intention shows that companies should introduce a strong and reliable MPS that could meet consumers' expectations, particularly the expectations of technology enthusiasts. The company should not only focus on utility of the system, but also add value to their use.

Interestingly, the relationship between perceived benefits and consumer intention to use MPS was not supported. As found in a previous study, trust helped as a mediator to significantly improve the relationship. Hence, we can assume that in the context of Nepal, trust towards the MPS companies may be missing. Hence, the company must ensure that consumers have positive net value with discounts, rewards, or at least by not imposing additional charges. The company or app providers should also advertise and boost MPS through celebrities and role models with sizeable fan followings, so that consumers can trust their testimonials and start using the services.

The implications discussed above are just a few examples of the types of initiatives that managers could implement to attract users, build trust, and increase frequency of use. Managers are also encouraged to use these research findings as the foundation for their own ideas and marketing strategies.

Limitations and Future Research

A few limitations in this study should be mentioned. To begin with, the results obtained in this paper represent only the population of Kathmandu Valley. Therefore, generalization of the findings to MPS users across the country as a whole or any other market outside of this country is not warranted. Likewise, because of the anonymous and deceptive nature of social media, data collected through online channels may be questionable in terms of reliability because respondents may or may not be who they claim to be, or meet the criteria established for the targeted sample. Furthermore, the absence of researchers in an online self-administered survey means that if respondents do not understand any part of the questionnaire, they have no convenient way of getting further explanation. Finally, the theoretical limitation of this study was that it was done using UTAUT and PC Theories, but there might be other factors influencing adoption intention.

Based on these limitations, recommendations are made concerning opportunities for future studies. Future research could consider broadening the scope of the study, collecting data from a wider range of users from the whole country, and comparing the results to make them more generalizable. Second, in terms of data collection, future researchers should collect surveys in person. This will ensure that the respondents meet the pre-established criteria for the targeted sample, and that all respondents have a clear understanding of the questionnaire, as well as a convenient way to obtain clarification if any confusion or misinterpretation arises. Finally, future research should also consider examining the mediating effect of trust on the relationship between perceived benefit and

behavioral intention, as well as introducing new variables to the existing model to gain a better understanding of the nature of this dynamic relationship.

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