The Role of Perceived Risks on Mobile Payment Adoption: Evidence from Asia

Abstract: Mobile has become an expected method of payment irrespective of the geographical location or the level of technology adoption across the developed and developing countries. The differences of adoption rates between China and Japan are significant, warranting further research into the barriers to mobile payment. To fill this research gap, we propose and empirically test a theoretical model of mobile payment adoption by users in China, Taiwan, and Japan. A decision-tree method was used to analyse 726 questionnaire responses. The results reveal that innovators, early adopters, and the early majority categories are concerned about the performance risk of mobile payment adoption and innovators, early adopters, and the late majority categories are concerned about the security risk of mobile payment adoption. The findings will help 5G mobile services vendors develop consumer trust and increase the contributions of the mobile industry to GDP.

Keywords: mobile payment, perceived risk, innovation adoption, cybersecurity, privacy, Asia

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1. Introduction

The global mobile payment market exceeds $601.3 billion (Business Insider, 2018) and is expected to reach $4,573.8 billion by 2023. Other sources (MarketsandMarkets, 2018) predict that the global digital payment market will be worth $ 10.07 trillion by 2026, with 5G being the key to the development. The Asia Pacific, is predicted to generate a revenue of $ 3.62 trillion in the year 2026, owing to its extensive market penetration towards digital payment coupled with cashless economy. The more developed markets seeking to become the 5G global leaders (e.g. Japan), are expected to see rapid 5G growth by 2025, accounting for half of total mobile connections. However, for the rest of the region (e.g. China), 5G opportunities are less attractive because there is still more potential for leveraging the capabilities of 4G, which is to remain the dominant mobile technology. It is yet to be seen whether mobile users in emerging markets of the Asia Pacific will see the advantages and pay more for 5G services, particularly when 4G services satisfy their needs. The focus across the Asia Pacific markets is to push innovation in areas such as mobile commerce and payment (GSM Association, 2019).

An analysis of the popularity of mobile payment across Asia, including China (Alipay), India (Visa), and the US (Apply Pay and Android Pay), undertaken by Mordor Intelligence (2018), uncovered that threats such as *cybercrime* form the major barriers to mobile payment adoption. Payment method changes have also contributed to the transition from cash to cashless payment in retail (Arvidsson, 2014). Further, payments via smartphones have raised concerns about risks amongst consumers (Saridakis et al., 2016). Statistics show that 72% of UK consumers are worried about risks associated with the use of contactless and smartphone payment methods (Thales, 2016). Nearly a quarter of UK mobile users reported that mobile payments were not secure at all (Ofcom, 2016). Also, hacking and intercepting, loss of phone, insufficient security provided by companies, and unauthorized usage have been highlighted as major concerns related to mobile payment in the US (Statista, 2015). Although the mobile payment industry has arguably reached maturity, concerns regarding privacy and security risks persist (Albashrawi and Motiwalla, 2019).

Studies in the literature have investigated factors that negatively affect perceived risks in the mobile banking and online shopping environments (e.g. Kim and Lennon, 2013; Mann and Sahni, 2013), as these perceived risks impede the mobile payment industry development (Choi and Choi, 2017). They also have a negative influence on consumer acceptance of mobile payment (Yang et al., 2015) and their trust in this payment method (Park et al., 2019). Research has showed that *perceived usefulness* (de Luna et al., 2018), *favourable attitude* (Park et al., 2019), and *service quality* (Liébana-Cabanillas et al., 2019) positively influence consumer willingness to use mobile payment. Mobile payment has led to a positive perception of in-store prices, which has increased willingness to pay (Falk et al., 2016). *Security* (Oliveira et al., 2016; Shao, et al., 2019), *trust* (Zhou, 2013; Gao and Waechter, 2017), and *risk* (Cocosila and Trabelsi, 2016) have emerged as the key factors affecting mobile payment adoption. While the importance of perceived risks has been highlighted frequently in the literature, the details about consumers' attitudes towards these risks and the link between perceived risks and the types of consumers need further research attention (e.g. Liébana-Cabanillas et al., 2019; Park et al., 2019).

Rogers' (2010) typology of innovation adoption has been successfully applied to explain advanced technology adoption by consumers by splitting them into five categories: innovators, early adopters, early majority, late majority, and laggards. In our study, we apply these five consumer categories across the users of mobile payment. Following Dey (2002), Kabari and Nwachukwu (2013), and Ramezankhani, Kabir, Pournik, Azizi, and Hadaegh (2016), this research uses a decision tree classification method to investigate the link between perceived risks of mobile payment and the five consumer categories. Hence, the following research questions are put forth:

RQ1: What are the major perceived risks of mobile payment adoption in China, Taiwan, and Japan?

RQ2: What is the association between perceived risk of mobile payment adoption in China, Taiwan, and Japan and the category of mobile payment user?

The study answers the calls in the literature to provide insight about the barriers to mobile payment adoption in the developed countries of Asia Pacific (Fahey, 2019; Mobile Economy Report on Asia Pacific, 2019). China is the leading country in mobile payment adoption, Japan is pursuing the wide applications of 5G because of the Olympics, and Taiwan is following behind while its government stabilizes the regulation. We aim to reveal the drivers of mobile payment success in these countries in order to enable the innovator countries to realize the potential of 5G mobile payment.

2. Literature Review

2.1 Mobile Payment

The process of payment in which mobile devices are used to execute transactions for products or services, anytime and anywhere, is known as mobile payment. It is an alternative to traditional payment methods by cash or credit card (Selvadurai, 2014), as it uses communication devices (Dahlberg et al., 2008) to carry out the payment authorisation and execution of financial transactions (de Luna, 2018). Mobile payments have also been shown to increase sales in physical stores (Liu et al., 2015). The acceptance of mobile payment depends on the willingness to accept new technologies (Liébana-Cabanillas and Lara-Rubio, 2017; Qasim, and Abu-Shanab, 2016). New smartphone functions, such as near field communication, support mobile payment use (Oliveira et al., 2016), even in physical stores (De Kerviler et al., 2016), thus reducing costs and increasing retail outlet profitability (Chen and Li, 2017). Individual factors such as previous experiences and external factors such as market competition also influence the willingness to adopt mobile payment (Zhu et al., 2017).

Extant research has identified the factors affecting mobile payment adoption, including acceptance, risk, perception, trust, and willingness (Cocosila and Trabelsi, 2016; de Luna et al., 2018; Liébana-Cabanillas et al., 2019; Oliveira et al., 2016; Park et al., 2019; Shao, et al., 2019; Zhou, 2013). Attitude is also an important factor which influences mobile payment intention (Wang and Dai, 2020). Perceived usefulness and trust are deemed significant drivers of behavioral intention to use Apple Pay (Pu et al, 2020). Regarding the relation between *acceptance* and mobile payment use, Selvadurai (2014) indicates that the majority of consumers choose the account provider offering the largest variety of mobile payments, which enhances user experience and offers competitive differentiation in the market (Hayashi and Bradford, 2014). While companies use marketing campaigns to influence consumer decisions on the short-term usage of mobile payment, they do not change the long-term purpose (Zhu et al., 2017). Also, smartphone limitations negatively influence the user experience, which varies widely due to the variety of smartphone models and application vendors (Zhou, 2014). Additionally, the connection between mobile payment and traditional payment methods plays an important role in building trust in mobile payment (Cao et al., 2018).

Cybersecurity issues tend to dominate the decision to adopt mobile payment. With regard to *risk*, perceived threats of hackers and malware that threatens mobile devices have been shown to be the major reasons for their low usage rate (Zhou, 2014), though the influence of the emerging risks on mobile payment is still unclear (Selvadurai, 2014). Mobile payments may reduce financial losses in retail outlets, as they have been proven to be safer than credit card payments (Hayashi and Bradford, 2014). Yet early adoption of mobile payment has created perceptions of risks and uncertainty (Xin, 2015), in particular amongst consumers who have lower trust in technologies and mobile services driven by concerns related with privacy, security, and erroneous payment transactions (Dinh et al., 2018).

With regard to the *perception* factor, studies show (Xin, 2015) that consumers are uncertain and do not trust mobile payment companies. Additionally, *self-efficacy* is a major factor influencing the resolution to use mobile payment in stores (Nel and Heyns, 2017). Thus, when more retailers make mobile payment available to consumers this will lead to the improvement of user perceptions and self-efficacy (Dinh et al., 2017). Moreover, mobile payment's ease of use reduces time and cost for consumers (Nguyen and Nguyen, 2018). Mobile payment also involves uncertainty and risk, and users need to build trust to mitigate the perceived risks and increase continuance of usage (Zhou, 2014). Additionally, the use of mobile payment also promotes consumer participation and increases loyalty (Hayashi and Bradford, 2014), as consumers form their perception about trust in mobile payment in advance (Nel and Heyns, 2017). Research shows that once consumers form trust towards mobile payment they continue to use this method according to their understanding of the level of security (Zhu et al., 2017). Trust in mobile payment providers is a significant factor affecting *willingness* to use (Xin, 2015). Conversely, the availability of additional mobile services has little effect on use (Nel and Heyns, 2017), as consumers could stop using mobile payment even if providers offered additional services (Zhou, 2014).

2.2 Perceived Risk

Perceived risk strongly influences the consumer decision process in any purchasing environment (Gillett, 1976). Perceived risk is defined as a likelihood of loss due to uncertainty related to unexpected outcomes when making purchase decisions (Featherman and Pavlou, 2003). The ability to accept perceived risk affects financial transaction decisions (Forsythe and Shi, 2003), as perceived risk has been linked to consumers' subjective expectations, thereby extending its influence on the mobile payment decision-making process.

The literature on perceived risks has focused on the key risk categories: financial, privacy, performance, psychological, time, and security. *Financial risk* indicates a possible monetary loss due to the use of mobile payment methods (Featherman and Pavlou, 2003). It is advantageous to use mobile payment when other payment methods incur higher costs (Luarn and Lin, 2005) or when the cost of continuous usage leads to a possible financial loss. Additionally, financial risk is associated with monetary expenses and maintenance costs. The uncertainty regarding mobile payment authorisation might increase mobile users' concerns (Yang et al., 2015), as system malfunction during financial transactions could lead to potential losses (Baganzi and Lau, 2017).

Privacy risk indicates the risk of personal information exposure (Featherman and Pavlou, 2003), as consumers are concerned about the exposure and misuse of their personal data involved in mobile payments. Disclosure and misuse of personal information cause consumers to lose control over their personal data (Khalilzadeh et al., 2017) allowing providers to harvest, process, transfer, and sell their personal information (Yang et al., 2015), thus helping these providers to gain insight on users' non-public data and shopping behaviour (Thakur and Srivastava, 2014). Sensitive information such as personal identification, credit card information, and other financial data makes many customers uncertain and concerned about their privacy (Baganzi and Lau, 2017).

Performance risk relates to system malfunctions that affect mobile payment services provided to users (Featherman and Pavlou, 2003). Performance can be volatile due to the limitations in smartphone capabilities; this volatility in turn raises users' concerns (Yang et al., 2015). Consumers expect mobile payment to improve the efficiency of daily tasks (Khalilzadeh et al., 2017); however, the instability of wireless connections and the limited processing capabilities of mobile devices increase performance risk (Choi and Choi, 2017).

Psychological risk refers to frustration, perceived anxiety, and psychological pressure (Lim, 2003). Compared to online payment or credit card payment, mobile payment is a novel and complex service. For example, consumers might feel anxious because of a failed transaction (Yang et al., 2015). Psychological risk of mobile payment is also associated with unfamiliarity, unreliability, and fear (Trachuk and Linder, 2017).

Additionally, *time* risk indicates the delays experienced by using mobile payment because of user uncertainty, the learning curve of mobile applications, or the risk of an incomplete payment process (Featherman and Pavlou, 2003). Moreover, consumers occasionally experience longer transaction time, causing inconvenience. The need for additional time to become experienced with the mobile payment system and to troubleshoot its problems is also a time risk factor affecting users (Choi and Choi, 2017).

Finally, *security* risk refers to the risk of uncontrolled transactions and loss of financial information (Aktruzan and Tezcan, 2012). It is also associated with the perceived payment method security, security of information at rest and in transit, and cybersecurity overall (Kolsaker and Payne, 2002). Cybersecurity is the link between the perceived risk and the consumer attitude (Khalilzadeh et al., 2017); it assures information confidentiality, integrity, and service availability (Flavián and Guinalíu, 2006). Consequently, sales increase only when the perceived security of the payment transaction data and other sensitive information is high (Thakur and Srivastava, 2014).

2.3 The Mobile Economy: Current Position of the Asia Pacific

Within the current year, mobile technologies and services contributed 5.3% of GDP in the

Asia Pacific, which amounted to $1.6 trillion of economic value added. Further, according to intelligence from GSMA (2018), the mobile ecosystem generated 18 million jobs and contributed nearly $165 billion in tax towards public sector. However, across the Asia Pacific, a commitment to 5G has occupied varied priority status by country. Developed markets, including South Korea and Japan, aspire to lead the global innovation in 5G networks and fully exploit the promise of new innovative services and connected devices running on 5G. By 2025 at least 50% of all mobile connections will be underpinned by 5G in Japan and Taiwan, surpassing 4G.

However, 5G opportunities are met with caution by the rest of the region. In China and many other developing countries, the domination of 4G is expected to last over the next decade, with 70% of the connections remaining at 4G through 2025. This sluggish adoption has been explained by the fact that operators in countries such as China have yet to recoup the significant costs incurred when 4G was rolled out in those regions. Further, users in China have a lower expectation of migrating to expensive 5G services whilst 4G and 3G networks deliver a ‘good enough’ service satisfying user needs.

In China, the proportion of mobile subscribers among the total population is set to reach that of Japan only by 2025. Yet the rate of mobile adoption is higher in China, and both countries are expected to increase their mobile adoption rate to 88% by 2025. China is leading the shift to mobile payment in the Asia Pacific (eight countries out of the ten top global mobile payment adopters are from this region), maintaining 86% of subscribers using mobile payments in stores over 2018 and 2019 In addition to mobile payments, China surpasses Japan and Taiwan by online shopping frequency: 65% versus 47% of mobile users frequently order goods with their mobiles in China and Japan, respectively (GSMA, 2019). While Japan, China, and Taiwan appear to have different national priorities with regard to 5G innovation, the subscriber choices and user adoption of mobile services, including mobile payments, across these regions warrant a closer exploration of the cultural difference which may be behind the drivers of mobile payment services innovation and adoption (Fahey, 2019).

3. Research Method

3.1 Conceptual Model

This study utilizes perceived risks and types of consumers as the classification categories. The literature has classified perceived risks into distinct categories such as financial, privacy, performance, psychological, monetary, time, and security (Lim, 2013; Yang et al., 2015;

Thakur and Srivastava, 2014). We merged monetary risk with financial risk to adopt the six fundamental risks in mobile payment. This contributes to theory by applying the innovation adoption curve for classifying adopters of innovation into five different categories: innovators, early adopters, early majority, late majority, and laggards (Rogers, 2010). *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, are driven by the usefulness of new technologies. *Late majority* adopters are always sceptical about new technologies and do not accept them before they reach the maturity stage. Finally, *laggards* are old-fashioned consumers, and most of them refuse to accept new technologies. Figure 1 shows the conceptual model used for the C4.5 decision tree learning algorithm (Quinlan, 1993).

Decision Tree Learning Method (C4.5 Algorithm)	
Attributes (Perceived Risk)	**Category** (Type of Consumer)
• Financial • Privacy • Performance • Psychological • Time • Security	• Innovators • Early Adopters • Early Majority • Late Majority • Laggards

Figure 1: Conceptual model

Current mobile payment research commonly adopts survey-based inferential approaches to investigate specific topics on mobile payment, such as value-risk perception (Cocosila and Trabelsi, 2016), intention on m-payment service (Liébana-Cabanillas et al., 2020), drivers and barriers (Moghavvemi et al., 2021), and innovation resistance (Kaur et al., 2020). Our research joins the ongoing conversation on perceived risk on mobile payment adoption and associates the perceived risk with the category of mobile payment user. The decision tree method offers a complements the traditional inferential methods. By doing so, we provide a contribution to the discussion on whether early adopters and innovators take less consideration of risk factors than the other groups and what nuances could they have.

3.2 Decision Tree Learning Algorithm

Decision trees have been used in classification problems since the seminal work by

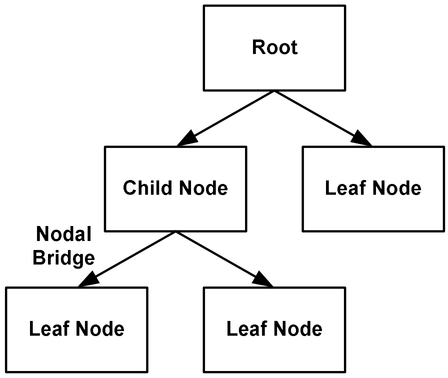
Breiman et al. (1984). The basis for the classification process must be known prior to establishing the classification model. Additionally, tree-structured models are established based on class labels and using actual data entries to build up a concise model (Agrawal et al., 1998). According to these models, common characteristics and rules can be summarized and used to predict other unclassified or new data. Moreover, the processes of decision trees include data training and testing processes. Each data entry in the training data is used to shape a decision tree based on data attributes. Each internal node represents a decision point and a testing condition, whereas each branch represents the testing results and the leaf nodes show the classification results. Finally, after defining a decision tree, its validity is verified by test data.

Figure 2(a) shows an example of a decision tree, which includes four nodal types. The first type is the root node (starting node), where the processing of new data begins. The second type is the child node (i.e., internal node), which represents individual testing conditions and stores minimal data to determine the subsequent data branch. Acting as a link between these two nodes is the nodal bridge. Each branch represents a testing result and functions as a nodal bridge. The fourth type is the leaf node, which represents various class labels. All data landing on this node exhibits identical characteristics.

This study applies a C4.5 algorithm that uses information entropy to build a decision tree based on training data (Figure 2(b)). 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.

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

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



Input: training set T;

set of classes $C:\{C_1, C_2, ..., C_m\}$;

Output: a decision tree TR;

if T contains examples, all in the same class

then

build a single leaf L;

if T contains examples of different classes

then

build a partition T';

build child node N for each subset in the partition;

Recursively call the algorithm on each subset;

Figure 2: (a) structure of a decision tree; (b) C4.5 algorithm

4. Results

4.1 Instruments and Data Collection

The questionnaire design featured four parts: demographic data, perception of risks, and satisfaction with mobile payment adoption. The items for financial risk, privacy risk, performance risk, psychological risk, and time risk were adapted from Yang et al. (2015). The items for time risk were adapted from Thakur and Srivastava (2014). The types of technology adoption were taken from 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 5-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. In addition, the questionnaire gathered participants' demographic data: gender, age, marital status, occupation, educational background, experience of mobile payment use, and motivation for mobile payment use. Finally, participants were asked to classify their satisfaction with the payment method based on two 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 the original (traditional Chinese) to simplified Chinese and to Japanese, and pilot tests were conducted leading to some adjustments in questionnaire items. A three-month timeframe was established for data collection, from February to 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 in Taiwan, China, and Japan. Despite their apparent cultural similarities, these three countries have significant differences in mobile consumer behaviour, as shown by previous successful studies of the three nations to better understand their online activity that reflects individual cultures in the Asia Pacific (e.g. Dwivedi et al., 2008; Gibbs et al., 2003; Gong, 2009; Singh et al., 2003; Thatcher et al., 2006; Trappey and Trappey, 2001).

4.2 Demographics

The survey data collected from the target nations showed a prevalence of female respondents and is summarized in Table 1. The majority of participants were in the age group of 21 to 30, which characterized 63.3% of respondents from Taiwan, 51.9% from China, and 44.4% from Japan. In education, 96.7% of Taiwanese participants, 81.9% of Chinese participants, and 66.0% of Japanese participants had an educational level of bachelor's degree and above. Occupations were more diverse among Taiwanese participants, while students comprised a plurality of the Chinese participants (49.4%) and a significant percentage among Japanese respondents (31.5%).

Table 1: Demographic data from Taiwan (TW), China (CN), and Japan (JP) samples

Sample Size: TW: 242; CN: 243; JP: 241	**Country**		
Gender	**TW**	**CN**	**JP**
Male	31.0%	40.7%	44.0%
Female	69.0%	59.3%	56.0%
Marital status			
Married	23.1%	33.7%	25.7%
Unmarried	76.9%	66.3%	74.3%
Age			
20 or below	0.4%	15.6%	10.4%
21–30	63.3%	51.9%	44.4%
31–40	20.2%	13.2%	21.6%
41 or above	16.1%	19.3%	23.7%
Education			
High school or below	2.5%	10.3%	20.3%
Bachelor's	64.0%	71.2%	56.0%

Master's	32.7%	10.7%	10.0%
Doctoral	0.8%	4.1%	0.0%
Others	N/A	3.7%	13.7%
Occupation			
Student	12.0%	49.4%	31.5%
Finance	13.6%	5.8%	0.8%
IT	14.5%	4.5%	6.2%
Self-employed	4.5%	8.6%	2.1%
Service	13.6%	6.6%	15.8%
Manufacturing	9.9%	2.1%	3.3%
Education	5.8%	7.4%	9.5%
Sales	7.0%	2.5%	7.5%
Others	19.0%	13.2%	23.2%
Using experience			
Yes	67.8%	95.9%	55.2%
No	32.2%	4.1%	44.8%
Payment used			
Apple Pay	39.7%	27.2%	30.7%
Samsung Pay	1.7%	2.1%	0.0%
Android Pay/Google Pay	3.3%	3.3%	3.7%
Alipay	12.0%	93.4%	1.7%
LINE Pay	39.3%	3.7%	22.0%
WeChat Pay	10.7%	94.2%	4.1%
JKOPay	9.9%	N/A	N/A
Others	N/A	11.1%	62.8%
Reasons			
Convenience	64.9%	97.5%	58.5%
Cash back	40.5%	12.4%	22.8%
Secure	2.9%	28.8%	2.5%
Peer influence	7.9%	8.6%	1.2%
Rewards in loyalty program	2.1%	2.9%	0.8%
Others	N/A	7.4%	39.3%

Additionally, 95.9% of Chinese participants were experienced users of mobile payment methods, versus 67.8% of Taiwanese participants and 55.2% of Japanese participants. Combining age and user experience across these three countries, the data revealed that younger subscribers use mobile payment as an essential method in China. The main payment methods in Taiwan were reported as Apple Pay (39.7%) and LINE pay (39.3%), while in China they were Alipay (93.4%) and WeChat Pay (94.2%), and Apple Pay (30.7%) and LINE pay (22%) in Japan. The reasons to use a mobile payment method in the three countries were similar: convenience (64.9%) and cash-back offers (40.5%) in Taiwan; convenience (97.5%), security (28.8%), and cash-back offers (12.4%) in China; and convenience (58.5%) and cash-back offers (22.8%) in Japan.

Table 2 shows a summary of the differences in perceived risks (average score) among the three countries. Taiwanese participants scored higher than did Chinese and Japanese in five categories of perceived risks, with the exception of time risk. Overall, the attitude of Taiwanese participants towards perceived risks of mobile payment methods was heightened, while the Japanese participants were the least concerned about risks. In particular, Taiwanese participants were mostly concerned about privacy risk (3.67), the highest average score among all risks. The average score of concern about their information being collected, tracked, and analysed was 4.08 for the Taiwanese participants, which was higher than the scores for Chinese (3.51) and Japanese (3.11) participants. It appears that Taiwanese participants were the most concerned about risks of using mobile payment methods. All participants, regardless of their country of origin, had serious concerns about the disclosure of their private data via mobile payments use.

Table 2: Summary of differences in perceived risks among Taiwan, China, and Japan

*Number of Respondents: TW: 242; CN: 243; JP: 241	TW	CN	JP
Financial Risk	**2.88**	**2.81**	**2.51**
1. The use of mobile payment (m-payment) would cause the exposure of personal bank accounts and passwords.	2.84	2.62	2.56
2. Malicious or unreasonable charging could occur.	2.23	2.44	2.20
3. A careless operation could lead to a surprising loss.	3.37	3.33	2.73
4. The use of m-payment could cause financial risk.	3.07	2.86	2.55
Privacy Risk	**3.67**	**3.35**	**2.84**
5. Private information could be misused, inappropriately shared, or sold.	3.44	3.28	2.67
6. Personal information could be intercepted or accessed.	3.61	3.32	2.80
7. Payment information could be collected, tracked, and analysed.	4.08	3.51	3.11
8. Privacy could be exposed when using m-payment.	3.55	3.28	2.77
Performance Risk	**2.78**	**2.68**	**2.56**
9. The payment system might be unstable or blocked.	3.51	3.01	2.99

10. The payment system does not work as expected.	2.54	2.24	2.31
11. The performance level might be lower than designed.	2.43	2.59	2.41
12. The service performance might not match its advertised level.	2.63	2.87	2.55
Psychological Risk	**2.95**	**2.60**	**2.82**
13. Mobile payment would cause unnecessary tension (e.g., concerns about errors).	2.66	2.37	2.61
14. A system malfunction in m-payment could cause unwanted anxiety and confusion.	3.29	2.88	3.13
15. The usage of m-payment could cause discomfort.	2.90	2.56	2.71
Time Risk	**2.71**	**2.50**	**2.76**
16. Time loss could be caused by instability and low speed.	3.32	3.01	2.98
17. It might take too much time to learn how to use mobile payment.	2.41	2.24	2.76
18. More time is required to fix payment errors offline.	3.03	2.67	3.07
19. Using m-payment may waste time.	2.09	2.08	2.20
Security Risk	**3.29**	**2.98**	**2.92**
20. There might be mistakes, since the accuracy of the inputted information is difficult to check from the screen.	2.92	2.63	2.70
21. The battery of the mobile phone might run out or the connection could be interrupted while paying.	3.57	3.21	3.34
22. The bill information might be typed wrongly.	3.39	3.09	2.74
Satisfaction and Willingness			
23. Do you feel satisfied with the mobile payment method you use?	**3.69**	**3.90**	**3.23**
24. Will you continue using the same mobile payment method?	**3.86**	**4.07**	**3.36**

Japanese participants scored higher than did others in the time risk category (2.76), and their average score regarding the risk of "More time is required to fix payment errors offline" was the highest (3.07). This might reflect the Japanese participants' fear of wasting their time trying to use mobile payment methods and fixing their problems compared to pre-paid cards (e.g., Suica and PASMO). Interestingly, Chinese participants scored the highest in the satisfaction (3.90) and willingness (4.07) categories; however, with regard to the perceived risks, scores were moderate. Japanese participants had the highest and the lowest perceived risk scores; nonetheless their satisfaction (3.23) and willingness scores (3.36) were also the lowest. Taiwanese participants had the highest perceived risk scores, while the satisfaction (3.69) and willingness scores (3.86) were moderate. We infer that the infrastructure of mobile payment may be mature in Japan though still growing in Taiwan. In China, the market drives consumers to use mobile payment methods.

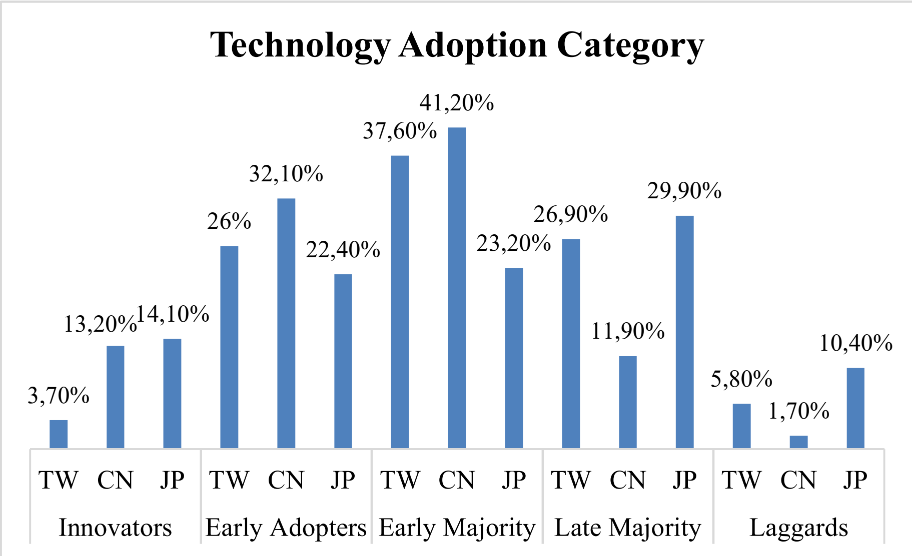


Figure 3: Distribution of technology adoption categories

Additionally, we found that the averages of financial risk, performance risk, psychological risk, and time risk in the three countries' samples were all below 3.0, indicating that participants were less concerned about these risk types. Moreover, the average scores of privacy risk for Taiwanese and Chinese participants were high, while the scores were close to neutral for Japanese participants. It appears that participants were concerned about privacy issues of mobile payments (e.g., about the possibility of leakage of their personal and payment information). Finally, the average score of security risk for Taiwanese participants was higher than 3.0 while it was close to 3.0 for Chinese and Japanese participants. This indicates that Taiwanese participants may worry more than Chinese and Japanese participants about security issues of mobile payment (e.g., disconnection).

Figure 3 shows the distribution of the technology adoption categories among the three countries' samples. Participants were asked in the questionnaire to select one category to which they belonged. Results revealed that participants from China (13.2%) and Japan (14.1%) were more innovators than those from Taiwan (3.7%). This indicates that Chinese and Japanese like to try new technologies and applications such as mobile payment. According to the results, most participants in the three samples were in the early adopters, early majority, and late majority categories: 90.5% in Taiwan, 85.2% in China, and 75.5% in Japan. Japanese participants had the highest percentage of those in the late majority (29.9%) category, which might be because Japan is the most conservative country among these three. Interestingly, among Japanese participants, 10.4% identified as laggards, which also reflected the phenomenon of less usage of mobile payment methods until 2018 in this country.

4.3 Data Analysis

4.3.1 Classification Rules

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. In addition, we used the concepts of *support* and *confidence* to examine the extracted rules. *Support* indicates the percentage of training data for which the 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 the rule is. *Confidence* indicates that if the outcome of the training records for which the left-hand side of the 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 data set and the type of data set may influence the accuracy, our results are acceptable (Mantas and Abellán, 2014).

Each sample generated three rules, shown in Table 3. We found that the most important joint perceived risks among the three countries' samples were performance risk and security risk. Additionally, psychological risk is emerging 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 the three samples: financial risk (Taiwanese), time risk (Chinese), and privacy risk (Japanese). Specifically, Taiwanese participants, who considered 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 considered that service performance matched 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 considered that mobile payment works as expected and were 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 considered that mobile payment systems work very well, belong in the innovators category (rule 1 with 75.0% accuracy and covering 1.8% of data).

Table 3: Results of the decision trees

Taiwan, 5-fold cross-validation (average accuracy: 62.78%)

Dimensions		Rules	Support	Confidence
Financial Risk	Rule1	IF 2. Malicious and unreasonable charging occurs >= 5 THEN Category = Late Majority	1.8%	75.0%
Performance Risk	Rule2	IF 9. The payment system might be unstable or blocked < 2 THEN Category = Early Majority	4.9%	63.6%
Psychological Risk & Security Risk	Rule3	IF 15. The usage of m-payment could cause discomfort < 3 AND 22. The bill information might be typed wrongly >= 5 THEN Category = Innovators	2.2%	60.0%
China, 5-fold cross-validation (average accuracy: 62.84%)				
Dimensions		**Rules**	**Support**	**Confidence**
Psychological Risk	Rule1	IF 15. The usage of m-payment could cause discomfort >= 5 THEN Category = Early Majority	4.1%	55.6%
Security Risk	Rule2	IF 20. There might be mistakes, since the accuracy of the inputted information is difficult to check from the screen >= 5 THEN Category = Early Majority	5.0%	54.5%
Performance Risk & Time Risk	Rule3	IF 12. The service performance might not match its advertised level < 3 AND 16. Time loss could be caused by instability and low speed >= 4 THEN Category = Early Adopters	7.3%	68.8%
Japan, 5-fold cross-validation (average accuracy: 59.63%)				
Dimensions		**Rules**	**Support**	**Confidence**
Performance Risk	Rule1	IF 10. Overall, The payment system does not work as expected >= 5 THEN Category = Innovators	1.8%	75.0%

Performance Risk & Privacy Risk	Rule2	IF 10. Overall, the payment system does not work as expected < 2 AND 5. Private information could be misused, inappropriately shared, or sold >= 4 THEN Category = Early Adopters	4.1%	77.8%
Security Risk	Rule 3	IF 22. The bill information might be typed wrongly >= 5 THEN Category = Late Majority	7.8%	52.9%

In relation to security risk, Taiwanese participants, who perceived that the usage of mobile payment could not cause psychological discomfort and fully trusted the accuracy of the mobile payment bill, belong in the innovators category (rule 3 with 60.0% accuracy and covering 2.2% of data). Chinese participants, who fully trusted the accuracy of the entered 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 trusted 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 considered 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). Chinese participants, who psychologically perceived that the usage of m-payment would not cause discomfort, belong in the early majority category (rule 1 with 55.6% accuracy and covering 4.1% of data).

4.3.2 Metrics

Decision trees are built using training and testing data with the outcomes generating the confusion matrix. This confusion matrix is used to measure the performance of the built model regarding predicted case and true class. Different evaluation measures are used such as *precision*, *recall*, and *F1-score*. *Precision* is the number of true positives divided by the total number of respondents labelled as belonging in the positive class (**Eq.(3)**). *Recall* is the number of true positives divided by the total number of respondents who actually belong in the positive class (**Eq.(4)**). Finally, F_1*-score* is a harmonic measure calculated by weighted precision and recall (**Eq.(5)**). In particular, *TP* (true positive) indicates the number of respondents correctly labelled as belonging in the positive class. *FN* (false negative) wrongly denotes that a predicted class does not exist, when it does, while *FP* (false positive) wrongly indicates that a predicted class exists, when it does not.

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+F} \tag{4}$$

$$F_1 - Score = \frac{2*Precision*Recall}{Precision+Reca} \tag{5}$$

This research used 80% of data as training data to build decision trees, including 223, 218, and 218 respondents from Taiwan, China, and Japan, respectively. Figure 4 shows that Taiwan had the highest precision score (62.9%) while China had the highest recall (64.0%) and F_1-score (63.4%). Conversely, Japan had the lowest score on all three metrics. Possibly, Taiwanese and Chinese samples reflected good results of decision trees while Japanese respondents were diverse, thus scoring lower than the other two countries.

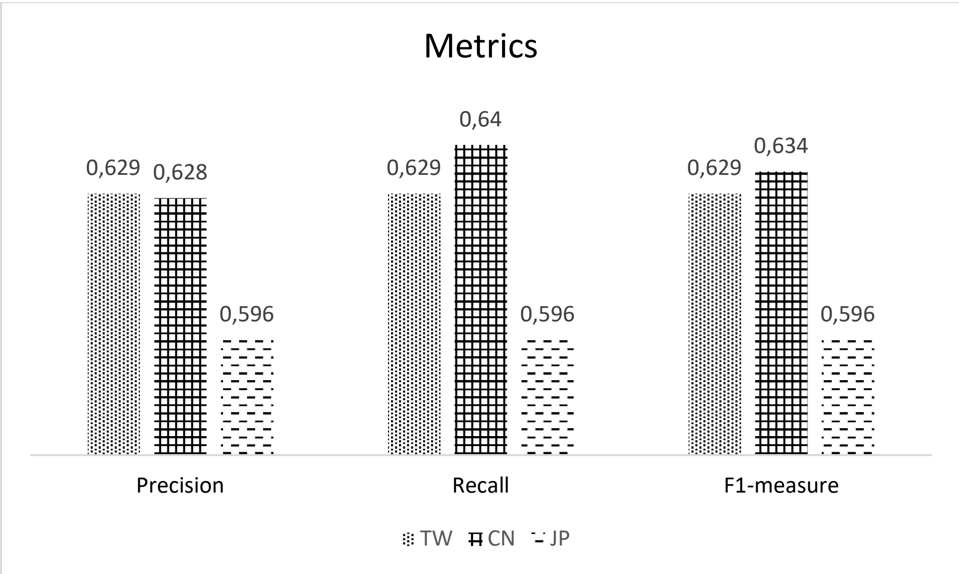


Figure 4: Comparison of metrics among the three countries

4.4 Discussion

In 2019, the mobile payment penetration in China and Taiwan reached, 86% (PwC, 2019*)* and 62.2% (Taiwan News, 2020)[1] respectively, while Japan still displayed very low scores

[1] https://www.taiwannews.com.tw/en/news/3861779

(21.5%) (eMarkerter, 2020)[2]. The QR code-based method is still the preferred approach among consumers in all three countries, while the leading mobile payment services are Alipay and Wechat Pay in China, PayPay in Japan, and LINE Pay in Taiwan. QR codes are easy to use but also vulnerable to scammers. In China, the research of Shuai et al. (2018) indicates that security and technology risks were considered as relatively high. Financial risk, credit risk, policy and regulation risks were considered as medium risks. In Japan, cash is convenient for consumers who have concerns about breaches of personal information (privacy issue). Low knowledge of how to use new technology is also a concern for Japanese users (Morlan, 2019). In Taiwan, security and privacy issues are the biggest concerns (hackers, virus, misuse, and over-charge) according to the report from VISA Consumer Payment Attitudes Study (2020)[3]. Our findings confirmed that security and performance risks are important to Chinese users; financial, security, and performance risks are important to Taiwanese users; and security and privacy risks are important to Japanese users.

The outcomes from the decision trees revealed that performance risk and security risk are the key factors in mobile payment usage for the three countries. Regarding performance risk, Taiwanese participants in the early majority category believe that the mobile payment system is stable, while Chinese participants in the early adopters category trust that the benefits of mobile payment would meet their expectations. Interestingly, Japanese participants in the innovators category consider that the overall use behaviour is different from what they expected, while those in the early adopters category think that the overall use behaviour matched their expectations. Thus, we infer that innovators have high expectations when they voluntarily try mobile payment for the first time. Overall, we presume that early adopters and the early majority trust the performance (e.g., stability) of mobile payment. The effect of performance in mobile payment on willingness was also identified by works in the literature (Oliveira et al., 2016; Yang and Forney, 2013; Qasim and Abu-shanab, 2016). Hence, we put forward our first proposition:

Proposition 1: Innovators, early adopters, and the early majority are concerned about the performance risk of mobile payment adoption.

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[2] https://www.emarketer.com/content/japan-s-cashless-vision-starting-come-fruition

[3] VISA Consumer Payment Attitudes Study (2020) https://www.visa.com.hk/dam/VCOM/regional/ap/hongkong/global-elements/documents/visa-whitepaper-hk-final-compressed.pdf

Regarding the security risk, Taiwanese participants in the innovators category and Japanese participants in the late majority category are highly concerned about billing errors that might cause information theft, while Chinese participants in the early majority category fully believe that the accuracy of input information is difficult to verify on screen and might cause payment errors. Overall, we presume that innovators, the early majority, and the late majority have concerns about the security of mobile payment systems. Moreover, Taiwanese and Chinese participants identify the psychological risk, while Taiwanese participants in the innovators category feel safe using mobile payment. Conversely, Chinese participants in the early majority category feel completely unsafe using mobile payment. We infer that mobile payment is extremely popular and convenient in China, though the society or regulators may make users feel unsafe regarding fraud. We hypothesize that government regulation and protection of technology may affect the perceived security risk regarding mobile payment. Hence, we present the second proposition:

Proposition 2: Innovators, the early majority, and the late majority are concerned about the security risk of mobile payment adoption.

5. Implications

Our findings show that Taiwanese participants in the late majority category are fully concerned about the possibility that mobile payment might cause unreasonable charges, which is classified as a perceived financial risk. The reason for this is that the Taiwanese government did not allow mobile payment methods until early 2017 thus users are still learning and developing a new mindset towards this payment option. Additionally, Chinese participants in the early adopters category care more about time risk and are afraid of time loss due to unstable or slow payment processes, while Japanese participants in the same category worry about privacy risks such as the misuse, inappropriate sharing, or selling of their private information. We conclude that early adopters care more about time and privacy risks, while the late majority care more about financial risks, consistent with the findings of previous works (Cocosila and Trabelsi, 2016; Wang et al., 2019). In summary, high usage of mobile payment in China is linked to speed and time, while low usage of mobile payment in Japan is associated with privacy concerns. Taiwanese care more about financial risks of mobile payment usage. These results are of particular interest given the fact that we could have access to data from three different countries from the same region which allows to contrast results in a comparable setting and thus support informed decisions from mobile payment operators willing to approach these markets as well as policy makers and researchers on the developed Asia Pacific.

With the significant yearly growth of registered mobile money accounts (by 38% in 2018), the pace of innovation in the region has not kept up with this speed. In other mobile services, such as OTT media in Asia, great success has been demonstrated as mobile payment has been integrated into platforms alongside a suite of other services. A number of start-ups have successfully entered the mobile commerce and payments scene and achieved first-mover advantage. There is a significant gap between China and Japan in mobile payment services trust, and lessons can be learned from the scenario of Sub-Saharan African operators, which have realized the need to diversify their mobile money proposition. Our results can help mobile operators in Asia to achieve the necessary diversification and address various customer requirements to be competitive.

The routes could include expanding beyond basic peer-to-peer cash transactions and providing an integrated suite of financial services, including savings, credit, insurance, and wealth management. These also may be enhanced by offering dedicated enterprise solutions and opening their APIs (GSMA, 2019) to encourage start-ups in this space. By opening up their APIs, mobile operators have the potential to enable the building of a vendor and developer ecosystem. The findings of this research can help mobile service operators and start-ups formulate strategies to gain consumer trust and alleviate perceived risks amongst various customer segments. By understanding the relationship between perceived risks and mobile payment adoption, companies can tailor strategies for different countries by focusing on specific aspects such as privacy protection, security assurance, or saving time. Some of these strategies could involve drafting well-defined privacy specifications to ease consumers' concerns about their data protection, securing the transaction process to reduce the possibility of being hacked, and minimizing the steps in mobile payment (e.g., QR code-based) to speed up the mobile payment process. Furthermore, companies could explore further types of monetization and could embrace partnerships with third parties to help overcome compliance constraints. Mobile operators could work with governments to forge new mobile payment regulations and ethical requirements, thus alleviating the concerns and anxieties of consumers with regard to mobile payment adoption.

6. Conclusion

A range of conditions are necessary to enable success of mobile payment as part of 5G services, including a stable, underpinning regulatory framework; agreement of operators and service providers on the required standards; and the widespread accessibility of 5G devices. Established local market conditions such as competitive dynamics, ‘good enough’ legacy services, affordability of mobile devices, and tariffs will influence the rate of mobile payment adoption across 5G networks. One of the key factors affecting this adoption is customers’ perception of value in this service and trust in the technology. The proliferation of mobile payments globally has yet to deliver the same success in Asia Pacific or to facilitate a new wave of commercial innovation. This study investigated six types of perceived risks regarding mobile payment adoption in China, Taiwan, and Japan. Using responses from 726 individuals—242 from Taiwan, 243 from China, and 241 from Japan—we used the decision tree method, in which average accuracy values were 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. Our results reveal that the importance of the perceived risks of mobile payment adoption and their variation across developed Asia-Pacific countries: security and performance risks are predominant in China; financial, security, and performance risks prevail in Taiwan; and security and privacy risks are prominent in Japan. These outcomes also link perceived risks with mobile payment adoption categories. Innovators, early adopters, and early majority are concerned about performance risks while innovators, early majority, and late majority are concerned about security risks. Because of this category, mobile payment operators need to prepare appropriate strategies to deal with it when approaching local markets in these three countries. For example, achieving privacy protection, security assurance, and saving time to alleviate the concerns and anxieties of consumers could be extremely impactful. We recommend that stakeholders in the mobile payment industry develop appropriate business strategies to reach more consumers and thus open further monetization opportunities.

7. Limitations and Future Research

This research has several limitations which open avenues for future research. Firstly, the number of respondents could be larger in order to increase the generalization power of our findings. Despite our significant data collection efforts and support received in all three countries, we encourage future research to test our hypothesis larger data sets. Secondly, mobile payment methods could be explored in a cross-country perspective. This will require firm-level data on top of the individual-level data used in this work and the connection to the different operators. Thirdly, different data mining methods could be used for enhancing comparison and to further extend the scope of our results. Future research could expand to more Asian countries such as South Korea, Thailand, Vietnam, and Indonesia and draw conclusions on the regional context. Other classification methods (e.g., SVM or Naïve Bayes) may be applied to compare the differences in results and provide more opportunities for practical impact.

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