Revisiting Mobile Payment Risk-Reduction Strategies: A Cross-Country Analysis

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Abstract

Mobile payment risk has become a critical cybersecurity factor in the cashless society. The outbreak of COVID-19 helped proliferate mobile payments that also bring significant risks to users. Using the AI methods this study analyzed six dimensions of mobile payment risks (financial, privacy, performance, psychology, time, and security) in a survey of 748 respondents from three countries (UK, Taiwan, Mozambique). The decision tree method was employed to identify and analyse critical perceived risks. The ANOVA test provided insights on the perceived risks between countries. The ANOVA test showed that UK users were concerned about financial and time risks; those in Mozambique were concerned about performance, psychological, and security risks; and those in Taiwan were concerned about privacy risks. The results revealed that decision trees outperformed other methods (such as neural networks, logistic regression, support vector machine (SVM), random forest, and Naïve Bayes models). Performance risk (Taiwan and Mozambique) and security risk (UK) are the most significant factors. Cultural differences influence mobile payment risk perception in different countries. The risk-reduction strategies were also matched to the critical factors by the decision tree. This showed that simplification and risk-sharing strategies were the major tactics in all three countries. The clarification strategy works for Taiwan and

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Mozambique, which focuses on the benefits of using mobile payments. The results suggest that enterprises should improve and simplify the mobile payment process and collaborate with the third parties to reduce and share cybersecurity risk.

Keywords: mobile payment; risk-reduction; cyber threats; technology trust; privacy concerns; Taiwan; Mozambique; UK

1. INTRODUCTION

Starting with the launch of Apple Pay in 2014, the transition to cashless society has rapidly accelerated. However, fraudulent transactions through mobile applications have caused considerable losses and highlighted the growing importance of cybersecurity (Benson and McAlaney, 2019). Technologically advanced countries from various geographies, including Sweden, China, France, and the United States, continue to exploit the potential of mobile payments. In Asia, leading mobile payment methods include Alipay and WeChat Pay (China), PayPay and LINE Pay (Japan), Naver Pay and Kakao Pay (South Korea), and LINE Pay and JKOPay (Taiwan). In Europe, Apple Pay and Google Pay are popular in the UK, Germany, and France. In Africa, M-Pesa is the leading mobile wallet in Kenya, Nigeria, South Africa, and Egypt. Mordor Intelligence (2022) indicated Asia Pacific had high, Europe has medium, and Africa had low regional growth rate of the mobile payments market. McKinsey (2022) reported South Africa having the highest revenue per mobile payment transaction, followed by the United Kingdom and Taiwan. Although the outbreak of COVID-19 forced the adoption of mobile payment services, perceived risks still considered critical to the use of mobile payment services and warrant further investigation.

Barriers that hinder the intention to use mobile payments, such as perceived risk, have been examined (Liébana-Cabanillas et al., 2013; Liébana-Cabanillas et al., 2021). Yang et al. (2015) indicated that performance, financial, and privacy risks have a strong negative effect on consumer intention to use mobile payment services. In addition, psychological and privacy risks undermine the adoption of mobile payment services (Cocosila and Trabelsi, 2016). De Kerviler et al. (2016) specified that financial and privacy risks are key drivers for the adoption of mobile payment services. Studies have investigated factors that negatively affect perceived risks in mobile banking and online shopping environments (e.g., Kim and Lennon, 2013; Mann and Sahni, 2013); such risks impede the development of mobile payment systems (Choi and Choi, 2017) and negatively influence public acceptance of mobile payments (Yang et al., 2015) and decrease consumer trust in such services (Park et al., 2019). Soutter et al. (2019) suggested that the need to eliminate risks associated with mobile money transfer services in Sub-Saharan Africa had led to the adoption of decentralised technologies such as blockchain; risks related to the process of sending and managing money through mobile devices still represent a major concern in this region.

Mobile payment services enable mobile financial transactions; however, risk reduction strategies aiming to decrease mobile payment service risks lag behind. In the context of risk reduction strategies, extant literature focuses on tactics of responding to risks associated with consumer purchase behavior. Risk mitigation and risk sharing have been shown to help firms react effectively when facing a risk; these are commonly adopted across many sectors. Studies indicate that information seeking is a crucial strategy for reducing financial risk, the latter is a major perceived risk by consumers of mobile payment services (Bruwer et al., 2013). Perceived risks increase both the frequency of information seeking and the frequency of stock market transactions (Cho and Lee, 2006), and they negatively influence perceptions of resource scarcity (Nam et al., 2019). In leisure industry, hotel reputation influences perceived risks (Garretson et al., 1996). In marketing, brand loyalty is the most effective moderator of risk, whereas celebrity endorsement is the least beneficial moderator (Mitchell and Greatorex, 1990).

McKinsey (2022) report that risk assessment is critical to the reduction of risk of financial crime in digital payments. Verizon (2022), also identified safety and security issues as major concerns connected to mobile payments. The counter measures leading to avoidance strategies of mobile payment risk are also essential, for example protecting smartphones, using VPN, and being aware of malware (Smith, 2020). Although the literature exploring mobile payment risks is prolific (e.g Chang and Benson, 2022), studies have yet to investigate which risk reduction strategies can best resolve risks to individuals in mobile payments and thus increase their acceptance by users. To fill the research gap, in our study we aimed to identify critical mobile payment risks and analyze corresponding risk reduction strategies. Individual mobile payment users from Europe, Asia and Africa formed the study population. We analyzed six perceived risks established by Yang et al. (2015) and Thakur and Srivastava (2014) using a decision tree algorithm. We addressed two research questions: (1) what are the critical perceived risks for mobile payment users in each country? and (2) what are the risk reduction strategies corresponding to the perceived risks in each country? Many studies focus on a single country analysis, this research offers valuable insights by comparing user behavior across countries from three continents. As such, UK is the leader in mobile payments adoption, Taiwan is ahead of the technology curve for mobile devices, whilst Mozambique is the destination of many economically-motivated mobile money transfers and payments. Hence the study offers unique and practical insights for the above geographies and the international companies offering mobile payment applications, devices and technologies.

2. LITERATURE REVIEW

2.1 Mobile Payment Risks

Mobile payments refer to the use of a mobile device to make payments for goods and services (Chen and Nath, 2008). Mobile payment research comprises four streams: behavior, technology, risk, and context (Leong et al., 2022). Mobile payment systems utilize two common technologies: QR-codes and NFC (near-field-communication-based technologies) (Tew et al., 2022). Researchers proposed that emotions (affect, anxiety, and anticipated regret) may influence mobile payment adoption (Verkijika, 2020). Mobile payment services, such as Apple Pay, are used to digitally process high-security transfers from a registered user's bank account to another bank account (Ng and Yip, 2010). Scholars have previously applied the technology acceptance model (TAM), unified theory of acceptance (UTA) and use of technology to investigate the factors influencing intention to use mobile payment services (Chung and Kwon, 2009; Kleijnen et al., 2004; Yu and Fang, 2009). Li et al. (2019) investigated consumer perception of Alipay in China and Bailey et al. (2020) examined the US millennial's mobile payment usage. Interestingly, Al-Qudah et al. (2022) showed that perceived risk is negatively and weakly linked to the intention to use mobile payments. Other researchers used perceived risk to explain privacy and security concerns related to mobile payment services (Luarn and Lin, 2005; Wang et al., 2003). Perceived risk is an inhibiting factor (Liu et al., 2019) and a barrier to users on intention to use mobile payment (Pal et al., 2020).

Studies have also examined determinants of intention to use mobile payment services, and some determinants include: perceived risk, perceived convenience and self-efficacy (Pal et al., 2021), privacy risk, performance expectancy, effort expectancy, social influence, facilitating conditions (Lee et al., 2019), and perceived benefits versus perceived risk (De Kerviler et al., 2016). Other studies have also identified perceived risk as a major factor negatively influencing intention to use mobile payment services (Cocosila and Trabelsi, 2016; Liébana-Cabanillas et al., 2013; Thakur and Srivastava, 2014). Manrai and Gupta (2022) discovered performance risk and financial risk may not have significant influence on intention to use mobile payment.

Existing literature highlighted critical mobile payment risks. For example, Chang et al. (2022) indicated that financial risk, privacy risk, security risk, performance risk, social risk, time risk, and psychological risk are central to mobile payment usage. Cocosila and Trabelsi (2016) showed that time, social, psychological, and privacy risks are crucial factors that influence behavioral intention of mobile payment users. Pal et al. (2021) identified that financial, privacy, security, and performance risks influenced intention to use mobile payments. Thakur and Srivastava (2014) indicated that security and privacy risks affected behavioral intention of mobile payment users. To summarise the extant studies, this study categorizes risks related to mobile payment service into six categories: financial risk, privacy risk, security risk, performance risk, time risk, and psychological risk. According to Featherman and Pavlou (2003), financial risk indicates monetary loss, privacy risk is regarding personal information exposure, performance risk relates to system failures, and time risk indicates the perceived uncertainty and delays by using mobile payment. Psychological risk refers to frustration, anxiety, and pressure (Lim, 2003) and security risk represents uncontrolled transactions and loss of financial information (Kolsaker and Payne, 2002). Accordingly, the present study considered financial risk, privacy risk, performance risk, psychological risk, time risk, and security risk in its investigation of the link between perceived risk and risk reduction strategies.

2.2 Risk Reduction Strategies

Perceived risk is the subjective judgment of an individual regarding likelihood of encountering risk and replies on affective status (Gierlach et al., 2019). Bauer (1960) was the first to apply perceived risk in marketing to examine consumer uncertainty. To avoid uncertainty, consumers adopt certain strategies in their decision-making process to reduce risk. This behavior is critical because purchasing decisions may result in losses, such as time loss (time and energy), hazard loss (health and physical safety), ego loss (psychological), and money loss (monetary) (Roselius, 1971). Perceived risk influences the willingness to provide sensitive information online during a transaction (Lee et al., 2016). Researchers explored risk reduction strategies in the e-commerce context (Chang and Ko, 2004; Ding, 2007; Lee, 2014). Scholars have also empirically examined the link between perceived risk and risk reduction strategies. For example, studies looked at risk reduction strategies in the context of food safety (Yeung et al., 2010), in the purchase of plane tickets online (Kim et al., 2009) or travel packages (Mitchell and Vassos, 1998), and in crowd investing (Angerer, et al., 2018). Commonly adopted risk reduction strategies include information search, such as seeking advice from experts and additional product/service information (Cho and Lee, 2006). Previous research merely focused on the context-aware solutions, whilst the understanding of mobile payment risk reduction strategies is still lacking.

Mitchell et al. (2003) suggested that common risk reduction strategies for purchasing organizational professional services can be categorized into: clarification, risk-sharing, simplification, and safeguarding strategies. The concept of risk reduction strategy was also applied to the context of uncertainty avoidance. In tourism industry, Fuchs and Reichel (2011) compared risk reduction strategies by different types of visitors and travel destinations. Adam (2015) investigated the risk perceptions and risk reduction strategies of backpackers. Veréb et al. (2018) examined the risk perception of terrorism in tourism cities. In the organizational context, Pemer et al. (2018) showed that cultural differences result in different level of uncertainty avoidance of professional services usage. Harvey et al. (2021) examined the impact of leadership in terms of personal and organizational risk reduction. In service context, Sengupta et al. (2018) applied the concept of risk reduction to propose a risk-based service taxonomy among client, provider, and customer. Savas-Hall et al. (2021) examined the relationships between perceived risks and intentions for service adoption. Hence, mobile payment services must anticipate risk concerns and service providers need to be equipped with mitigation measures. As such, this study adopted the risk reduction strategies proposed by Mitchell et al. (2003) for analysis of mobile payment services. Clarifying, simplifying and risk-sharing strategies are robust (Mitchell et al., 2003). These risk-reducing strategies can be deployed at the organisational level to address the end user risk perceptions.

2.3 Geographical Contextualization of the Study

We have collected data in three different countries –Taiwan, the United Kingdom and Mozambique- from three different regions – Asia, Europe and Africa– as extant literature highlighted differing regional growth rates of mobile payments respectively ordered from high to low (Mordor Intelligence, 2022). In particular, we were interested in understanding how similar the mobile payment risk reduction strategies would be in different regions with a varied adoption rate. Extant literature (e.g., Chang et al., forthcoming) largely focuses on mobile payment risks in individual regions but a cross-country perspective would explore risk behaviors in a broader perspective.

UK relies on the security of its financial sector which contributes 31.9% of Gross Value Added (GVA) to the British economy according to Office for National Statistics (2022). The growth of mobile payments in the country pushes vendors and services to offer streamlined mobile shopping and mobile transactions through leveraging smartphones' native technology and simplifying payment processes.

The development of interoperable instant payment infrastructure is rapidly emerging in Taiwan, Singapore, Hong Kong and the adjacent the ASEAN region (Research and Markets, 2022). UK Finance, a trade association of financial institutions operating in the country, showed that losses from mobile payments fraud grew by 20% before the pandemic (£456m in 2019), while only 30% of fraudulent transaction are reimbursed to the consumer (Finextra, 2019). On the other hand cyber threats have been shown to originate in less developed countries where deterioration in the economic situation drives cyber crime, such as Mozambique highlighted by World Bank Report (2022). The recent Mozambique Country Economic Update (2021) notes that continuing harnessing the power of mobile technology supports sustainable and inclusive growth in the medium term. With a population of half of the UK living in rural areas (31m) mobile payments remain the main way to sustain livelihood of the majority of residents.

The 2022 report on Key Payments Trends highlighted the need for fraud management solutions in order to protect from the growing threat of online fraud and cybercrime. We therefore have three regions showing marked differences in their attitudes towards mobile payment technologies: UK depending on the protection of financial transactions as pivotal to the economy and its population has heightened concern about cyberthreats; Taiwan providing both integrated payment solutions and mobile devices while showing trust influencing slow adoption of mobile payment; Mozambique population relies on mobile payments as having a lack of alternatives while being one of the source countries of cyber attacks sustaining organized crime. The novel approach of this study to the empirical testing of the mobile payment risk reduction strategies is discussed next.

3. METHODOLOGY

3.1 Research Process

The data were collected from respondents in three countries (TW, MZ, and UK) using an online method. The research data started with the cleaning process and as a preliminary method, we conducted ANOVA analysis among three countries to explore if there is an interaction effect between the factors. After the data conversion, the decision tree algorithm, and other competing models to compare the outcomes were applied. The analytical results were generated into a binary tree with if-then rules. The essential perceived risk then are identified accordingly and matched to the risk reduction strategies. Then a decision tree algorithm was applied to analyse data samples collected from the three countries.

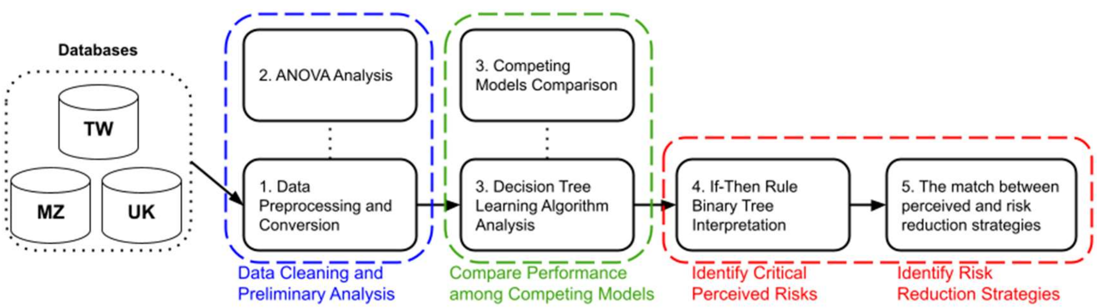

Figure 1 The research design and research process

Figure 1 illustrates the research design and research process in this study. Of the data samples collected from each country, 70% were used as training data and 30% were used as test data. Competing models such as neural network, logistic regression, support vector machine (SVM), random forest, and Naïve Bayes models were used for performance comparison. Fourth, decision tree learning algorithm is a supervised learning method uses data labels for analysis. Binary trees generated from algorithm were interpreted as if-then rules to explain the labels (high or low) of intention to use mobile payment service. Finally, perceived risks were matched to risk reduction strategies among three countries. This research offers practical insights and implications for stakeholders.

3.2 Decision Tree Learning Algorithm

Decision tree learning is among the most commonly used machine learning algorithms. In the learning process, a decision tree is generated through a set of labeled training instances with tuples of attributes and class labels. Decision tree learning is a recursive process executed using a training dataset. The time complexity of a typical decision tree algorithm such as C4.5 has can be expressed as follows: (m, n^2), where m is the size of the training data and n is the number of attributes (Quinlan, 1993). A decision tree is a rule-based algorithm that divides a domain into multiple linear spaces (**Figure 2**). If the predicted classes are discrete, then the generated tree is a classification tree.

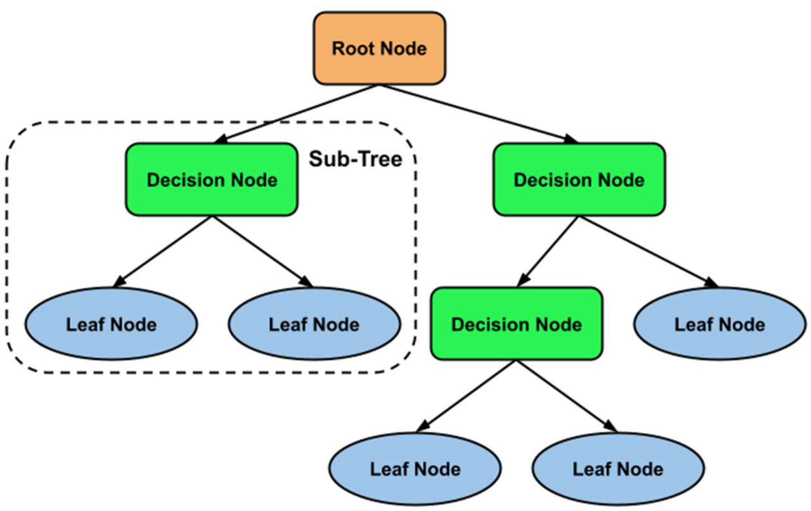

Figure 2 Decision Tree

A decision tree algorithm uses entropy to measure impurities or randomness in a dataset (Shang et al., 2013). The entropy value typically ranges between 0 and 1, with a value closer to 0 indicating more reliable data. The entropy for the classification of a set S with respect to c states is expressed as follows:

$$Entropy(S) = -\sum_{i=1}^{c} P_i log2^{P_i} \quad (1)$$

where P_i is the proportion of samples in a subset and i is the attribute. Furthermore, a decision tree algorithm uses information gain to measure segmentation performance. A higher level of information gain indicates better outcomes. On the basis of the concept of entropy, data gain $Gain$ (S, A) can be expressed as follows (Liu et al., 2013):

$$Gain(S, A) = Entropy(S) - \sum_{v} \frac{|S_v|}{|S|} Entropy(S_v) \quad (2)$$

where v belongs to $v(A)$ and the range of attribute A is $v(A)$. S_v is the subset of set S equal to the value of attribute v.

A decision tree algorithm is a supervised learning method and can be used to predict a target class. Decision tree classifiers such as C4.5 and CART have strong precision, optimized splitting parameters, and enhanced tree pruning methods. Nevertheless, the size of the training dataset influences the precision of the test set. Moreover, decision tree algorithms are associated with concerns about robustness, scalability adaptation, and height optimization. However, such algorithms generate rules that are simple to interpret and understand. This research will use Orange Data Mining package (3.36 version) which is a free toll for data analysis and offers certain popular models, such as decision trees, SVM, logistic regression, and Naïve Bayes for performance comparison.

4. DATA COLLECTION AND ANOVA RESULTS

The questionnaire developed for the study comprised three parts: demographic data (including gender, age, marital status, occupation, educational level), perceived risk (Thakur and Srivastava, 2014; Yang et al., 2015), and intention to use mobile payment service. The questionnaire included 22 questions regarding perceived risk: 4 items regarding financial risk, 4 regarding privacy risk, 4 regarding performance risk, 3 regarding psychological risk, 4 regarding time risk, and 3 regarding security risk (**Table 1)** using a five-point Likert scale: 1 (*strongly disagree*), 2 (*disagree*), 3 (*neutral*), 4 (*agree*), and 5 (*strongly agree*). The questionnaire was administered to users in Taiwan, Mozambique, and the United Kingdom.

Table 1 Questionnaire

Financial Risk	**Source**
1. The use of mobile payment (m-payment) would cause the exposure of personal bank accounts and passwords.	Yang et al. (2015)
2. Malicious or unreasonable charging could occur.	
3. A careless operation could lead to a surprising loss.	
4. The use of m-payment could cause financial risk.	
Privacy Risk	
5. Private information could be misused, inappropriately shared, or sold.	
6. Personal information could be intercepted or accessed.	
7. Payment information could be collected, tracked, and analysed.	
8. Privacy could be exposed when using m-payment.	
Performance Risk	
9. The payment system might be unstable or blocked.	
10. The payment system does not work as expected.	
11. The performance level might be lower than designed.	
12. The service performance might not match its advertised level.	
Psychological Risk	
13. Mobile payment would cause unnecessary tension (e.g., concerns about errors).	
14. A system malfunction in m-payment could cause unwanted anxiety and confusion.	
15. The usage of m-payment could cause discomfort.	
Time Risk	
16. Time loss could be caused by instability and low speed.	
17. It might take too much time to learn how to use mobile payment.	
18. More time is required to fix payment errors offline.	
19. Using m-payment may waste time.	

Security Risk	Thakur and Srivastava (2014)
20. There might be mistakes, since the accuracy of the inputted information is difficult to check from the screen.	
21. The battery of the mobile phone might run out or the connection could be interrupted while paying.	
22. The bill information might be typed wrongly.	

A total of 241 (Taiwan), 271(UK), and 236 (Mozambique) questionnaire responses respectively. The reliability test revealed that the Cronbach's alpha values were higher than 0.9 for all three countries (0.938, 0.909, and 0.943 for Taiwan, Mozambique, and the United Kingdom, respectively). An analysis of variance (ANOVA) was also conducted, and the results indicated an interaction effect between the factors, i.e. results in (**Table 2**) indicated that the respondents in the United Kingdom were concerned about financial and time risks; those in Mozambique cared were concerned about performance, psychological, and security risks; and those in Taiwan were concerned about privacy risk.

Table 2 Summary of one-way ANOVA results for three countries

	Taiwan (N=241)	Mozambique (N=236)	UK (N=271)	Overall mean	Overall S.D	*F*	*p*-value
Financial	2.88	3.08	3.10	3.03	.85	5.48	.004**
Privacy	3.67	3.16	3.01	3.27	.90	40.29	.000***
Performance	2.78	3.43	3.27	3.17	.84	45.36	.000***
Psychological	2.95	3.32	3.15	3.14	.94	9.93	.000***
Time	2.71	2.93	3.32	3.00	.79	43.28	.000***
Security	3.29	3.35	3.14	3.26	.84	4.34	.013**

* $p < 0.05$
** $p < 0.01$
*** $p < 0.001$

Of the respondents in Taiwan, the majority (63.3%) were aged 21–30 years. Regarding educational level, 96.7% of the respondents in Taiwan had a bachelor's degree or above. Occupations were more diverse among the respondents in Taiwan than among those in Mozambique and the United Kingdom. The respondents in Taiwan, 69% were women and 31% were men. The reason is that the popular mobile payment method is LINE Pay which is the QR-code based method bundled with instant messenger "LINE application". Female users spent more time on LINE application than male users in terms of shopping, payment, and game in the application due to convenience. Additionally, 67.8% of the respondents in Taiwan had experience using mobile payment services. In Taiwan, mobile payment usage was not popular before COVID-19 pandemic because only can be used to limited shops and restaurant. According to the report of Mastercard survey, Taiwanese consumers had increased mobile payment usage over 75% by mid-2021. The main mobile payment services used in Taiwan were reported to be Apple Pay (39.7%) and LINE Pay (39.3%). The participants in the three countries provided similar reasons for using mobile payment services: convenience (64.9%) and cashback offers (40.5%). Of the respondents in Mozambique, 55% were women and 45% were men. Additionally, 70.3% of the respondents in Mozambique had a bachelor degree, 17.4% had a high school diploma or lower, 7.2% had a master's degree, and 4.7% had a doctoral degree. We also noted that of the respondents in Mozambique, 32.2% were aged 21–30 years, 41.1% were aged 31–40 years, and 26.3% were aged ≥41 years. M-Pesa was reported to be the most commonly used mobile payment service in Mozambique (46.24%), followed by Conta de Moeda Electrónica (CME) (19.95%), PayPal (7.98%), Carteira Móvel (7.75%), and e-Mola (5.4%). Apple Pay (2.11%), Android Pay (4.69%), and Samsung Pay (2.58%) were not popular in Mozambique. All respondents in Mozambique had experience using mobile payment services, and their reasons for using such services were convenience (66.7%) and security (20.5%). Of the respondents in the United Kingdom, 58% were women and 42% were men. Furthermore, 33.6% of the respondents in the United Kingdom were aged 21–30 years, 37.6% were aged 31–40 years, 25.1% were aged ≥41 years, and 3.7% were aged ≤20 years. Regarding educational level, 38.7% of the respondents in the United Kingdom had an undergraduate degree, 45.4% had A levels or below, and 15.1% had a master's or doctoral degree. We also noted that 35.1% of the respondents in the United Kingdom used Apple Pay, and 21.4% used Android Pay; the major reasons for using mobile payment services included convenience (81.5%) and security (11.4%).

Table 3 Comparison of one-way ANOVA results between various age groups

Taiwan						
Age	Financial	Privacy	Performance	Psychological	Time	Security
21-30	2.80 (F= 4.05, p= **0.003**)	3.67 (F= 2.34, p= 0.058)	2.69 (F= 4.37, p= 0.002)	2.86 (F= 3.67, p= **0.007**)	2.67 (F= 2.83, p= **0.027**)	3.23 (F= 1.29, p= 0.279)
31-40	2.81 (F= 0.12, p= 0.974)	3.60 (F= 1.09, p= 0.371)	2.69 (F= 1.55, p= 0.204)	2.78 (F= 2.76, p= **0.039**)	2.78 (F= 1.35, p= 0.266)	3.27 (F= 0.82, p= 0.522)
41 or above	3.275641 (F= 2.06, p= 0.109)	3.73 (F= 2.32, p= 0.077)	3.22 (F= 1.11, p= 0.369)	3.51 (F= 3.23, p= **0.024**)	3.12 (F= 1.08, p= 0.380)	3.56 (F= 0.592, p= 0.671)
Mozambique						
Age	Financial	Privacy	Performance	Psychological	Time	Security
21-30	3.15 (F= 1.38, p= 0.256)	3.27 (F= 1.31, p= 0.277)	3.45 (F= 2.03, p= 0.117)	3.31 (F= 0.71, p= 0.548)	2.91 (F= 1.80, p= 0.155)	3.24 (F= 2.54, p= 0.063)
31-40	3.01 (F= 1.15, p= 0.322)	2.96 (F= 1.30, p= 0.278)	3.33 (F= 4.41, p= **0.015)**	3.35 (F= 0.58, p= 0.564)	2.93 (F= 1.05, p= 0.353)	3.36 (F= 5.61, p= **0.004988)**
41 or above	3.11 (F= 3.10, p= **0.034**)	3.30 (F= 0.60, p= 0.617)	3.53 (F= 1.11, p= 0.353)	3.32 (F= 1.85, p= 0.149)	2.94 (F= 4.69, p= **0.005**)	3.45 (F= 0.78, p= 0.511)
UK						
Age	Financial	Privacy	Performance	Psychological	Time	Security
21-30	3.03 (F= 0.46, p= 0.765)	2.96 (F= 0.720, p= 0.581)	3.18 (F= 1.61, p= 0.178)	3.06 (F= 0.94, p= 0.446)	3.20 (F= 1.23, p= 0.304)	3.08 (F= 0.74, p= 0.569)
31-40	3.10 (F= 0.39, p= 0.818)	3.00 (F= 0.22, p= 0.925)	3.30 (F= 0.11, p= 0.978)	3.16 (F= 0.64, p= 0.636)	3.38 (F= 0.86, p= 0.491)	3.11 (F= 2.33, p= 0.061)

41 or above	3.22 (F= 1.90, p= 0.121)	3.10 (F= 1.28, p= 0.286)	3.35 (F= 1.01, p= 0.409)	3.29 (F= 1.08, p= 0.375)	3.43 (F= 1.45, p= 0.229)	3.27 (F= 1.52, p= 0.207)

We observed that for the respondents in Taiwan, the scores of financial risk (p = .003812) and time risk (p = .026772) for the 21–30-year age group were significantly different from those for other age groups (**Table 3**). The use of mobile payment services in Taiwan is became popular during COVID-19 via food delivery services. However, most consumers are still concerned about secure payment environment and the leaks of financial data (Chang and Benson, 2022). The scores of psychological risk were significant in all age groups, suggesting that Taiwanese users feel anxiety and pressure when using mobile payment services. For the respondents in Mozambique, the scores of performance risk (p = .014835**)** and security risk (p = .004988**)** for the 31–40-year age group differed significantly from other age groups; the score for time risk (p = .005319**)** was significant in the ≥41-year age group, indicating that older people care about speed when using mobile payment services. For the respondents in the United Kingdom, the scores for all perceived risks did not differ significantly between the three age groups.

To classify the collected data, we converted the data from ordinal to nominal formats. To ensure the internal consistency and bias reduction for each country, this study used relative mean value for data conversion for each country. First, the mean score of all items under a particular perceived risk in each data sample was calculated. Second, the mean score of the same perceived risk in all data samples was calculated to determine its relationship with intention to use mobile payment services. Third, the score of each perceived risk was converted to a categorical format (e.g., low [L] or high [H]) by comparing the mean score of this risk in each data sample with the mean score of the same risk in all samples. If the mean score of the perceived risk in each sample was higher than the mean score of the same risk in all samples, the perceived risk was categorized as H (and vice versa). Finally, categorical data were thus derived to represent the level of perceived risk in each data sample and were used for classification in the selected models to determine the relationship of the perceived risk with intention to use mobile payment services. For example, for data sample D1, the scores of the four items under financial risk were 5, 2, 4, and 4; the mean score of financial risk in data sample D1 was thus 3.75. The mean score of financial risk in all data samples was 2.88, which was lower than 3.75; therefore, the level of financial risk in D1 was categorized as H.

5. RESULTS OF THE DECISION TREES METHOD

In this section, results data analysis from Taiwan, Mozambique, and UK based on decision tree learning algorithm and generated if-then rules in a 4-level tree are discussed. The rules reveal the importance of risk by a top-down appearance. The detailed explanation of extracted rules from decision trees for three countries is provided in the discussion.

5.1 Taiwan

The decision tree analysis revealed major nodes that could be used to segment low intention to use mobile payment services. These nodes were **performance risk**, **psychological risk**, and **security risk** (**Fig. 3**). We specifically focus on the uniqueness of low intention to use mobile payment services in the decision tree. Accordingly, one rule was extracted to identify low intention to use mobile payment services as follows.

Rules 1: If (performance risk = high) ∩ (psychological risk = high) ∩ (security risk = low/high) → intention to use = low

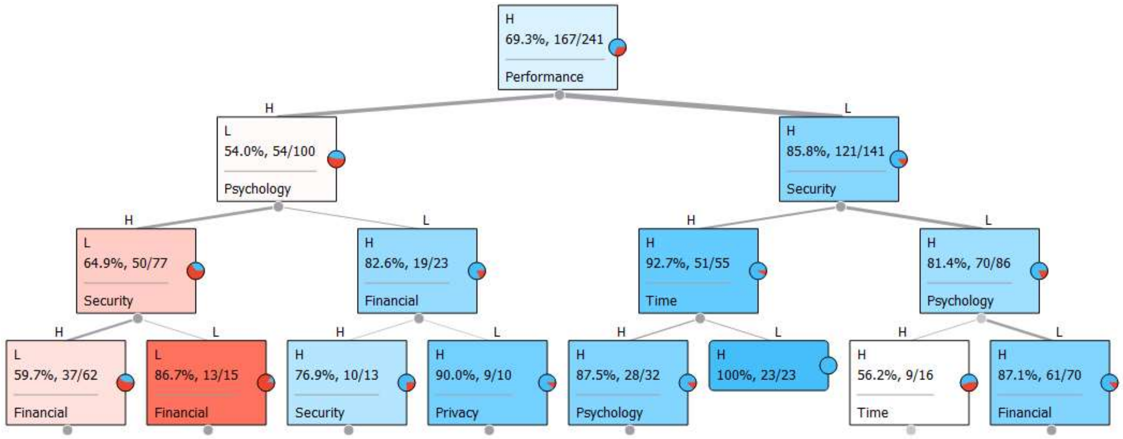

Figure 3 Decision tree of Taiwanese Samples

5.2 *Mozambique*

The decision tree analysis revealed major nodes used to segment high intention to use mobile payment services. These nodes were **performance risk**, **time risk**, and **privacy risk** (**Fig. 4**). High intention to use mobile payment services in the decision tree emerged. Accordingly, two rules were extracted to identify high intention to use mobile payment services as follows.

Rule 1: If (performance risk = low) ∩ (time risk = low) ∩ (privacy risk = high) → intention to use = high

Rule 2: If (performance risk = low) ∩(time risk = high) ∩ (psychological risk = low) → intention to use = high

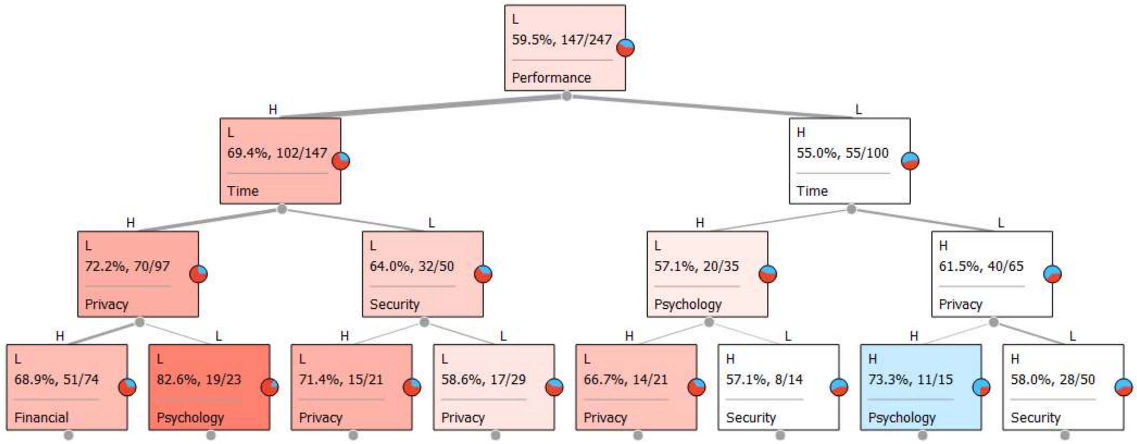

Figure 4 Decision Tree of Mozambique samples

5.3 The United Kingdom

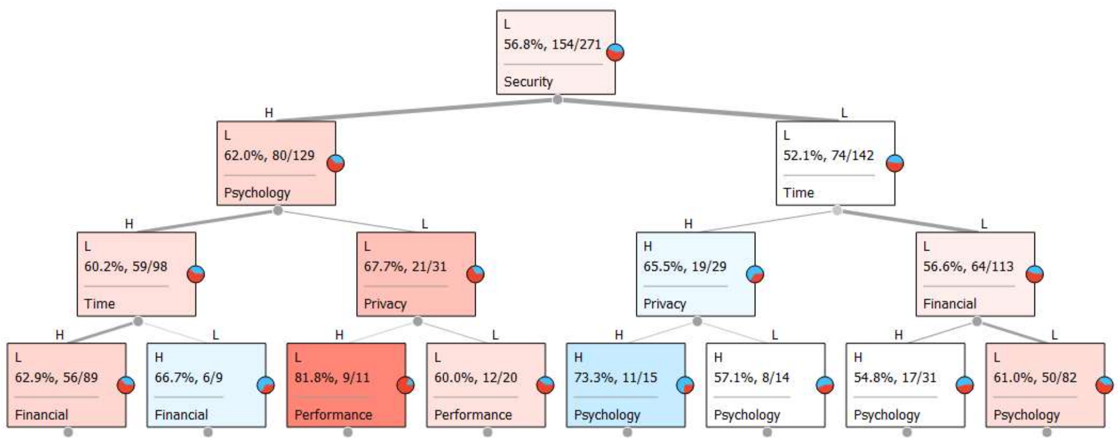

Figure 5 Decision tree of UK Samples

The decision tree analysis revealed major nodes that could be used to segment high intention to use mobile payment services. These nodes were **security risk**, **time risk**, **privacy risk, and financial risk** (**Fig. 5**). We found the uniqueness of high intention to use mobile payment services in the decision tree. Accordingly, one rule was extracted to identify high intention to use mobile payment services as follows.

Rules 1: If (security risk = low) ∩ (time risk = low) ∩ (financial risk = low) → intention to use = high

Rule 2: If (security risk = low) $\cap$ (time risk = high) $\cap$ (privacy risk = low) $\rightarrow$ intention to use = high.

5.4 Metrics and Model Comparison

We performed 10-fold cross-validation to verify our decision tree learning algorithm. Decision trees are typically developed using training and test data, and a confusion matrix can be used to determine the performance of a decision tree model. Specifically, a confusion matrix can be used to measure the performance of a developed model by comparing the predicted class and true class. The metrics in such matrix include accuracy, precision, recall, and F1-score. Accuracy refers to the ratio of the number of correct predictions to the total number of input samples. Precision refers to the number of true positives divided by the total number of respondents labeled as belonging to the positive class. Recall refers to the number of true positives divided by the total number of respondents who actually belong to the positive class. Finally, F1-score is a harmonic measure calculated using weighted precision and recall.

In this study, we used 30% of the data samples to examine the performance of our decision tree learning algorithm with other competing models, namely random forest, neural network, logistic regression, SVM, and Naïve Bayes models. Our comparison of the performance metrics revealed that for the sample collected in Taiwan, the decision tree learning algorithm generally outperformed the other models (**Table 4**); specifically, the area under the curve (AUC) was 0.716, accuracy was 0.775, F1-score was 0.771, precision was 0.767, and recall was 0.775. For the sample collected in Mozambique, the competing models exhibited similar performance levels; nevertheless, the decision tree learning algorithm was still superior to the other models, exhibiting an AUC of 0.62, accuracy of 0.646, F1-score of 0.650, precision of 0.655, and recall of 0.646.

Finally, for the sample collected in the United Kingdom, the decision tree learning algorithm had superior performance metrics, exhibiting an AUC of 0.443, accuracy of 0.533, F1-score of 0.515, precision of 0.516, and recall of 0.533. In summary, the decision tree learning algorithm demonstrated the best predictive power for the sample collected in Taiwan, followed by those collected in Mozambique and the United Kingdom (**Fig. 6**).

Table 4 Summary of comparison of performance metrics between competing models

	AUC	**Accuracy**	**F1**	**Precision**	**Recall**
DT-TW	0.716	0.775	0.771	0.767	0.775
RF-TW	0.653	0.75	0.745	0.741	0.75
SVM-TW	0.786	0.75	0.75	0.75	0.75
NN-TW	0.709	0.738	0.74	0.742	0.738
LR-TW	0.705	0.75	0.75	0.75	0.75
NB-TW	0.622	0.725	0.733	0.745	0.725
DT-MZ	0.62	0.646	0.65	0.655	0.646
RF-MZ	0.589	0.622	0.63	0.652	0.622
SVM-MZ	0.573	0.659	0.643	0.641	0.659
NN-MZ	0.613	0.61	0.61	0.61	0.61
LR-MZ	0.639	0.634	0.627	0.623	0.634
NB-MZ	0.646	0.622	0.626	0.631	0.622
DT-UK	0.443	0.533	0.515	0.516	0.533
RF-UK	0.423	0.533	0.491	0.502	0.533
SVM-UK	0.421	0.589	0.561	0.578	0.589
NN-UK	0.476	0.522	0.51	0.509	0.522
LR-UK	0.442	0.511	0.427	0.427	0.511
NB-UK	0.412	0.478	0.46	0.456	0.478

DT: decision tree, RF: random forest, SVM: support vector machine, NN: neural network, LR: logistic regression, NB: Naïve Bayes, TW: Taiwan, MZ: Mozambique, UK: United Kingdom

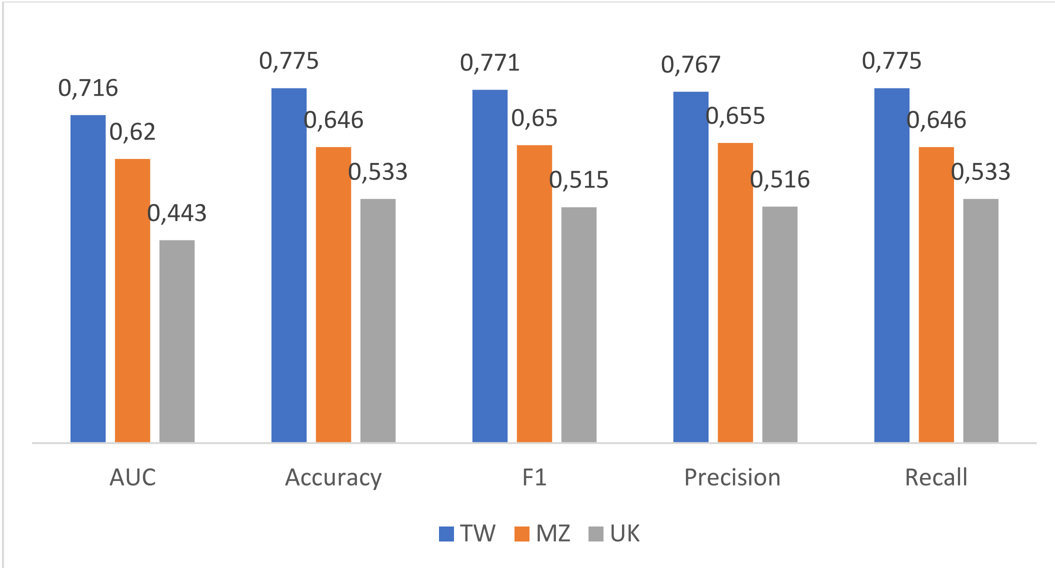

Figure 6 Metrics of decision trees among three countries

6. DISCUSSION AND IMPLICATIONS

6.1 Discussion

In addition to the decision tree analysis, the results of ANOVA showed that perceived risks are different from age and country. Specifically, financial risk and time risk are important to young generation (21–30-year age group) and performance risk and security risk are important to the 31-40 year age group. In the comparison among countries, financial risk and time risk are significant to UK users, performance risk, psychological risk, and security risk are significant to Mozambique users, and privacy risk is significant to Taiwanese users. According to a report from the Taiwan Network Information Center (2005), the top reasons for not using mobile payment services among Taiwanese users were (1) concerns about safety (32.7%), (2) lack of knowledge about how to use such services (14.7%), (3) lack of trust in the technology (6.4%), and (4) lack of knowledge about the usefulness of the services (4.2%). The Visa Consumer Payment Attitudes Study (2020) specified that Asian users (Hong Kong, Taiwan, and Macau) did not use the Visa service because they were concerned about losing their phones or their phones being stolen (50%), concerned about their phones getting hacked (46%), concerned about their phones being used for payment without their permission (41%), and concerned about software viruses affecting their phones (29%). The study also reported that despite digital wallet usage reaching 60% in Taiwan, cash still dominates the market (60%). In addition, the utilization of mobile contactless payment services and in-app mobile wallet services reached 40% and 20% in Taiwan, respectively. The slow adoption of mobile payment services in Taiwan can be attributed to government regulations and Taiwan's conservative culture. The findings of the aforementioned report and study indicate that Taiwanese users care about security risk (lack of safety) and performance risk (technology and usefulness), which are consistent with our findings. Moreover, the use of mobile payment services may cause anxiety because of concerns such as phones being stolen, hacked, or affected by software viruses, which are related to psychological risk. Accordingly, mobile payment service providers must enhance their information and communication technology (ICT) infrastructure to assure a safe and reliable mobile payment environment and must strengthen data protection policies to alleviate perceived psychological risk. Such risk reduction strategies may expand the potential market of mobile payment services in Taiwan.

M-Pesa is the most representative mobile payment service in Africa (Benson et al., 2024; Lashitew et al., 2019), and it has evolved to a more complete banking service, covering most of the operations offered by traditional commercial banks (Morawczynski and Miscione, 2008; Mothobi and Grzybowski, 2017). Mozambique recorded an exponential growth of mobile payment services, which is related to the exponential growth of mobile phone devices in the country. In 2020, the majority of mobile money transactions in Sub-Saharan Africa involved bill payments and bulk disbursements; the COVID-19 outbreak also increased the proportion of merchant payments

(GSMA, 2021). Deficiencies in transportation and landline phone infrastructures have expedited the expansion of cellular-based telecommunications, which required a comparatively small investment (Brouwer and Brito, 2012). Mozambican users find mobile banking “easy to use, expect few problems, and grow accustomed to it very quickly” (Baptista and Oliveira, 2015). Moreover, Batista and Vicente (2017) revealed that the availability of mobile payment services in rural Mozambique increased people’s willingness to remit. Lashitew et al. (2019) also indicated an association between exposure to crime risk and fast adoption of mobile payment services; this can be attributed to the weak institutional protection of such services under such circumstances. Accordingly, these findings demonstrate the importance of performance, time, and privacy risks in Mozambique.

Mobile payment services in the United Kingdom were determined to be superior to those in other European countries in 2020 (Statista, 2022). The annual UK Finance report for 2021 showed that 32% of the adult population was registered for some form of mobile payment in 2020 and 50% of the registered users made payments frequently. The popularity of remote banking services (72% for online banking and 54% for mobile banking) in 2020 demonstrates the importance of simplified payment processes in the United Kingdom. Fraud risk (fraudulent transactions), data-related risk (data losses), and privacy risk (physical privacy and data privacy) were determined to be the major concerns associated with mobile payment services in the United Kingdom (Financier Worldwide Magazine, 2014). Merbecks and Bruck (2012) identified critical factors for mobile payment service adoption, such as security (53%), convenience (44%), and time saving (42%). Security-related concerns included cybercrime, fraudulent activity, and attacks on personal and sensitive user data. Mobile payment service risks may involve weaknesses in mobile applications, network vulnerabilities, malware injection, and data breaches. In the United Kingdom, the perceived risks influenced the perceived usefulness of mobile payment services (Hampshire, 2017).

6.2 Risk reduction strategies

This study investigated perceived risks for mobile payment services in three countries, namely Taiwan, Mozambique, and the United Kingdom, and determined the corresponding risk reduction strategies (**Table 5**). We adopted the risk reduction strategies by Mitchell et al. (2003): clarification, simplification, and risk-sharing for this study. Our decision tree learning algorithm revealed that the top three risks in Taiwan were performance risk (level 1), psychological risk (level 2), and security risk (level 2). Specifically, performance risk was the most critical factor, which indicates outcomes that may not meet consumers' expectations regarding mobile payment services, followed by psychological risk and security risk. Psychological risk refers to anxiety and confusion associated with the use of mobile payment services, and security risk indicates concerns about data theft, leaks, or modification. Relevant risk reduction strategies for Taiwanese users may include simplification, clarification, and sharing strategies. The mobile payment process can be simplified to reduce its complexity; for example, the process can be simplified by streamlining the transaction process to a minimal number of steps. In addition, collaborating with credible services such as Apple Pay, Android Pay, or Samsung Pay can improve perceptions of the stability and reliability of mobile payment service performance. Showing customers the benefits and process of using mobile payment services can also add clarity and thus reduce confusion and hesitation. Furthermore, collaboration with third-party companies can improve the credibility of mobile payment programs and provide guarantees to customers that the transaction process is secure and safe.

Our decision tree learning algorithm demonstrated that performance risk was the most critical factor for Mozambique users (level 1), followed by time risk (level 2) and privacy risk (level 3). Performance risk can be mitigated by simplifying and clarifying mobile payment processes. Time risk indicates concerns about time wastage due to complex and inconvenient payment processes. In Mozambique, users are concerned about the convenience and performance of mobile payment services; these concerns can be alleviated by simplifying mobile payment processes and clearly specifying the purpose of mobile payment services. Privacy risk refers to concerns about the loss of personal information or sensitive data. Risk-sharing strategies such as collaboration with credible companies can help reduce consumers' perceptions of privacy risk.

Our decision tree learning algorithm shows that security risk was the most critical factor for UK users (level 1), followed by time risk (level 2) and financial/privacy risk (level 3). Cybersecurity threats affecting mobile payment services, such as data leaks, may contribute to concerns about security risk; therefore, risk sharing with trusted ICT companies to provide secure infrastructure can reduce users' concerns. Furthermore, the loss of time (time risk) can be improved by simplifying the payment processes. Our findings from the United Kingdom differ from those for Taiwan and Mozambique where UK respondents emphasized financial risk; this indicates that UK users were primarily concerned about losing money when using mobile payment services. Risk sharing with trustworthy mobile payment services such as Apple Pay can reduce the concerns about losing money. In summary, simplification and risk-sharing strategies are useful tactics for these three countries.

Table 5 Mobile payment risk and risk reduction strategies among three countries

		Risk-reducing Strategy		
Country	**Risk (importance)**	**Simplifying**	**Clarifying**	**Risk-Sharing**
Taiwan	Performance (level	X	X	

	1)			
	Psychological (level 2)	X	X	X
	Security (level 2)			X
Mozambique	Performance (level 1)	X	X	
	Time (level 2)	X		
	Privacy (level 3)			X
UK	Security (level 1)			X
	Time (level 2)	X		
	Financial/Privacy (level 3)			X

6.3 Implications

This study primarily demonstrated major mobile payment service risks in Taiwan, Mozambique, and the United Kingdom and identified relevant risk reduction strategies based on consumer perceptions in these countries. The stakeholders associated with mobile payment risk include user, government, firm (receiver of payment), and mobile payment service provider. Users from the Asia-Pacific region, Africa, and Europe may have different cultural perspectives and place diverse levels of importance on perceived risks regarding mobile payment services. Specifically, in Europe, cybersecurity is a critical issue that has warranted attention from both governments and private firms. In 2024, the European Commission announced its intention to emphasize network resilience, consumer privacy protection, and risk reduction of monetary fraud (EURACTIV, 2024; ENISA, 2024). In Asia, certain digital payment services have significantly increased banking security risks. Governments can regulate mobile payment methods to reduce relevant risks. Firms can collaborate with mobile payment service providers (telecommunication corporation or banks) to offer simple, friendly, and secured transactional process. Firms also need to re-allocate resources based on perceived risk levels to strengthen cybersecurity culture and reduce the impact of cyber threats.

7. CONCLUSION

Mobile payment service risks have surfaced as a critical issue dictating)or otherwise) their growth rates in Asia, Europe and Africa. Therefore, risk reduction strategies must be identified to improve the security of mobile payment services. This study collected data on the perceptions of mobile payment service risks in three countries (regions): Taiwan (Asia-Pacific region), Mozambique (Africa), and the United Kingdom (Europe). We used a decision tree learning algorithm to identify critical perceived risks of mobile payment services and their influence on consumer intention to use such services. We compared the performance of this algorithm with that of other models, namely random forest, SVM, neural network, logistic regression, and Naïve Bayes models. Our results showed that the decision tree learning algorithm outperformed these models. The algorithm indicated that performance risk was the most critical perceived risk in both Taiwan and Mozambique; however, in the United Kingdom, security risk was the most critical perceived risk. We also determined that psychological and security risks were critical concerns for Taiwanese users; time and privacy risks were critical concerns for Mozambique users; and time, financial, and privacy risks were critical concerns for UK users. A possible explanation for these findings is that cultural differences between the three regions which influence the respondents' perceptions of the mobile payment services risks. This study identified perceived risks and the corresponding risk reduction strategies (simplification, clarification, and risk sharing) for each country. The results demonstrate that simplification and risk-sharing strategies are useful tactics for all three countries. Simplification strategies entail the development of simple and easy to use mobile payment processes for users, and risk-sharing strategies involve cooperating with third parties to reduce and transfer the risks of mobile payment services.

Existing literature also addressed how mobile payment can improve risk sharing in global markets in terms of key factors, such as alternative payment services from decentralized financial institutions in China (Huang et al., 2020), credibility and accuracy of technologies in South Korea (Shin and Lee, 2021), performance expectancy in United States (Jung et al., 2020), and digital literacy in India (Pal et al., 2021). Our results also identified critical stakeholders in risk reduction strategies that reflect the experience from successful markets, including private firms, government, and mobile payment service providers. Firms can apply these risk reduction strategies proactively to address potential mobile payment risks and quickly respond to market demands. Governments can offer user-centric regulatory environment and risk reduction policy. Mobile payment service providers can provide secure platforms for the transactional processing. Hence, this research can help all mobile payment stakeholders in the process of identifying appropriate risk reduction strategies to reassure their users.

8. LIMITATIONS

This study has several limitations. Firstly, the study population was relatively small (under 750 respondents). The results of performance metrics may be influenced by age and gender of respondents. Moreover, larger size of training samples for selected methods may enhance the accuracy and precision. Future studies could include a larger population to enhance the quality of the data; moreover, decision tree learning algorithms are more accurate when they are based on a large sample size. Secondly, the differences in cultural backgrounds between the three countries may have influenced our findings; hence, future research could comprehensively investigate the influence of such differences to determine the influence of consumer behavior on perceived risk. Finally, other perceived risks, such as social risk, were not analyzed in this study; therefore, future studies could analyze such risks. Additional data regarding mobile payment risks can help firms better understand how to respond quickly and appropriately to such risks.

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The authors report there are no competing interests to declare.

Data availability statement
The data sets associated with the paper were collected on purpose for this research and can be made available upon reasonable request.

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