# A Comparison of the Different Types of Risk Perceived by Users that Are Hindering the Adoption of Mobile Payment

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**Abstract.** Recent research has established that the risk perceived by users is one of the main reasons why, despite offering numerous benefits, the worldwide adoption of mobile payment remains surprisingly low. This pilot study aims to establish more specifically what types of risk have a negative effect on the adoption of mobile payment by proposing a new research model solely focused on the risk dimension. The model is composed of 6 types of risk that were extracted from the existing literature investigating mobile payment adoption. A 5-point likert scale-based questionnaire was used to collect sample data to test the model. The data was subsequently analysed by conducting a reliability analysis of the scale and a regression analysis aiming to quantify the effect of the variables on the users' intention to use mobile payment. The results of the study suggest that Security Risk is the highest deterrent, followed by Financial Risk, Social Risk, Privacy Risk and Time Risk while Psychological Risk was not found to have any negative effect on the users' Intention of Use. These findings potentially have implications for stakeholders such as mobile phone manufacturers and banking organisations as testing the research model on a larger sample of data would identify more precisely what aspects of mobile payment should be improved to increase its appeal to consumers. Furthermore, the proposed model can assist further research aiming to identify what features could reduce the risk perceived by potential mobile payment users.

**Keywords:** Mobile payment adoption · User acceptance · Hindering factors · Perceived Risk

## 1 Introduction

Several innovative payment technologies have been developed within the last thirty years, including contactless credit cards which have become extremely popular and are now overtaking traditional payment methods. Mobile payment is a notable example of a new payment technology which is gaining popularity among users as it takes advantage of the ever-increasing number of mobile phone owners [23, 24]. Mobile payment is defined [7] as a purchase of a good or service performed by a mobile device using a mobile communication network. Different types of technologies have been


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designed to perform mobile payment including near field communication (NFC) [3], magnetic secure transmission (MST) and sound base waves technologies. Mobile payment technology offers many benefits for both users and merchants including convenience, mobility, quicker transactions and lower costs [14]. Consequently, mobile payment was expected to become the preferred payment method by the end of the decade [13]. However, research has shown that the world-wide acceptance of mobile payment remains very far from the booming success it was predicted to reach [8]. For instance, the adoption of mobile payment is particularly limited in Western Europe [25] although most of the adult population owns a smartphone.

As a result, research on mobile payment has focused on trying to identify the hindering factors of its adoption. As demonstrated recently [20], several studies have established that the risk perceived by users is a major barrier to their acceptance of mobile payment technologies. Furthermore, [8] the risk perceived by users has been found to diminish the positive impact of the benefits they perceive. However, research has been inconstant as to what types of risk are included in the broad definition of Perceived Risk and as a consequence, the results of recent studies are not easily comparable. This pilot study aims to address this gap by extracting the different types of risk identified in recent research in order to measure and compare their effect on the consumers' intention to use mobile payment.

## 2 Background

While research aiming to analyse users' attitude towards innovative technology has been based on a variety of models throughout the last decade, mobile payment adoption studies have mainly focused on two particular behavioural intention models: the TAM and UTAUT models [4, 15].

The acceptance model was developed by Davis *et al.* in 1989 to measure the acceptance of information technologies (IT) and information systems (IS) [18]. It was initially composed of two main constructs: Ease of Use and Perceived Usefulness but was later adapted to the study of mobile payment adoption and now includes additional variables such as compatibility, social influence and risk perception depending on the needs of the research. [15]

The Unified Theory of Acceptance and Use of Technology results from the combination of the TAM with seven other models and was designed by Venkatesh *et al.* in 2003 [26, 27]. The UTAUT was initially composed of three main constructs (Expected Performance, Expected Effort and Social Influence) but was also flexibly modified with the addition of relevant variables to suit recent studies on mobile payment adoption [1].

More specifically, in studies investigating the relationship between risk perception and mobile payment adoption, research models have mainly included two variables: Intention of Use and Perceived Risk.

The variable Intention of Use was derived from the Theory of Reasoned Action and the Theory of Planned Behaviour which argues that individuals' actions are decided by their intention to act [2]. Previous studies on social behaviour have demonstrated that Intention of Use is a reliable variable to predict user behaviour. This justifies why Intention of Use has been consistently selected as the dependent variable in research on mobile payment adoption [17].

The variable Perceived Risk in research on payment technology acceptance was defined by Gupta and Kim [11] as "a consumer's perception about the uncertainty and the adverse consequences of a transaction performed by a seller". Several researchers including Yang et al. [30] and Schmidthuber, Maresch and Ginner [25] have demonstrated that Perceived risk has a negative effect of the users' Intention of Use. Nonetheless, the definition of Perceived Risk greatly varies from one paper to another. Some studies broadly define perceived risk as the expectancy of loss while many others include different types of risk within the main variable Perceived Risk. For instance, Ma et al. [16] included Financial Risk and Information Risk in Perceived Risk while Hongxia, Xianhao and Weidan [12] only mentioned Security Risk in their definition of Perceived Risk.

Although all those variations of Perceived Risk relate closely to the fear of a negative outcome, they do not refer to the same aspects of mobile payment and can therefore not be compared or addressed the same way. As a result, it was suggested that the individual testing of each different type of risk as well as a comparison of their effect would be relevant to better understand how mobile payment is perceived and increase its appeal to consumers.

## 3 Research Method

### 3.1 Research Model

Most recent studies on mobile payment adoption were based on the TAM or the UTAUT model and included the test of constructs such as Perceived benefits, Perceived Usefulness and Perceived Risk against the variable Intention of Use. This study proposes a new research model based on the TAM, solely focused on the risk dimension to study the impact of different types of risk perceived by users on their intention to use mobile payment.

The main variable Perceived Risk was divided into 6 constructs which correspond to the different types of risk that have been extracted from previous studies investigating the relationship between risk perception and mobile payment adoption. Since recent research has already demonstrated the hindering effect of these constructs, 6 hypotheses were formulated to assume their negative relationship with Intention of Use. This research model provides an opportunity to reinforce or challenge the findings of previous studies while allowing a comparison of the different types of risk to establish which one is the greatest deterring factor.

The first three constructs identified are Perceived Time Risk, Perceived Social Risk and Perceived Psychological Risk which were established by Cocosila and Trabelsi [5] following an investigation of user views on contactless payment via smartphones. Perceived Time Risk corresponds to the perception of users that they may waste time if they subscribe to mobile payment services. Perceived Social Risk refers to their fear of facing judgement or disapproval from their social circle. Finally, Perceived Psychological Risk is the general feeling of anxiety that users might experience regarding the decision of using mobile payment. The findings of Cocosila and Trabelsi [5] established a negative relationship between those variables and Intention of Use. The following hypotheses could therefore be formulated for this study:

**H1.** Perceived Time Risk has a negative effect on Intention of Use.
**H2.** Perceived Social Risk has a negative effect on Intention of Use.
**H3.** Perceived Psychological Risk has a negative effect on Intention of Use.

The 4$^{th}$ construct identified, Perceived Privacy Risk, stems from the combination of constructs identified in different studies which were named differently but essentially described the same concept. Ma *et al.* [16] describe it as Perceived Information Risk while Cocosila and Trabelsi [5] and De Kerviler, Demoulin and Zidda [8] call it Perceived Privacy Risk. Ooi and Tan [19] also include a similar construct named Privacy Concern. All these variables were described as the fear of losing control over one's personal data and were therefore combined into one construct: Perceived Privacy Risk. Surprisingly, only 50% of those studies demonstrated a negative relationship between Perceived Privacy Risk and Intention of Use. In order to test this construct, the following hypothesis was formulated:

**H4.** Perceived Privacy Risk has a negative effect on Intention of Use.

The 5$^{th}$ construct identified is Perceived Financial Risk which was defined by Liébana-Cabanillas, Sánchez-Fernández and Muñoz-Leiva [15] and De Kerviler, Demoulin and Zidda [8] as the users' expectation of financial loss. Precedent research in mobile payment adoption has established that this construct has a strong negative effect on the users' Intention of Use which justifies the 5$^{th}$ hypothesis:

**H5.** Perceived Financial Risk has a negative effect on Intention of Use.

Finally, the last construct identified is Perceived Security Risk which was defined by Hongxia, Xianhao and Weidan [12] as the fear that a dangerous outcome might result from the use of mobile payment. They argue that this construct is particularly relevant since the investigation conducted by iResearch company in 2009 showed that 48% of phone users refuse to use mobile payment due to security concerns. Consequently, the following hypothesis was formulated:

**H6.** Perceived Security Risk has a negative effect on Intention of Use.

The final research model that was designed for this study following the proposed hypotheses can be found in Fig. 1.

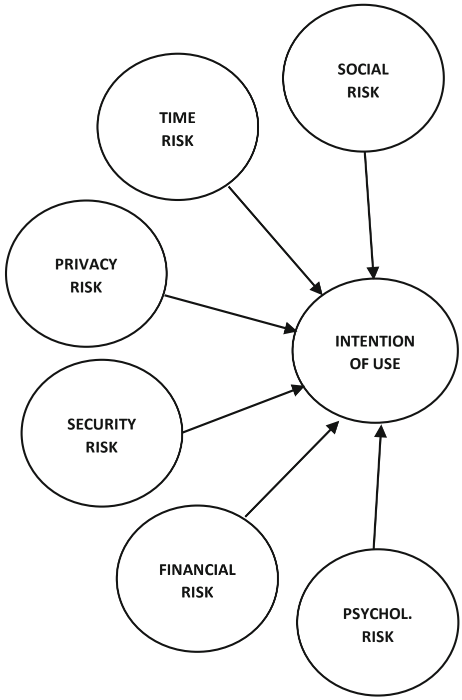


**Fig. 1.** Research model

## 3.2 Data Collection

An online survey was conducted to collect data from December 10th 2018 to January 3rd 2019. The survey was based on a questionnaire using a 5-point Likert scale ranging from "strongly agree" to "strongly disagree". This can be justified by the qualitative nature of the question as risk perception is concerned with opinions and therefore requires a metric scale that can measure intangible variables [31]. Furthermore, online questionnaires using 5- or 7-point Likert scales have been broadly used to collect data for the study of mobile payment adoption [20].

The questionnaire used to test the model was designed by combining and adapting questionnaire items from existing literature to fit the research model. The survey was split into two parts: the first part investigated the demographic characteristics of the respondents while the second part measured their opinions about statements directly linked to the constructs tested.

Each variable was tested via 3 statements in the questionnaire with a similar meaning but phrased differently. Cresswell [6] argues that testing a variable using several similar items reduces the risk of bias and allows a better reliability of the scale. The statements were randomly placed in the questionnaire to avoid redundancy for the respondents.

A questionnaire summary including all the questionnaire items can be found in Appendix B. Due to time and cost constraints, the questionnaire-based survey was delivered online only via Google Form which provided the opportunity to collect data efficiently and quickly [22].

### 3.3 Data Analysis

**Respondent Profile Analysis.** Once a sufficient number of questionnaires were collected, a profile of the respondents was established in order to identify any unbalanced characteristics that could influence the results of the test [10]. The respondents were then split into two categories: those who use mobile payment and those who do not use it. Since the study is trying to establish what factors are deterring consumers from starting using mobile payment, the answers of respondents who are not currently using mobile payment only were used to test the model.

**Reliability Analysis.** The program SPSS was chosen to conduct the statistical analysis of the data due to the high number of features it offers and to avoid costs [29]. Prior to analysing the data, a test of reliability of the scale was performed by calculating the Cronbach's Alpha coefficient. Reliability refers to the consistency of results produced by a measure: if the reliability of a measure is high, the results are more likely to be accurate and repeatable under consistent conditions [17]. Tian and Dong [28] argue that the Cronbach's alpha coefficient analysis is the most common reliability test for likert type scales. It aims to verify the internal consistency of the questionnaire by measuring whether similar scores are produced by items testing the same construct.

**Regression Analysis.** Due to its suitability to small sample sizes, a structural equation modelling (SEM) approach has been favoured to analyse data in recent research on mobile payment adoption [21]. For this pilot study, the relationship of the variables was established by performing a regression analysis. This method aims to measure the direct effect of independent variables on a dependant variable by calculating the path coefficient beta.
The value of the coefficient beta ranges between 0 and 1; the bigger the coefficient is, the higher the effect of the variable is. Additionally, a positive deviation path coefficient indicates that the independent variable has a positive effect on the dependant variable while a negative coefficient indicates a negative effect. This statistical analysis also produces the indicator p which establishes the significance of the relationship. The relationship is considered significant when $p < 0.05$ with the significance level being represented as follows: $^{*}p < 0.1$ $^{**}p < 0.05$ $^{***}p < 0.01$ [17].

## 4 Results

### 4.1 Data Sample

A total of 33 questionnaires were received among which 1 was invalid, leaving a total of 32 valid questionnaires. The characteristics of the sample can be found in Table 1.

**Table 1.** Profile of respondents

| Characteristics of the sample (N = 32) | | | |
|---|---|---|---|
| Item | Type | Frequency | Percentage |
| Gender | Female | 18 | 56.3 |
| | Male | 14 | 43.8 |
| Age | Under 18 | 0 | 0 |
| | 18–24 | 7 | 21.9 |
| | 24–31 | 14 | 43.8 |
| | 31–38 | 5 | 15.6 |
| | Above 38 | 6 | 18.8 |
| Education | High School | 0 | 0 |
| | College | 3 | 9.4 |
| | University | 13 | 40.6 |
| | Master/PhD | 16 | 50 |
| Owns mobile phone | Yes | 32 | 100 |
| | No | 0 | 0 |
| Purchase frequency | Once a month | 2 | 6.3 |
| | Once a week | 12 | 37.5 |
| | Once a day | 9 | 28.1 |
| | Several times a day | 9 | 28.1 |
| Uses mobile payment | Yes | 12 | 37.5 |
| | No | 20 | 62.5 |

The profile shows that the gender of the respondents is relatively equal between male (56.3%) and female (43.8%). While all the respondents are older than 18, the 24-31-year-old category (43.8%) seems to be more represented than the other age categories. This unbalance can be considered acceptable as the majority of technology users tend to be relatively young [16]. However, 90.6% of the respondents indicated they had been in further education which is a strong unbalance compared to the general population and could potentially affect the reliability of the results. Lastly, all the respondents own a mobile phone and the majority of them (93.7%) carry out purchases at least once a day which seems plausible. This suggests that most of the respondents are potential candidates for mobile payment. However, only 37.5% of them use mobile payment which confirms the claim that it is not widely adopted by users.

The questionnaires of the respondents who do not use mobile payment only were used for the next stage of the research as this study is focusing of the factors that are deterring consumers from using mobile payment. A final total of 20 questionnaires were included in the statistical analysis.

### 4.2 Reliability Analysis

The assessment of reliability of the scale is necessary to ensure that the results are accurate and would be found consistently if repeating the experiment. It is agreed that if the value for the Cronbach's alpha coefficient is equal or greater than 0.7, it indicates that the scale is sufficiently reliable to be used [28].

The coefficient is determined by calculating the covariance of answers for items related to the same variable. As can be seen in Table 2, the results of the Cronbach's alpha coefficient are all above 0.7 which indicates a sufficient reliability of the questionnaire.

**Table 2.** Reliability analysis results

| | Cronbach's alpha coefficient | Number of elements |
|---|---|---|
| Intention of use | 0.855 | 3 |
| Privacy risk | 0.824 | 3 |
| Security risk | 0.862 | 3 |
| Financial risk | 0.858 | 3 |
| Social risk | 0.861 | 3 |
| Time risk | 0.718 | 3 |
| Psychological risk | 0.750 | 3 |

## 4.3 Regression Analysis

Table 3 shows the results of the regression analysis that was conducted on the answers of respondents not using mobile payment. The standardised coefficient beta quantifies the relationship on the tested variable with the dependant variable Intention of Use.

**Table 3.** Regression analysis results

| Model | | Non standardised coefficients | | Standardised coefficient Beta | T value | Sig. |
|---|---|---|---|---|---|---|
| | | Coefficient beta | Standard error | | | |
| 1 | Dependant variable: intention of use | 5.455 | 1.783 | | 3.060 | 0.009 |
| | Privacy risk | −0.172 | 0.227 | −0.216 | −0.757 | 0.462 |
| | Security risk | −0.319 | 0.339 | −0.318 | −0.938 | 0.365 |
| | Financial risk | −0.226 | 0.284 | −0.285 | −0.797 | 0.440 |
| | Social risk | −0.108 | 0.219 | −0.154 | −0.493 | 0.630 |
| | Time risk | −0.021 | 0.230 | −0.022 | −0.092 | 0.928 |
| | Psychol. risk | 0.057 | 0.284 | 0.076 | 0.199 | 0.845 |

The results indicate that 5 out of the 6 tested constructs have a negative relationship with the dependant variable Intention of Use while one construct, Psychological Risk, has a positive relationship. The beta coefficients are respectively −0.216 for Privacy

Risk, −0.318 for Security Risk, −0.285 for Financial Risk, −0.154 for Social Risk, −0.022 for Time Risk and 0.076 for Psychological risk.

The significance indicators are greater than 0.05 for all the variables which indicates that the relationships are not significant at this stage. However, the statistical significance of results cannot be calculated accurately if the size of the sample is too low [9]. In this case, only a small sample of data was collected due to this pilot study being primarily focused on the research model rather than on the results. The significance of the relationships can therefore not be calculated until a full-scale study is conducted.

# 5 Discussion

## 5.1 Analysis

As can be seen in Fig. 2, the results of the study suggest that each type of risk tested has a hindering effect on the users' intention to use mobile payment except from Psychological Risk.

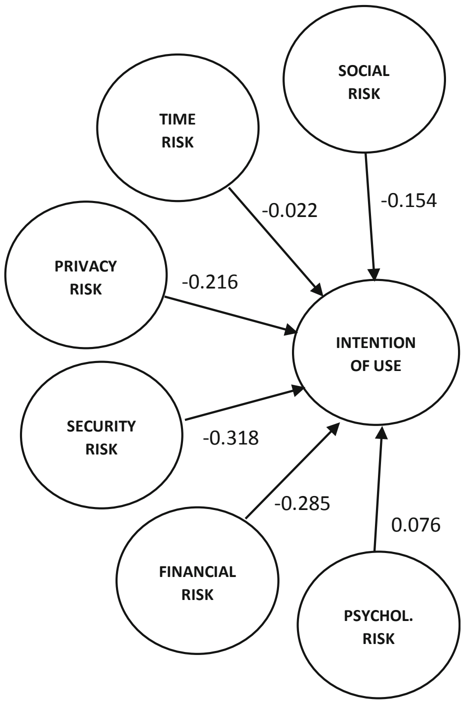


**Fig. 2.** Research model results

Social Risk and Time Risk have a small to moderate negative effect on the users' intention to use mobile payment. This partially supports the findings of Cocosila and Trabelsi [5]. However, the results also show that Psychological Risk has a positive effect on their intention of use which contradicts their results. Overall, this suggests that H1 and H2 are verified while H3 is not. Privacy Risk has a relatively higher negative effect on the users' intention to use mobile payment which corroborates the findings of several researchers including De Kerviler, Demoulin and Zidda [8], Cocosila and Trabelsi [5] but contradict the results of Ma *et al.* [16]. Nonetheless, these results support H4. Security Risk and Financial Risk both have a substantial negative effect on the users' intention to use mobile payment according to the results. This does not only verify H5 and H6 but also supports the results of multiple studies including the papers of Liébana-Cabanillas, Sánchez-Fernández and Muñoz-Leiva [15], Hongxia, Xianhao and Weidan [12], De Kerviler, Demoulin and Zidda [8], Yang *et al.* [30] and Ma *et al.* [16].

As can be seen in Table 4, it can be concluded that 5 out of the 6 proposed hypotheses have been verified.

**Table 4.** Hypotheses testing results

| Hypothesis | Path | Result |
|---|---|---|
| H1 | RISK → IU | Supported |
| H2 | SOCIAL RISK → IU TIME | Supported |
| H3 | PSYCHOLOGICAL RISK → IU | Unsupported |
| H4 | PRIVACY RISK → IU | Supported |
| H5 | FINANCIAL RISK → IU | Supported |
| H6 | SECURITY RISK → IU | Supported |

This research model does not only aim to clarify the definition of Perceived Risk but also allow a comparison of the effects of the different types of risk perceived by users on their intention to use mobile payment. This provides an opportunity to establish what types of risk specifically have the highest hindering effect on mobile payment adoption.

As can be seen in Fig. 3, the results of this study indicate that Security Risk is the type of risk that has the highest negative effect on the users' Intention of Use, followed closely by Financial Risk which is the second most hindering type of risk. Privacy Risk

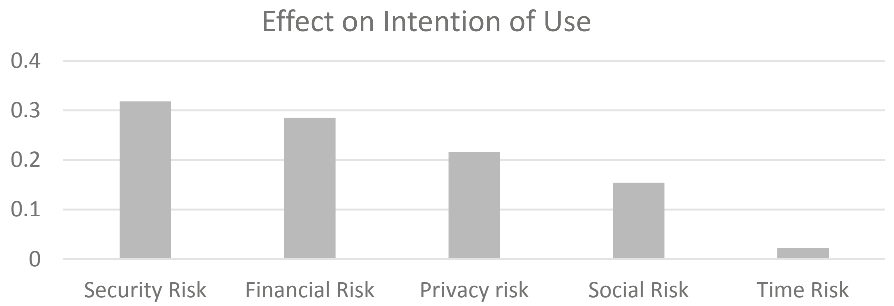


**Fig. 3.** Comparison of the effects of each type of risk on Intention of Use

and Social Risk respectively rank 3rd and 4th with a more moderate effect while time Risk seems to have the lowest negative effect.

These results do not match the findings of Cocosila and Trabelsi [5] who compared Time Risk, Social Risk, Psychological Risk and Privacy Risk and established that Psychological Risk was the most hindering factor followed by Privacy Risk, Time Risk and finally Social Risk.

However, it corroborates the findings of Hongxia, Xianhao and Weidan [12] and Ma *et al.* [16] who respectively established that Security Risk is the greatest hindering factor and that Financial Risk has a higher negative effect than Privacy Risk.

To summarise, the results of this study have shown that 5 out of the 6 types of risk identified have a negative effect on the users' Intention of Use and are therefore hindering mobile payment adoption. Financial risk, Security Risk have a relatively strong negative effect; Privacy Risk and Social Risk have a moderate negative effect while Time Risk has a minor negative effect which corroborates the results of several studies. However, psychological risk was not found to have any negative effect on the Intention of Use which contradicts the results of Cocosila and Trabelsi [5]. Finally, a simple comparison of the beta coefficients suggests that Security Risk has the highest hindering effect, followed by Financial Risk, Privacy Risk, Social Risk and finally Time Risk.

The findings of this pilot study have several implications for stakeholders within the mobile payment industry including mobile phone manufacturers, retailers and banking organisations. The ranking of the different types of risk perceived by users should be used to effectively prioritise the aspects of mobile payment that need improving. The primary focus should be to implement stronger security mechanisms to increase the safety of mobile payment and thus reduce the risk of dangerous outcomes and financial loss such as hacking, identity theft and financial fraud. Additionally, the marketing of mobile payment should aim to increase mobile device owners' confidence by showing that security is one of the main priorities of the mobile payment industry. Finally, further effort should be made to increase transparency regarding how the data of mobile payment users will be used and protected.

## 6 Limitations

Although this study proposes a valid research model, the data sample used to test the constructs was not substantial enough to give accurate results. It is therefore suggested that this research model should be tested on a larger sample of data to verify these findings. Cocosila and Trabelsi [5] suggest using the So per size sample calculation to estimate the required size for the sample. A larger sample will also allow an accurate analysis of the significance of each relationship calculated. Furthermore, the larger the data sample is, the better the population is represented. For instance, the characteristics profile of the sample indicated that more than 90% of the respondents had been in further education which does not necessarily reflect the population of the UK and constitutes a risk of bias.

Another major limitation of this study which may affect the accuracy of the results is the possible confusion of respondents regarding the definition of mobile payment.

3 respondents were informally questioned after completing the survey to discuss the clarity of the test, 1 of the respondents explained that they confused mobile payment with the action of purchasing an item or service on the internet from their mobile phone. This suggests that some of the answers may have been biased due to respondents misinterpreting the subject of the questions. It is therefore suggested that a brief definition of mobile payment should be added to the questionnaire to ensure all respondents understand what mobile payment refers to and thus improve the accuracy of the results.

Finally, although the findings of this study bring further insight into the issues associated with mobile payment, they do not provide any solution to improve them. It is therefore suggested that further research aiming to establish what features or security mechanisms can reduce the risk perceived by potential users would be beneficial to further increase the appeal of mobile payment. Additionally, mobile payment acceptance could be further understood by studying the effect of demographics on the types of risk perceived.

## 7 Conclusions

A new research model including 6 constructs was proposed to investigate the effect of different types of risk perceived by mobile device users on their intention to use mobile payment. A quantitative empirical study was conducted to verify the proposed research model by collecting data via a 5-point likert scale-based questionnaire and conducting a regression analysis to quantify the relationships between the model constructs. The results suggest that Security and Financial Risk are the first and second highest areas of concern for potential users of mobile payment. Privacy and Social Risk also seem to be moderate deterring factors while Time Risk has a minor negative effect on their intention to use mobile payment. Psychological Risk on the other hand was not found to have any hindering effect. However, this study presents a number of limitations such as the size of the data sample and the lack of clarification on mobile payment within the survey. It was therefore suggested that the research model should be tested on a largest sample using an improved questionnaire to verify the accuracy of the results. Nonetheless, the findings of this study provide the mobile payment industry with an interesting insight into the perceptions of mobile device users which can be used to increase the appeal of mobile payment. Finally, new areas of study investigating potential solutions and user demographics were suggested to further increase the users' willingness to adopt mobile payment.

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