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Perceived risks toward mobile payment adoption: A three-country analysis

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ABSTRACT

Mobile payment adoption has been a growing phenomenon ever since the introduction of Apple Pay in 2014 with exponential growth of cashless and contactless payment methods forecasted for the next five years. Past literature has investigated factors that negatively affect perceived risks in mobile banking and online shopping but details about consumers' attitudes towards these risks, differences among consumers, and the link between perceived risks and types of consumers remained understudied. To fill in this research gap, we have used a C4.5 decision tree learning algorithm with data surveyed from Taiwan, China and Japan to match the most used attributes of perceived risk - financial, privacy, performance, psychological, time, and security - with type of consumer according to the innovation adoption curve: innovators, early adopters, early majority, late majority, and laggards. Results allowed us to raise the following three propositions: (1) Innovators, early adopters, and early majority are concerned about the performance risk of mobile payment adoption, (2) Innovators, early adopters, and late majority are concerned about the security risk of mobile payment adoption, and (3) Culture of cashless economy is the key factor in mobile payment adoption.

Keywords: mobile payment, perceived risk, technology adoption, privacy, financial risk

INTRODUCTION

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According to a 2018 report by Business Insider, the global mobile payment market garnered 601.3 billion USD in 2016 and is expected to reach 4,573.8 billion USD by 2023. In the same year, MarketsandMarkets reported that the global digital payment market would worth 86.8 billion USD also by 2023. Existing literature showed that *perceived usefulness* (de Luna et al., 2018), *favorable attitude* (Park et al., 2019), and *service quality* (Liébana-Cabanillas et al., 2019) positively influenced consumer willingness to use mobile payment. Furthermore, mobile payment led to a positive judgment on store prices, which increased willingness to pay (Falk et al., 2016). *Security* (Oliveira et al., 2016; Shao, et al., 2019), *trust* (Zhou, 2013), and *risk* (Cocosila and Trabelsi, 2016) were identified as the most affecting factors on mobile payment adoption.

A 2018 report by Mordor Intelligence investigated the popularity of mobile payment in various countries including China (Alipay), India (Visa), and the US (Apply Pay and Android Pay) to find out that threats such as *cybercrimes* or *malwares* are the major issues to mobile payment adoption. Payment method changes has also been contributing to facilitate the transition from cash to cashless payment in the retail industry (Arvidsson, 2014). Moreover, consumers are concerned about risks regarding payment by smartphones. A 2016 survey by Thales e-Security concluded that 72% of the UK consumers are worried about risks associated with using contactless payment or smartphone paying methods. According to a 2016 report by Ofcom, nearly a quarter of the UK mobile users reported that mobile payments were not secure at all. Although the mobile payment industry is arguably already in maturity stage, concerns regarding privacy and security risks still exist.

Past literature investigated factors that negatively affect perceived risks in mobile banking or online shopping environment (e.g. Kim and Lennon, 2013; Mann and Sahni, 2013), as these perceived risks slow down mobile payment industry development (Choi and Choi, 2017). They also negatively influence mobile payment consumer acceptance (Yang et al., 2015) and trust in this payment method (Park et al., 2019). While the importance of perceived risks is discussed in many works, details about consumers' attitudes towards these risks, differences among consumers, and the link between perceived risks and types of consumers need further investigation.

According to Rogers (2010), consumers can be classified into five categories: innovators, early adopters, early majority, late majority, and laggards. In our study, we match these five consumer categories with existing users in the mobile payment industry. In addition, our research applies a decision tree classification method to link perceived risks regarding mobile payment with different types of consumers. Hence, we investigate two research questions:

RQ1: How can perceived risks be used to classify mobile payment users into categories?

RQ2: What are the differences between categories of perceived risks regarding mobile payment?

METHOD

Conceptual Model

This study utilizes perceived risks as the major attributes and types of consumer as the classification categories. Existing literature classified perceived risks into distinct categories such as financial, privacy, performance, psychological, monetary, time, and security. We merged monetary risk with financial risk to adopt the six fundamental risks in mobile payment. Moreover, this study applies the innovation adoption curve for classifying adopters of innovation into five different categories: innovators, early adopters, early majority, late majority, and laggards. *Innovators* are risk takers who adopt new technologies in their early stages, while *early* *adopters* play a vital role by promoting new technologies and recommending them to others. *Early majority* adopters, who are considerate and prudent, concern themselves with the usefulness of new technologies. *Late majority* adopters are always skeptical about new technologies and do not accept them before they reach maturity stage. Finally, *laggards* are old-fashioned consumers and most of them refuse to accept new technologies.

Decision Trees

Decision trees as flowchart-like structures have been used for processing classification problems ever since the seminal work from Breiman et al. (1984). The basis for the classification process must be known prior to establishing the classification model. This study applies a C4.5 algorithm that uses information entropy to build a decision tree based on training data. Each node of the decision tree represents an attribute of the data that can effectively split samples into subsets of class or other attributes. The calculation of the C4.5 algorithm can be divided into **Eq. (1)** and **Eq. (2)**. In **Eq. (1)**, *D* is the data set that includes *m* (classified results), where the probability of each result m is p_m. The C4.5 uses a gain ratio to solve this problem by considering splitting information. For example, if we have a feature D that has a distinct value for each record, then *Info(D)* is 0, thus *Gain(A)* is maximal. In **Eq. (2)**, *GainRatio(A)*is the proportion of information generated by the split that is useful for the classification. This study uses the notion of *GainRatio* to rank attributes and to build decision trees. Hence, each node is located with the attribute with highest *GainRatio* among the attributes (not yet considered) in the path from the root.

$$Gain(A) = Info(D) - Info_A(D) \text{, where } Info(D) = \sum_{i=1}^{m} - p_i \log_2 p_i \qquad \textbf{(1)}$$

$$SplitInfo_A(D) = -\sum_{j=1}^{v} \frac{|D_j|}{|D|} \times \log_2 \frac{|D_j|}{|D|} \text{ and } GainRatio(A) = \frac{Gain(A)}{SplitInfo_A(D)} \qquad \textbf{(2)}$$

RESULTS

Instruments and Data Collection

The questionnaire design consisted of four parts: demographic data, perceived risks, satisfaction with mobile payment (Yang et al., 2015; Thakur and Srivastava, 2014), and types of technology adoption (Rogers, 2010). It included 22 questions regarding perceived risks: four questions regarding financial risk, four regarding privacy risk, four regarding performance risk, three regarding psychological risk, four regarding time risk, and three regarding security risk. We used a five-point Likert scale, as follows: (1) strongly disagree, (2) disagree, (3) neutral, (4) agree, and (5) strongly agree. As previously discussed, types of technology adoption were categorized as innovators, early adopters, early majority, late majority, and laggards. Participants needed to select one type based on their own perception in addition to other demographic data including gender, age, marital status, occupation, educational background, experience of mobile payment use, and motivation for mobile payment use. Finally, they had to classify their satisfaction with the payment method based on 2 questions.

In this study we adopted random sampling by collecting responses online. The online questionnaires were administered through Google forms in three languages: Traditional Chinese, Simplified Chinese, and Japanese. Certified translators were used to translate from original Traditional Chinese to Simplified Chinese and to Japanese, and pilot tests were conducted leading to some questionnaire item changes and adjustments. A three-month time-frame was established for data collection, between February and April 2019. A total of 726 valid responses were gathered, with the following split: 242 from Taiwan, 243 from China, and 241 from Japan. Data was collected sequentially, i.e., country by country, one after the other, starting in Taiwan, then China, and finally Japan.

Data Analysis

We randomly selected 90% of data for training (model construction) and 10% of data for testing (model examination) from each sample, following a holdout data dividing method. Classification rules were extracted using conditional statements (if-then statements). In addition, we used the concepts of *support* and *confidence* to examine the extracted rules. *Support* indicates the percentage of training data for which left-hand side of the rule is true. If for an observation the left-hand side of the rule is true, then the rule applies for this observation. This measures how widely applicable is the rule. While *confidence* indicates that if the outcome of the training records for which the left-hand side of rule is true, then the percentage of records for the right-hand side is also true. This measures the accuracy of the rule. Additionally, we conducted k-fold cross-validation (k = 5) and the results were 62.78%, 62.84%, and 59.43% for Taiwanese, Chinese, and Japanese samples, respectively. Since the noise in the dataset and type of dataset may influence the accuracy, our results are fairly acceptable (Mantas and Abellán, 2014).

We found that the most important joint perceived risks among the three countries' samples are performance risk and security risk. Additionally, psychological risk is emphasized in two countries (Taiwan and China) and it could be considered as the second most important perceived risk regarding mobile payment. Moreover, other risk types were extracted from all three samples such as financial risk, time risk, and privacy risk from Taiwanese, Chinese, and Japanese samples, respectively. Specifically, Taiwanese participants, who consider that the payment system is stable and could be used smoothly, belong in the early majority category (rule 2 with 63.6% accuracy and covering 4.9% of data). While Chinese participants, who consider that service performance match their expectations and time loss could be caused by instability and low speed, belong in the early adopters' category (rule 3 with 68.8% accuracy and covering

7.3% of data). Furthermore, Japanese participants, who consider that mobile payment works as expected and are highly afraid of having their private information misused, inappropriately shared, or sold, belong in the early adopters' category (rule 2 with 77.8% accuracy and covering 4.1% of data). In addition, Japanese participants, who consider that mobile payment systems work very well, belong in the innovators category (rule 1 with 75.0% accuracy and covering 1.8% of data).

Regarding security risk, Taiwanese participants, who psychologically perceive that the usage of m-payment could not cause discomfort and fully trust the accuracy of the mobile payment bill, belong in the innovators category (rule 3 with 60.0% accuracy and covering 2.2% of data). While Chinese participants, who fully trust the accuracy of the inputted information via mobile payment, belong in the early majority category (rule 2 with 54.5% accuracy and covering 5.0% of data). Finally, Japanese participants, who fully trust the accuracy of the mobile payment bill, belong in the late majority category (rule 3 with 52.9% accuracy and covering 7.8% of data). Additionally, regarding financial risk, Taiwanese participants, who consider that mobile payment would not cause malicious or unreasonable charges, belong in the late majority category (rule 1 with 75% accuracy and covering 1.8% of data). While Chinese participants, who psychologically perceived that the usage of m-payment would not cause discomfort, belonged in the early majority category (rule 1 with 55.6% accuracy and covering 4.1% of data).

CONCLUDING REMARKS

Since the first launch of Apple Pay in 2014, mobile payment has become a popular method globally as cashless payment turned out to be the latest trend to facilitate commercial transactions. This study investigated six types of perceived risks regarding mobile payment adoption in China, Taiwan, and Japan. A total of 726 valid responses were collected including

242 from Taiwan, 243 from China, and 241 from Japan. Using the decision tree method, average accuracy values are 62.78%, 62.84%, and 59.43% for Taiwan, China, and Japan, respectively. Taiwan had the highest precision score (62.9%), while China had the highest recall (64.0%) and F_1-score (63.4%) scores. Additionally, we found that performance risk and security risk were the most important joint constructs among the three countries. Moreover, participants from Taiwan and China also identified a psychological risk. These results imply that culture also impact the perceived risk regarding mobile payment adoption; for example, financial risk in Taiwan (cautious culture), time risk in China (open culture), and privacy in Japan (conservative culture). Innovators, early adopters, and early majority were concerned about performance risk regarding mobile payment adoption; while innovators, early majority, and late majority were concerned about security risk regarding mobile payment adoption. Furthermore, companies can formulate suitable strategies to focus on specific aspects such as privacy protection, security assurance, and saving time to alleviate the concerns and anxieties regarding mobile payment adoption. We recommend that stakeholders in the mobile payment industry carry on appropriate business strategies to gather more consumers and thus rise operational leverage effects.

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