Resistance of facial recognition payment service: a mixed method approach

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Abstract

Purpose – Sellers view facial recognition mobile payment services (FRMPS) as a convenient and cost-saving way to receive immediate payments from customers. For consumers, however, these biometric identification technologies raise issues of usability as well as privacy, so FRMPS are not always preferable. This study uses the stressor–strain–outcome (S–S–O) framework to illuminate the underlying mechanism of FRMPS resistance, thereby addressing the paucity of research on users' negative attitudes toward FRMPS.

Design/methodology/approach – Drawing from the stressor–strain–outcome (S–S–O) framework, the purpose of this study is to illuminate the underlying mechanism of FRMPS resistance. To this end, they invited 566 password authentication users who had refused to use FRMPS to complete online survey questionnaires.

Findings – The findings enrich the understanding of FRMPS resistance and show that stressors (i.e. system feature overload, information overload, technological uncertainty, privacy concern and perceived risk) aggravate the strain (i.e. technostress), which then leads to users' resistance behaviors and negative word of mouth.

Originality/value – Advances in payment methods have profoundly changed consumers' consumption and payment habits. Understanding FRMPS resistance can provide marketers with strategies for dealing with this negative impact. This study theoretically confirms the S–S–O paradigm in the FRMPS setting and advances it by proposing thorough explanations of the major stressors that consumers face. Building on their findings, the authors suggest ways service providers can eliminate the stressors, thereby reducing consumers' fear and preventing resistance or negative word-of-mouth behaviors. This study has valuable implications for both scholars and practitioners.

Keywords Risk, Structural equation modeling, Self-service technology, Word of mouth, Surveys, Technology and service

Paper type Research paper

1. Introduction

Although mobile payment is a relatively new digital payment method, it is now widely used in mobile commerce; for example, the number of mobile payment users in China had reached 854 million by December 2020 (China Internet Network Information Center, 2021). While payment efficiency has improved, security remains a concern for users. Mainstream mobile payment platforms such as Alipay, WeChat Pay and Apple Pay have recently adopted biometric authentication technologies such as facial recognition in their mobile payment services (Liu, 2020). With these biometric technology improvements, the traditional character password is replaced by a "face" password to verify customers' identities, bringing greater convenience and higher security for consumers using payment systems.

With facial recognition mobile payment services (FRMPS), when making digital payments, logging into a bank account or accepting certain contracts, individuals' faces are treated as unique biometric authentication information that is recognized as a personal password. Recently, consumers' faces have begun to be tracked, recognized and memorized by visible or invisible cameras when entering specific Kohler (sanitary product outlet), BMW and Max Mara (clothing brand) stores in China (ChinaDaily, 2021). In addition, some mobile applications enabled by artificial intelligence (AI) (e.g. BeautyPlus) have attracted more than 300 million users by giving them wider access as an incentive for allowing their faces to be scanned (Meyer, 2020). However, disclosing users' facial image can threaten their property and privacy security. When users provide their own faces to such photo applications, the risk of personal data leaks increases, which compromises the safety of their facial images and information.

The authors would like to thank three anonymous referees of this journal for their constructive comments, the co-editor and associate editor for their support and encouragement.

Funding: This work was supported by the Shantou University STU Scientific Research Initiation Grant [STF20010] and by the Natural Science Foundation of Guangdong Province, Guangdong Basic and Applied Basic Research Foundation Grant [2021A1515012259], and also supported by the Ministry of Science and Technology (the National Science and Technology Council, NSTC) under the grant MOST #111-2410-H-002-012-MY2.

Received 29 January 2022
Revised 21 June 2022
3 August 2022
Accepted 6 August 2022

The current issue and full text archive of this journal is available on Emerald Insight at: **https://www.emerald.com/insight/0887-6045.htm**

Journal of Services Marketing
© Emerald Publishing Limited [ISSN 0887-6045]
[DOI 10.1108/JSM-01-2022-0035]

Although biometric information (e.g. fingerprints, facial images) is now protected as personal data in some countries with strict privacy laws, such as the USA and China, consumers still view FRMPS as having more uncertainties and have considerable privacy concerns and risks. In particular, as news reports continue to reveal data security leaks, consumers' intentions to adopt FRMPS are likely to decrease. This phenomenon inspired the exploration of FRMPS resistance undertaken herein. Given the expected rapid growth of the biometric authentication market, exploring why consumers reject the use of FRMPS is critical, as is identifying how to make them feel safer when adopting this kind of new technology.

Several gaps exist in the relevant literature. First, research has focused more on mobile payment services than FRMPS. For example, previous studies have examined the relationship among security, platform reputation and trust (Shao *et al.*, 2019); performance expectancy, effort expectancy and mobile payment acceptance (Al-Saedi *et al.*, 2020); and perceived ubiquity, security and mobile payment adoption (Johnson *et al.*, 2018). However, relatively scant research has assessed impacts of FRMPS specifically.

Second, prior studies center on positive behaviors such as mobile payment acceptance or adoption rather than FRMPS resistance (Al-Okaily *et al.*, 2020; Jia *et al.*, 2022; Lin *et al.*, 2020b). For example, studies have shown that when customers use mobile payment, they are most concerned with information and transaction security (Choi *et al.*, 2020). Other studies note that mobile payment services are committed to improving the security of users' property and assuring personal privacy protection to avoid personal information disclosure, theft and other situations (Loh *et al.*, 2020). Understanding the reasons for user resistance to FRMPS would shed light on how to improve security measures of mobile payment services.

Last, despite an increase in research on technology resistance, such as smart bank service resistance (Chouk and Mani, 2019; Lee, 2020), mobile wallet resistance (Leong *et al.*, 2020c), mobile payment resistance among the elderly (Cham *et al.*, 2021) and smart speaker resistance (Hong *et al.*, 2020), a systematic understanding of why consumers resist FRMPS remains elusive. Although a few studies have recently examined factors in the resistance to facial recognition systems (Liu *et al.*, 2021; Zhang, 2021; Zhang *et al.*, 2021), a more comprehensive understanding of how consumers respond to FRMPS is necessary.

To address these issues, we reviewed and built on the literature related to FRMPS resistance to determine the appropriateness of the model. We ultimately adopted a stressor–strain–outcome (S–S–O) model (Koeske and Koeske, 1993), identifying system feature overload, information overload, technology uncertainty, perceived risk and privacy concern as the stressors; technostress as the strain; and technological resistance and negative word of mouth (nWOM) as outcomes. In addition, considering that extant studies on mobile payment or technology resistance use only cross-sectional methods (Al-Saedi *et al.*, 2020; Chouk and Mani, 2019), we aimed to take a mixed methods approach: we supplement a deep learning-based artificial neural network (ANN) approach with a two-stage analysis method that can better explain users' decision-making processes (Chong, 2013; Leong *et al.*, 2020a, 2020c). To this end, we also included text mining and sentiment analysis (Humphreys and Wang, 2018) to ensure the consistency of theoretical research findings and perspectives among social discussions.

In summary, this study explores how stressors (system feature overload, information overload, technology uncertainty, perceived risk and privacy concern) trigger strain (technostress), which in turn facilitates subsequent FRMPS resistance and nWOM. The conceptual model developed is rooted in the S–S–O framework, and we test it using a three-stage mixed methods approach, including structural equation modeling (SEM), a deep learning-based ANN analysis, text analysis and sentiment analysis, to glean insights into FRMPS resistance.

2. Literature review

2.1 Facial recognition mobile payment services

Mobile payment is a derivation of third-party payment services that eliminates the time and location limits of traditional payment and enables users to pay whenever and wherever they choose (Johnson *et al.*, 2018). Users combine their bank cards with a third-party payment platform, conduct a variety of payment activities via their mobile phones and handle the query, transfer, payment and recharge features of their personal accounts, which provides great user convenience (Fan *et al.*, 2018). Prior research on mobile payments has mainly focused on the third-party platform (e.g. Alipay, WeChat Pay, Apple Pay, Line pay). For example, studies have found that compatibility, accessibility, ease of use and network externality can facilitate intention to use mobile payment (Lee *et al.*, 2019). Other research shows that security, platform reputation, mobility and customization can foster customers' trust, thus leading to continuance usage intention toward mobile payment (Shao *et al.*, 2019). Still other studies demonstrate that factors such as expectations for performance, effort, trust and social influence can influence acceptance of mobile payments (Al-Saedi *et al.*, 2020). Table 1 provides a summary of studies on mobile payment services.

Until recently, studies have focused on resistance to facial recognition payment systems (FRPS) (Liu *et al.*, 2021; Zhang, 2021; Zhang *et al.*, 2021). In particular, Liu *et al.* (2021) draw from the privacy perspective, showing that the perceived effectiveness of privacy policy has considerable associations with perceived privacy risk, privacy control and resistance to FRPS (Liu *et al.*, 2021). Zhang *et al.* (2021) investigate customer characteristics and find that perceived risk and personal innovativeness can trigger innovation resistance to FRPS. Zhang (2021) examines FRPS characteristics and shows that providing a secure, convenient and reliable system can reduce innovation resistance to FRPS. We identified two major research gaps during our literature review.

First, whereas FRPS are typically a contactless form of payment at self-checkout kiosks in offline stores (Mordor Intelligence, 2020), FRMPS are installed in third-party mobile payment platforms and assist customers in undertaking a variety of transactions via their mobile devices at any time and in any location. In addition, mobile payment enables advertisers to deliver targeted marketing messages about products or services, based on the receiver's location, personality, age and interests (Shao *et al.*, 2019). Analogous with mobile payment, the basic idea is that FRMPS can attain service ubiquity for their customers by enabling users to pay regardless of the temporal and physical limits put on them. The mobility and immediacy of tailored information offered by FRMPS make them capable of not only satisfying the requirements and preferences of individual consumers but also facilitating transactions in personalized

Table 1 Brief summary of past studies related to mobile payment service

Source	Context	Predictor(s)/Mediator(s)/Moderator(s)	Outcome(s)
Al-Okaily *et al.* (2020)	Mobile payment service – JoMoPay in the Jordanian	Effort expectancy; facilitating conditions; performance expectancy; price-value; social influence; security; awareness; privacy *Moderator: culture*	Intention to use
Al-Saedi *et al.* (2020)	Mobile payment service	Performance expectancy; effort expectancy; social influence; perceived trust; perceived cost; self-efficacy; perceived risk	Continued intention
Bailey *et al.* (2022)	Mobile payment service	Performance expectancy; effort expectancy; social influence; facilitating conditions; bank trust; perceived quality; system confidence; consumer innovativeness	Mobile payment use
Jia *et al.* (2022)	Mobile payment service	Cell phone use habit; computer use habit; online shopping habit; mobile service habit *Mediator: mobile payment habit*	Continued intention
Johnson *et al.* (2018)	Mobile payment service	Perceived ubiquity; security; privacy risk; trialability; ease of use; relative advantage; visibility	Mobile payment service adoption
Lee *et al.* (2019)	Mobile payment service – Kakao Pay in Korea	Compatibility; accessibility; indirect network externality; ease of use; trust; brand value; network externality *Mediator: satisfaction*	Intention to use
Lin *et al.* (2020b)	Mobile payment service – O'Pay in Taiwan	Relative advantage; service compatibility; security risks; perceived fees; social norms *Mediators: perceived value of mobile payment; social self-image*	Behavioral intention of mobile payment
Liu *et al.* (2021)	Facial recognition payment systems in China	Perceived effectiveness of privacy policy; perceived privacy risk; privacy control; privacy concern; perceived benefits	Resistance
Loh *et al.* (2020)	Mobile payment service	Monetary value; alternative attractiveness; trust; perceived security and privacy; switching costs; traditional payment habit; inertia	Switching intention to Mobile payment
Shao *et al.* (2019)	Mobile payment service – Alipay and WeChat pay in China	Security; platform reputation; mobility; customization *Mediators: customers' trust; perceived risk* *Moderator: gender*	Continued intention
Yuan *et al.* (2020)	Mobile payment service – Alipay in China	System quality; information quality; service quality *Mediators: satisfaction; trust; intimacy*	Loyalty
Zhang (2021)	Facial recognition payment systems in China	Attitudes toward previous products; customer motivation; customer self-efficacy; customer innovation; customer perceived risk *Mediator: innovation resistance*	Intention to use
Zhang *et al.* (2021)	Facial recognition payment systems in China	Convenience; reliability; security; no contact *Mediator: innovation resistance*	Intention to use

situations. Because previous research has focused on FRPS rather than FRMPS inhibitors (Liu *et al.*, 2021; Zhang, 2021; Zhang *et al.*, 2021), our investigation of FRMPS may provide a more thorough understanding of resistance.

Second, research on mobile payment authentication methods is limited. At present, mobile payment verification methods mainly include password and biometric authentication. Biometric authentication is based on innate biological (e.g. face shape, DNA, retinal characteristics) and behavioral characteristics (e.g. word trace, sound, key force) and is used to identify individuals (Miltgen *et al.*, 2013). Ogbanufe and Kim (2018) compare fingerprint authentication and credit card payment with a personal identification number (PIN) code and find that users exhibit greater security concerns about fingerprint authentication than about the traditional payment method (credit card payment with a PIN code). Breward *et al.* (2017) demonstrate that familiarity and trust in banks can facilitate greater acceptance of account security regarding fingerprint authentication in ATM transactions. However, these aforementioned studies focus more on fingerprint authentication than on facial recognition. Facial recognition differs from fingerprint authentication in that this type of biometric authentication is a combination of computer technology, biosensors, biostatistics, cloud-computing technology and the use of facial characteristics to ascertain user identity. These intrinsic attributes of the human face also have strong self-stability and serve as appropriate identification credentials. Therefore, understanding how consumers perceive FRMPS is important.

2.2 Stressor–strain–outcome model

Koeske and Koeske (1993) developed the S–S–O framework to illustrate the direct effect of stressors on strains, which consequently can influence an individual's behavioral outcomes. Stressors, which refer to environmental stimuli that produce stress, are generally considered "irritating, distressing, or destructive pressures experienced by individuals" (Koeske and Koeske, 1993, p. 111). A strain refers to "the behavioral, psychological, and physiological consequences found in people under stress" (Koeske and Koeske, 1993, p. 111). The final stage of the S–S–O model is the outcome or the implementation of actions, intentions or behaviors, which are referred to as stress coping behaviors. Coping refers to "making individual cognitive, emotional, and behavioral efforts to attempt to calm external and internal influences" (Koeske and Koeske, 1993, p. 111). Extant studies have empirically demonstrated the S–S–O framework in various contexts, such as social media fatigue or intention to discontinue usage of social networking sites (Dhir *et al.*, 2018; Masood *et al.*, 2020; Wang *et al.*, 2020; Zhang *et al.*, 2016, 2022), poor academic performance correlated with excessive use of social networking sites (Dhir *et al.*, 2019; Malik *et al.*, 2020; Masood *et al.*, 2020) and work exhaustion (Gaudioso *et al.*, 2017). These studies identify different stressors, strains and outcomes in each context. Table 2 provides a brief summary of previous investigations.

However, the majority of these studies use this paradigm within the context of social media usage, rather than new technology adoption. By contrast, the current study uses the S–S–O framework as its theoretical underpinning to shed light on the dark side of FRMPS.

3. Hypotheses development

3.1 System feature overload and technostress

Overload describes "an individual's subjective view and appraisal of the amount of people, objects, or information sources that are beyond their capacity to process" (Yu *et al.*, 2018, p. 1095). Scholars generally agree that overload is the most important contributor to the undesirable effects that can result from the use of information and communication technologies (Fu *et al.*, 2020). Studies in the information systems (IS) literature stream have used the term "overload" to explain the perception of various functions that surpass an individual's competence to process (Lin *et al.*, 2020a). Overload has also been linked to significant psychological changes among social media users (Fu *et al.*, 2020; Guo *et al.*, 2020; Whelan *et al.*, 2020). Previous studies have demonstrated that overload is a primary factor in users' psychological functioning, particularly when those users attempt to discontinue usage (i.e. change the current state of use to disuse) rather than engage in resistance behaviors (a user's attempt to maintain the current state and refusal to face changes). This study expands the examination on system feature overload and information overload, both of which are relevant in the context of FRMPS use.

System feature overload refers to "a given technology being too complex for a given task" (Karr-Wisniewski and Lu, 2010, p. 1062). It generally comes from a system complexity or a system pace of change, such as a service improvement or system upgrade (Lin *et al.*, 2020a). Agogo and Hess (2018) define "system complexity" as the amount of work required to make use of the technology. For example, alterations in a system's functionalities may necessitate a transition period during which the user makes efforts to acquire the new functions, and these alterations might cause the user to experience varied amounts of stress. Chouk and Mani (2019) show that perceived complexity can lead to resistance to a smart bank service.

Technostress refers to "a modern disease of adaptation caused by an inability to cope with the new information and communication technologies in a healthy manner" (Agogo and Hess, 2018, p. 575). Extant studies indicate that information overload and system feature overload as environmental stimuli can promote fatigue and decrease flow experience, which in turn can facilitate discontinuous intention toward a social networking service (SNS) (Lin *et al.*, 2020a). Likewise, Tugtekin *et al.* (2020) determine that system feature overload,

Table 2 Brief summary of past S–S–O studies

Source	Stressor (S)	Strain (S)	Outcome (O)
Dhir *et al.* (2019)	Privacy concerns; self-disclosure; parental encouragement; parental worry; parental monitoring; parental permission	Social media fatigue	Academic performance decrement
Gaudioso *et al.* (2017)	Techno-invasion; techno-overload	Work-family conflict; distress on job	Adaptive coping strategies; maladaptive coping strategies
Luqman *et al.* (2020)	Excessive hedonic use of SNS; excessive cognitive use of SNS; excessive social use of SNS	Poor sleep quality; cognitive function depletion	Poor academic performance
Malik *et al.* (2020)	Privacy concern; social comparison; self-disclosure; intensity of mobile instant messaging (MIM) use; fear of missing out	MIM fatigue	Academic performance decrement
Masood *et al.* (2020)	Excessive use of mobile SNSs	Cognitive distraction	Poor academic performance
Wang *et al.* (2020)	Social overload; invasion of privacy; social media habit; sunk costs; affective commitment	Regret; inertia	Discontinuance intentions
Zhang *et al.* (2016)	System feature overload; information overload; social overload	Social media fatigue; dissatisfaction	Discontinuance intention
Zhang *et al.* (2022)	Information overload; compulsive social media use; privacy concern; fear of missing out; time cost	Social media fatigue	Social media fatigue behavior

information overload and social overload trigger social media fatigue. Cao *et al.* (2020) identify information overload and system feature overload that could create technostress and fatigue and ultimately lead to resistance behavior toward a health app among older consumers. Thus:

H1. System feature overload is positively associated with technostress.

3.2 Information overload and technostress

Information overload refers to "users subjectively perceiving that the information they are receiving exceeds their capacity in the information system" (Karr-Wisniewski and Lu, 2010, p. 1062). Herein, we define it as FRMPS users' receipt of an amount of information that is greater than their capability to process it. In the S–S–O paradigm, previous research has shown that information overload is a significant source of stress that leads to poor psychological states in users. For example, Yu *et al.* (2018) discover that overload and excessive use of SNSs can result in social media fatigue. Cao and Sun (2018) reveal that information overload may result in exhaustion and regret and, subsequently, to intention to discontinue use of SNSs. Shi *et al.* (2020) demonstrate that stressors such as information and system feature overload can lead to technostress. Thus:

H2. Information overload is positively associated with technostress.

3.3 Technology uncertainty and technostress

Technological uncertainty refers to the unpredictability of the consequences of technological development. Tarafdar *et al.* (2011, p. 310) define it as follows: "continuing changes and upgrades in information technology unsettle users and create uncertainty for them in that they worry about constantly learning and educating themselves about new information technology." Studies show that technological uncertainty is an impeding factor for IS adoption (Agogo and Hess, 2018; Hong *et al.*, 2020). For example, Agogo and Hess (2018) propose that technological uncertainty can increase technology fear and computer avoidance behavior. Hong *et al.* (2020) document technological uncertainty and service intangibility as factors that may contribute to perceived risk and reluctance toward smart home utilization. Ragu-Nathan *et al.* (2008) indicate that technological uncertainty is a driver of job dissatisfaction. Thus:

H3. Technology uncertainty is positively associated with technostress.

3.4 Perceived risk and technostress

Perceived risk pertains to "an individual's risk calculation, which involves an assessment of the likelihood of negative consequences as well as the perceived severity of these consequences" (Xu *et al.*, 2011, p. 804). Many studies show that perceived risk is negatively correlated with the adoption of mobile payments (Al-Saedi *et al.*, 2020; Shao *et al.*, 2019; Sharma *et al.*, 2018). For example, Hong *et al.* (2020) propose the barriers of performance, financial, privacy and psychological risks as the main drivers for mobile wallet resistance. Kim and Park (2022) demonstrate that perceived risk leads to resistance to a smart home service. Overall, extant findings show consensus that perceived risk facilitates resistance. Thus:

H4. Perceived risk is positively associated with technostress.

3.5 Privacy concern and technostress

Privacy concerns refer to "individuals' inherent worries about possible loss of information privacy" (Xu *et al.*, 2011, p. 800). We define privacy concern as users' feelings about the risk of having their personal biometric data leaked to other parties while using FRMPS. Privacy represents a major barrier to new technology adoption in various contexts, including mobile payment services (Al-Okaily *et al.*, 2020; Gong *et al.*, 2019; Johnson *et al.*, 2018; Sharma *et al.*, 2018) and mobile app adoption (Hsieh and Li, 2022). Zhang *et al.* (2020) indicate that privacy concern, information overload and time cost are the main stressors for social media fatigue, and Lee (2020) shows that privacy risk, information privacy and physical privacy are the main drivers for resistance behavior toward mobile payment service. Risk barriers (e.g. privacy risk, security risk) are significant in influencing senior citizens' aversion to mobile payment services (Cham *et al.*, 2021). Biometric authentication captures large amounts of biometric data, including personal data about the face, iris, fingerprint and voice (Breward *et al.*, 2017; Miltgen *et al.*, 2013). Consequently, users could experience anxiety from their worries about fraudulent transactions or the loss of ownership of their biometric data (Breward *et al.*, 2017). Therefore:

H5. Privacy concern is positively associated with technostress.

3.6 Technostress and negative consequences

According to the S–S–O framework (Koeske and Koeske, 1993), when a user has unpleasant feelings induced by technology, they will adopt a coping strategy to mitigate negative emotions, such as denial and behavioral disengagement on the job (Gaudioso *et al.*, 2017), discontinuous behaviors toward social network sites (Wang *et al.*, 2020) and resistance behavior (Cao *et al.*, 2020). Resistance is "a process that occurs during adoption and which refers to a user's attempt to maintain the current state and refusal to face changes" (Ram and Sheth, 1989, p. 6). Several studies have proposed theoretical explanations for new technology resistance (e.g. usage, risk, value, tradition and image barriers) as reasons that consumers do not adopt mobile wallets (Leong *et al.*, 2020c). Moreover, Chouk and Mani (2019) reveal that perceptions of security, complexity and government surveillance regarding smart bank services are correlated with resistance to such services. Similarly, Kim and Park (2022) show that perceptions of trust, benefit and ease of use decrease resistant attitudes toward Internet of Things (IoT) services (Kim and Park, 2022). Cham *et al.* (2021) reveal that user technological anxiety leads to resistance to mobile payment service among older consumers. Likewise, Hong *et al.* (2020) find that perceived risk is triggered by service intangibility and technology uncertainty about smart speakers. Regarding technology use, technology fear can decrease behavioral intentions toward AI-based apps (Cabrera-Sánchez *et al.*, 2020). Technophobia (i.e. fear of technology) can trigger computer avoidance behavior (Agogo and Hess, 2018). Tarafdar *et al.* (2011) verify that technostress can decrease user satisfaction with information services. In summary, existing studies indicate that unpleasant emotions are associated with maladaptive behaviors. Thus:

H6. Technostress is positively associated with technological resistance.

H7. Technostress is positively associated with nWOM.

4. Methods

4.1 Sampling and data collection

The purpose of this study is to investigate the factors that contribute to FRMPS resistance. To achieve this end, we made an online survey available to current Alipay and WeChat Pay customers who used password authentication rather than facial recognition authentication when making mobile payments. We chose these platforms because together, Alipay and WeChat Pay make up more than 90% of China's mobile payment market, and they are expected to achieve a combined user base of approximately 2.5 billion users by 2025 (Statista, 2021). Alipay and WeChat Pay are payment apps and digital wallets that provide FRMPS function and allow users to send and receive money easily without using cash. The facial recognition market is likely to reach $12.75bn by 2026 (Mordor Intelligence, 2020); however, the adoption rate for FRMPS is still low (Paysafe, 2019).

We thus recruited respondents from Alipay and WeChat Pay customers who use mobile payment but had not yet adopted the facial recognition method. We used professional Chinese questionnaire firm WenJuanXing to recruit respondents. For this study, WenJuanXing charged us 12 yuan (approximately $1.86) for each valid sample. We used four criteria to screen respondents in this study:

1. before the survey, respondents had no experience in using FRMPS (nonusers of FRMPS);
2. they had used other mobile payment platforms;
3. frequency of use; and
4. how long they used mobile payment service.

In addition, we embedded two attention checks into the questionnaire to identify inattentive respondents who did not follow the survey closely (Oppenheimer *et al.*, 2009).

The initial sample included 600 questionnaires. Of the respondents, 25 failed to pass the attention checks and 9 respondents with incomplete answers were removed from the analyses. Ultimately, we identified 566 password authentication users who refused to adopt FRMPS. More than half these were Alipay users (50.71%) and WeChat pay users made up a substantial portion of the rest (40.29%). Among these 566 respondents, 291 were male (51.41%) and the remaining 275 respondents are females (48.59%), and their average age was 31.42 years. Most respondents had used mobile payment for more than three years (73.85%). Regarding average usage frequency, 1.94% of respondents used password authentication during mobile payment at least once a day, 4.59% twice a day, 10.42% three times a day, 27.92% four times a day and 55.12% more than five times. The sample profile was consistent with the government report of mobile internet users (China Internet Network Information Center, 2021), which demonstrates the representativeness of the sample. Moreover, our sample size (n = 566) conforms to the standard that "minimum sample size should be ten times larger than the structural paths directed at a particular latent construct in the structural model" (Hair *et al.*, 2011, p. 144; Hair *et al.*, 2012, p. 420).

4.2 Measures

We adapted the measures of system feature overload (Karr-Wisniewski and Lu, 2010), information overload (Karr-Wisniewski and Lu, 2010), technological uncertainty (Hong *et al.*, 2020), perceived risk (Loiacono, 2014), privacy concern (Zhao *et al.*, 2012), technostress (Cao *et al.*, 2020; Luqman *et al.*, 2017), resistance (Hong *et al.*, 2020) and nWOM (Weitzl *et al.*, 2018) from previous literature and revised them for the FRMPS context. As Table 3 shows, all items were based on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree).

4.3 Common method bias

We used Harman's one-factor procedure to investigate common method bias (Podsakoff *et al.*, 2003). After carrying out an exploratory factor analysis, we found that the first factor was responsible for 13.22% of the overall variation, indicating no cause for concern with common method bias. In addition, we used a method based on common latent factors to further evaluate the extent of the common method bias. In accordance with Leong *et al.* (2020b), we included a common method factor in the model. This factor's indicators included all the principal constructs' indicators, and the variance of each indicator that was substantively explained by the principal construct and by the method factor was determined. Table 4 shows the findings, which reveal that the average indicator variation that can be explained by the substantive factors is 0.7498, whereas the average variance that can be explained by the method factors is 0.0053 – a ratio of approximately 141:1. In addition, the majority of the method factor loadings do not exhibit substantial levels of significance. As a result, the extent of the variance caused by the common method was rather small. Therefore, we conclude that common method variance is not a concern.

4.4 Analytical method

First, we used partial least squares SEM (PLS-SEM). PLS-SEM is a nonparametric method and does not need to follow normal distribution (Hair *et al.*, 2017). We ran a normality test analysis in this study. All measurement items are significant, suggesting nonnormal of data ($p < 0.001$), according to Shapiro–Wilk and Kolmogorov–Smirnov analyses. Therefore, the data deviating from normal justify the use of PLS-SEM. In the second stage, we adopted the ANN analysis method. Most previous researchers studying FRPS use single-stage data analysis, the primary emphasis of SEM (Liu *et al.*, 2021; Zhang, 2021; Zhang *et al.*, 2021). However, studies show that to overcome this deficiency, a SEM model (linear and

Table 3 Measurement items

Item	Standardized item loadings
System feature overload (α = 0.86, rho_*A* = 0.86, CR = 0.91, AVE = 0.78)	
I feel distracted by many features included in facial recognition mobile payment which are not related to my main purpose	0.88
Some features in facial recognition mobile payment are too complex for me	0.87
Too many poor sub features in facial recognition mobile payment makes payment even harder	0.90
Information overload (α = 0.83, rho_*A* = 0.83, CR = 0.90, AVE = 0.74)	
I am often distracted by the excessive amount of information in facial recognition mobile payment	0.82
I feel that I am overwhelmed by too much information in facial recognition mobile payment	0.87
Processing too much payment relevant information is a burden for me in facial recognition mobile payment	0.90
Technological uncertainty (α = 0.84, rho_*A* = 0.85, CR = 0.91, AVE = 0.76)	
I think that the wireless network of facial recognition mobile payment is unstable	0.83
The technologies related to facial recognition mobile payment is questionable	0.89
I think that the technologies related to facial recognition mobile payment are undeveloped	0.89
Perceived risk (α = 0.87, rho_*A* = 0.88, CR = 0.92, AVE = 0.80)	
It is uncertain whether facial recognition mobile payment will operate as satisfactorily as expected when compared with password based mobile payment	0.91
The performance of facial recognition mobile payment may not match their advertised level when compared with password based mobile payment	0.91
Providing information for facial recognition mobile payment would involve more financial risk when compared with password based mobile payment	0.86
Privacy concern (α = 0.93, rho_*A* = 0.93, CR = 0.95, AVE = 0.83)	
I am concerned that others can find biometric information about me on facial recognition mobile payment	0.91
I am concerned about submitting biometric information on facial recognition mobile payment, because of what unauthorized third party might oversee it	0.90
I am concerned that the biometric information I disclose on the facial recognition mobile payment would involve many misused, inappropriately shared, or sold problems	0.92
I am totally concerned that the biometric information I disclose on the facial recognition mobile payment would bring about privacy-related problems	0.91
Technostress (α = 0.80, rho_*A* = 0.80, CR = 0.88, AVE = 0.71)	
I feel that I am forced to change habits to adapt to facial recognition mobile payment	0.85
I am threatened by facial recognition mobile payment	0.85
Learning how to operate facial recognition mobile payment makes me feel stressed	0.83
Resistance (α = 0.84, rho_*A* = 0.85, CR = 0.90, AVE = 0.68)	
I will feel uneasy if I use facial recognition mobile payment	0.83
Password-based mobile payment is better than using facial recognition mobile payment	0.79
I am reluctant to use facial recognition mobile payment	0.85
If I use facial recognition mobile payment, I will be dissatisfied with the method	0.83
Negative word-of-mouth (nWOM) (α = 0.84, rho_*A* = 0.85, CR = 0.90, AVE = 0.68)	
I will spread negative word-of-mouth about facial recognition mobile payment	0.80
I will badmouth my friends about facial recognition mobile payment	0.84
I advise other people not to b use facial recognition mobile payment	0.82
I wouldn't recommend facial recognition mobile payment to my friends and family	0.85

Note: All the factor loadings are significant at $p < 0.01$

compensatory) supplemented by a deep learning-based ANN model (nonlinear and noncompensatory) can produce more accurate predictions (Lee *et al.*, 2016). Research has also shown that ANN has superior ability to predict mobile banking adoption (Sharma and Sharma, 2019) and mobile payment use (Kalinic *et al.*, 2019; Liébana-Cabanillas *et al.*, 2018). Furthermore, compared with conventional linear statistical techniques, the ANN model is able to identify both linear and nonlinear associations between different constructs. In addition, the model possesses strong robustness and adaptability, as well as freedom from distribution assumptions such as normality, linearity and homoscedasticity (Leong *et al.*, 2020a, 2020c). Finally, SEM analysis "cannot rank the independent variables, so it may not provide enough information for IT/IS adoptions" (Ahani *et al.*, 2017, p. 570). Therefore, we structure the proposed framework by combining the two-stage method of SEM with an ANN analysis.

In the third stage, we conducted text analysis. Text mining refers to extracting feature words from texts and quantifying them to represent textual information. This technique can transform unstructured original texts into structured, highly abstract and characteristic information that computers can

Table 4 Common method bias analysis

Path	Substantive loading	Substantive variance	*T* statistics	Path	Method loading	Method variance	*T* statistics
System overload → SO1	0.880	0.774	73.750***	Method → SO1	0.000	0.000	0.010
System overload → SO2	0.870	0.757	63.400***	Method → SO2	−0.070	0.005	1.840
System overload → SO3	0.900	0.810	94.050***	Method → SO3	0.070	0.005	1.930
Information overload → IQ1	0.830	0.689	50.960***	Method → IQ1	−0.060	0.004	1.390
Information overload → IQ2	0.870	0.757	70.460***	Method → IQ2	0.020	0.000	0.480
Information overload → IQ3	0.890	0.792	86.290***	Method → IQ3	0.040	0.002	1.080
Technological uncertainty → TU1	0.840	0.706	56.290***	Method → TU1	0.000	0.000	0.100
Technological uncertainty → TU2	0.880	0.774	85.440***	Method → TU2	0.040	0.002	0.820
Technological uncertainty → TU3	0.890	0.792	93.220***	Method → TU3	−0.030	0.001	0.740
Privacy concern → PC1	0.920	0.846	124.040***	Method → PC1	−0.020	0.000	0.610
Privacy concern → PC2	0.900	0.810	96.650***	Method → PC2	0.060	0.004	1.700
Privacy concern → PC3	0.920	0.846	149.800***	Method → PC3	−0.090	0.008	2.900***
Privacy concern → PC4	0.910	0.828	124.920***	Method → PC4	0.050	0.003	1.400
Perceived risk → PR1	0.910	0.828	118.300***	Method → PR1	0.020	0.000	0.440
Perceived risk → PR2	0.910	0.828	106.240***	Method → PR2	0.110	0.012	2.870***
Perceived risk → PR3	0.860	0.740	59.090***	Method → PR3	−0.140	0.020	2.780***
Technostress → TS1	0.860	0.740	64.040***	Method → TS1	0.050	0.003	1.130
Technostress → TS2	0.860	0.740	58.130***	Method → TS2	−0.090	0.008	2.710***
Technostress → TS3	0.820	0.672	42.500***	Method → TS3	0.050	0.003	1.100
Resistance → resistance 2	0.820	0.672	52.820***	Method → resistance 1	0.030	0.001	0.520
Resistance → resistance 3	0.800	0.640	44.060***	Method → resistance 2	0.040	0.002	0.600
Resistance → resistance 4	0.850	0.723	56.480***	Method → resistance 3	0.120	0.014	1.990*
Resistance → resistance 1	0.840	0.706	59.060***	Method → resistance 4	−0.180	0.032	3.540***
NWOM → NWOM1	0.820	0.672	38.030***	Method → NWOM1	−0.070	0.005	1.930
NWOM → NWOM2	0.850	0.723	47.930***	Method → NWOM2	−0.040	0.002	1.300
NWOM → NWOM3	0.810	0.656	40.660***	Method → NWOM3	0.100	0.010	2.800***
NWOM → NWOM4	0.850	0.723	52.280***	Method → NWOM4	0.010	0.000	0.420***
Mean		*0.7498*				*0.0053*	

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; SO = system feature overload; IO = information overload; TU = technological uncertainty; PR = perceived risk; PC = privacy concern; TS = technostress; NWOM = negative word of mouth

recognize and process (Humphreys and Wang, 2018). Social media platforms such as Weibo in China (similar to Twitter) encourage users to freely express their views, which can lead to insightful comments (Sinha *et al.*, 2020). In this context, text analysis is a valuable method for evaluating patterns and can be used to investigate psychological and sociological constructs in consumer-generated digital text by either facilitating discovery or granting ecological validity (Humphreys and Wang, 2018). Therefore, we used the text to determine users' attitudes toward and perspectives of FRMPS. As such, the mixed method approach led to provide marketers for comprehensive understanding behind FRMPS resistance.

5. Results

5.1 Stage I: Measurement model

We carried out the analysis with SmartPLS 3.0 (Ringle *et al.*, 2015), conducted in accordance with PLS-SEM guidelines (Hair *et al.*, 2020). The control variables incorporated into the model were gender, age, frequency of use, length of use and income. As Table 3 shows, standardized item loadings ranged from 0.79 to 0.92, and the range of the composite reliability estimates was from 0.88 to 0.95. We conclude that the data have good convergent validity because the average variance extracted (AVE) values for all constructs were greater than 0.50 (Hair *et al.*, 2017). Furthermore, Table 5 shows that the values of correlation for all constructs fall below the estimate of the value of the square root of the AVE. The heterotrait–monotrait ratio was significantly lower than the cutoff value of 0.85 (Hair *et al.*, 2017). Consequently, we can confirm the reliability, convergent validity and discriminant validity of the measuring items used in this study.

5.2 Stage I: Structural model

In terms of the model fit, the values of the coefficient of determination (R^2) for technostress (0.51), resistance (0.49) and nWOM (0.34) suggest nearly moderate to strong predictive power (Hair *et al.*, 2017). The standardized root mean square residual value was 0.06, which is less than 0.08, indicating that the requirement was successfully fulfilled (Hair *et al.*, 2017). System feature overload (β = 0.17, $p < 0.05$), informational overload (β = 0.14, $p < 0.05$), technological uncertainty (β= 0.26, $p < 0.001$), perceived risk (β = 0.14, $p <$ 0.05) and privacy concern (β = 0.15, $p < 0.05$) exerted a positive influence on technostress, in support of *H1–H5*. Furthermore, technostress led to FRMPS resistance (β = 0.59, $p < 0.001$) and nWOM (β = 0.56, $p < 0.001$), in support of *H6*

Table 5 Discriminant analysis

Construct	1	2	3	4	5	6	7	8
Correlation matrix of the constructs and AVE values								
1. System feature overload	*0.88*							
2. Information overload	0.70	*0.86*						
3. Technological uncertainty	0.72	0.63	*0.87*					
4. Perceived risk	0.59	0.58	0.62	*0.89*				
5. Privacy concern	0.61	0.64	0.62	0.71	*0.91*			
6. Technostress	0.61	0.58	0.63	0.57	0.58	*0.84*		
7. Resistance	0.69	0.61	0.65	0.70	0.64	0.60	*0.83*	
8. Negative word of mouth	0.53	0.50	0.50	0.49	0.43	0.56	0.62	*0.83*
HTMT ratio								
1. System feature overload								
2. Information overload	0.84							
3. Technological uncertainty	0.84	0.76						
4. Perceived risk	0.68	0.68	0.73					
5. Privacy concern	0.68	0.72	0.70	0.79				
6. Technostress	0.73	0.72	0.76	0.68	0.67			
7. Resistance	0.81	0.73	0.77	0.82	0.72	0.73		
8. Negative word of mouth	0.62	0.59	0.59	0.57	0.48	0.68	0.73	

Notes: The upper part of table is correlation matrix of the constructs and AVE values. The square roots of the AVE estimates are the values in italic and running diagonally from top left to bottom right. The lower part of the table is HTMT ratios

and *H7*. In summary, as Figure 1 shows, all hypotheses were significantly supported.

5.3 Stage II: Artificial neural network

In the second stage, we performed three ANN models. Model A had five inputs (system feature overload, informational overload, technological uncertainty, perceived risk and privacy concern) and one output (technostress), Model B also had five inputs (system feature overload, informational overload, technological uncertainty, perceived risk and privacy concern) and one output (FRMPS resistance) and Model C had five inputs (system feature overload, informational overload, technological uncertainty, perceived risk and privacy concern) and one output (nWOM).The results showed that the number of neurons in the hidden layer (2) was between the number of input neurons (3) and output neuron (1) for Models A, B and C, suggesting no overfitting problem. In accordance with Leong *et al.* (2013), we computed the root mean square error (RMSE) and the correlation coefficient (R^2) to evaluate the model fit of the ANN models. The RMSE values were relatively small, indicating predictive accuracy (Table 6). Next, we calculated the R^2 values of Models A, B and C, which were 84.47%, 80.52% and 81.83%, respectively, indicating an outstanding model fit (Leong *et al.*, 2020a, 2020c).

Finally, we analyzed the relative importance of the precursors by conducting a sensitivity analysis (Leong *et al.*, 2020a, 2020c). Table 7 shows that technological uncertainty was the most essential stressor for technostress, followed by system feature overload, privacy concern, informational overload and perceived risk, consistent with the SEM findings. The consistency between the SEM and ANN models confirms our research model's predictive power. In addition, Model B shows that perceived risk was the most influential driver for FRMPS resistance, followed by system feature overload, technological uncertainty, informational overload and privacy concern. Finally, Model C revealed that system feature overload was the most influential factor for nWOM, followed by perceived risk, informational overload, technological uncertainty and privacy concern.

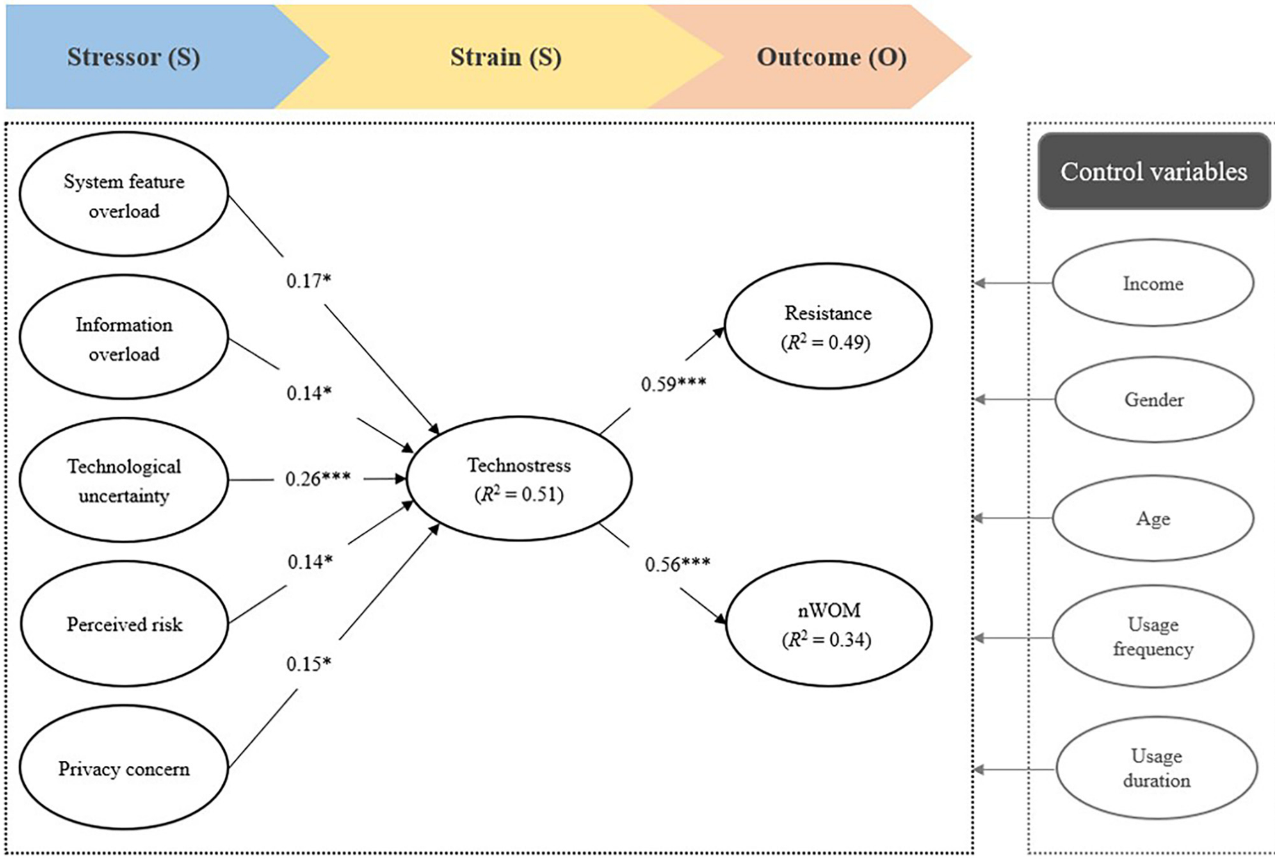
5.4 Stage III: Text mining and sentiment analysis

In the third stage, we collected data and cleansed it. First, we identified relevant posts, conversations and comments and extracted unstructured data from social media with the keywords "facial recognition payment," "biometric authentication payment," "fingerprint payment," "iris payment," "vein payment," "biometric and payment" and "voice payment." The data included ID, link and description, followed by the dates of the posts, post timing, number of likes, comments and sharing counts.

Second, we used text mining and visualization with graphs to show how many clusters of keywords in those texts related to FRMPS. We acquired 4,038 comments consisting of multiple keywords. We ultimately identified 5,154 keywords, which had a frequency of 17,223. The top 30 keywords include "mobile payment" (303), "face recognition" (209), "smart phone" (182), "personal information" (177), "biometric recognition" (150), "face" (141), "privacy" (132), "Alipay" (131), "fingerprint" (123), "system" (121), "password" (106), "data" (74), "Huawei" (68), "complex" (65), "useless" (65), "leak" (63), "ID card" (62), "abuse" (57), "wireless" (54), "high-tech" (50), "unlock" (46), "fraud" (45), "dislike" (43), "terrible" (43), "Taobao" (40), "Tencent" (40), "risk" (41), "certification" (41), "security concern" (38) and "protection" (37).

Finally, we conducted a text sentiment analysis, also referred to as "emotional polarity computation" (Sinha *et al.*, 2020), to determine whether FRMPS resistance exists. We used PaddleHub with the Senta (Baidu's deep-learning Chinese sentiment analysis tool) classifier to analyze the sentiments and found that 66.90% of users exhibited negative sentiments,

Figure 1 PLS path



Notes: Significance *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 6 RMSE values of artificial neural networks (ANN)

	Model A Inputs: SO, IO, TU, PR, PC Output: Technostress				Model B Inputs: SO, IO, TU, PR, PC Output: Resistance				Model C Inputs: SO, IO, TU, PR, PC Output: Negative word of mouth			
	Training		Testing		Training		Testing		Training		Testing	
ANN	*N*	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE	*N*	RMSE
1	504	0.105	62	0.118	504	0.101	61	0.101	513	0.105	53	0.084
2	506	0.107	60	0.082	506	0.100	55	0.106	513	0.107	53	0.114
3	510	0.103	56	0.096	510	0.101	50	0.091	520	0.102	46	0.114
4	501	0.101	65	0.116	501	0.100	28	0.098	514	0.104	52	0.104
5	504	0.104	62	0.102	504	0.100	45	0.097	499	0.104	67	0.101
6	503	0.106	63	0.085	503	0.100	62	0.114	522	0.105	44	0.096
7	497	0.103	69	0.089	497	0.100	54	0.095	514	0.101	52	0.127
8	513	0.104	53	0.087	513	0.100	54	0.095	507	0.104	59	0.100
9	507	0.108	59	0.112	507	0.102	57	0.098	509	0.106	57	0.083
10	517	0.107	49	0.103	517	0.101	50	0.084	517	0.104	49	0.101
Mean		0.105		0.099		0.100		0.098		0.104		0.102
SD		0.002		0.013		0.001		0.008		0.002		0.014
R^2		98.11%		84.47%		98.06%		80.52%		98.13%		81.83%

Notes: SO = system feature overload; IO = information overload; TU = technological uncertainty; PR = perceived risk; PC = privacy concern; *N* = sample size

Table 7 Neural network sensitivity analysis

ANN	Model A: Relative importance Output: Technostress SO	IO	TU	PR	PC	Model B: Relative importance Output: Resistance SO	IO	TU	PR	PC	Model C: Relative importance Output: Negative word of mouth SO	IO	TU	PR	PC
1	0.218	0.192	0.270	0.118	0.203	0.217	0.173	0.196	0.293	0.120	0.311	0.245	0.149	0.265	0.030
2	0.236	0.130	0.251	0.188	0.194	0.260	0.125	0.192	0.283	0.139	0.274	0.226	0.175	0.243	0.082
3	0.228	0.153	0.289	0.135	0.195	0.306	0.089	0.133	0.356	0.115	0.273	0.234	0.213	0.245	0.034
4	0.210	0.167	0.311	0.120	0.192	0.329	0.101	0.130	0.345	0.095	0.265	0.212	0.203	0.252	0.068
5	0.243	0.161	0.265	0.123	0.209	0.310	0.093	0.126	0.356	0.114	0.343	0.192	0.171	0.214	0.080
6	0.268	0.102	0.292	0.139	0.198	0.277	0.123	0.202	0.296	0.101	0.304	0.225	0.202	0.263	0.007
7	0.227	0.134	0.277	0.137	0.224	0.364	0.080	0.116	0.370	0.071	0.280	0.239	0.193	0.272	0.015
8	0.205	0.197	0.260	0.139	0.199	0.364	0.080	0.116	0.370	0.071	0.317	0.197	0.152	0.285	0.050
9	0.283	0.117	0.330	0.132	0.137	0.225	0.119	0.200	0.292	0.165	0.334	0.200	0.176	0.254	0.037
10	0.209	0.137	0.312	0.154	0.187	0.306	0.119	0.126	0.346	0.103	0.237	0.236	0.231	0.253	0.042
Average importance	0.233	0.149	0.286	0.138	0.194	0.296	0.110	0.154	0.331	0.109	0.294	0.221	0.186	0.255	0.044
Normalized importance (%)	81.4	52.2	100.0	48.4	67.7	89.5	33.4	46.5	100.0	33.1	100.0	75.1	63.4	86.7	15.1

Notes: SO = system feature overload; IO = information overload; TU = technological uncertainty; PR = perceived risk; PC = privacy concern

29.70% exhibited positive emotions and 3.39% exhibited neutral emotions pertaining to FRMPS. Figure 2 presents the word cloud, and Figure 3 shows the results of the sentiment analysis. The results of text mining and sentiment analysis identified privacy, risk, system, information and technological uncertainty as key concerns for FRMPS users, which also correspond to the SEM–ANN analysis findings.

6. Discussion

Despite the potential of FRMPS as a new technological payment method that enhances security and convenience for users, relatively few studies address the stressors that contribute to FRMPS resistance. We use the S–S–O framework to illuminate the underlying mechanisms of technology resistance. The results confirm the validity of the S–S–O framework and reveal that technology characteristics, as stressors, can lead to a strained state and negative outcomes. Furthermore, technostress significantly correlates with resistance and nWOM. Our research provides a comprehensive explanation of the crucial stressors of FRMPS resistance.

Figure 2 Word cloud

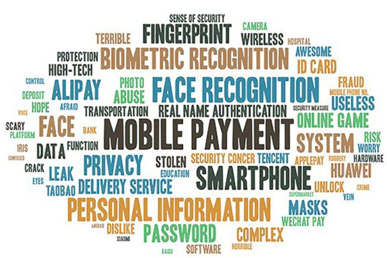
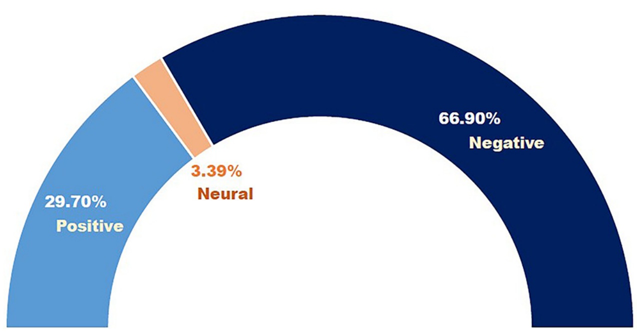


Figure 3 Results of the text sentiment analysis



6.1 Research findings

The findings suggest that perceived overload translates to higher technostress among FRMPS users. The findings echo previous research linking high information overload and system feature overload with negative consequences, such as emotional exhaustion (Cho *et al.*, 2019; Shi *et al.*, 2020) and social media fatigue (Tugtekin *et al.*, 2020). Our research expands on these studies and demonstrates that information overload, as well as system feature overload, increases the constrained individual cognitive load, which ultimately leads to technostress (*H1* and *H2*). In addition, the result of the ANN analysis reveals that system feature overload has the strongest predictive power for nWOM, possibly because, upon experiencing system feature overload, users tend to cope with this pressure by sharing with families and friends, which results in negative referrals.

Moreover, the results confirm that technological uncertainty promotes technostress (*H3*). Prior research shows that technological uncertainty results in technostress in the work environment (Tarafdar *et al.*, 2010, 2011); our study extends this finding to FRMPS. Both SEM and ANN analyses indicate that technological uncertainty is the most influential impeding factor for technostress. The possible reason may be that people perceive the inability to predict accurately the development of FRMP, making it the main stressor.

Furthermore, our data verify *H4*, which posits that perceived risk is positively correlated with technostress, thereby shedding further light on the underlying mechanism between risk and resistance behaviors and showing the vital role of technostress. According to the ANN analysis findings, perceived risk is the primary predictor for resistance, consistent with the text analysis findings. The keywords showed that mobile phone users frequently mentioned "useless," "fraud," "stolen" and "crack" as relating to various risks such as performance and financial risk. This result corresponds to previous findings of how perceived risk decreases adoption of mobile wallets (Leong *et al.*, 2020c) and IoT service (Hong *et al.*, 2020), which highlight the positive association between perceived risk and resistance.

H5 proposes that privacy concerns trigger technostress in the context of biometric data disclosure, in accordance with previous findings that privacy concern is the main inhibitor of adopting mobile app service, but providing privacy assurance can mitigate this concern (Hsieh and Li, 2022). Notably, our SEM analysis revealed that the correlation between privacy concern and technostress is relatively low. The ANN results further show that privacy concern plays a small role in driving resistance and nWOM. Overall, privacy concern did not necessarily increase nWOM. Prior studies have shown mixed results in terms of privacy concerns and negative emotions; for example, one investigation finds that privacy concern had an nonsignificant effect on mobile instant messaging fatigue (Malik *et al.*, 2020). We put forth several possible reasons for this inconsistent result. First, our research context is the mobile payment platform. Previous studies mainly discuss social networking sites, such as Facebook, so the nature of platforms is different. Second, the privacy settings of the mobile payment platform have changed relatively less over time and the setting method is simpler than Facebook, which has responded to criticism of its privacy policies and settings by changing them (Malik *et al.*, 2020). Thus, it makes sense that privacy concerns among Alipay or WeChat payment users do not trigger technostress.

Finally, we confirm that technostress can drive resistance to and nWOM about FRMPS (*H6* and *H7*). The results of the text analysis show that mobile payment users mentioned words expressing unpleasant emotional states, such as "dislike," "terrible worry," "scary," "afraid," "horrible" and "confused." When these users experienced stress, they resorted to coping strategies such as badmouthing and negative referrals to others. This result is in line with previous findings, which suggest that unpleasant feelings generally facilitate nWOM and switching intentions (Cai *et al.*, 2018), along with negative behavior toward new technologies (Gursoy *et al.*, 2019; Roy *et al.*, 2020).

6.2 Theoretical contributions

This research offers several theoretical contributions. First, our study does not focus on the bright side of new technologies or services but rather illuminates the dark side of using FRMPS, which has largely been overlooked. Prior research has investigated positive behaviors of users of mobile payments, including adoption (Bailey *et al.*, 2022; Cocosila and Trabelsi, 2016; Johnson *et al.*, 2018), continuous usage intentions (Alhassan *et al.*, 2020; Al-Saedi *et al.*, 2020; Jia *et al.*, 2022; Shao *et al.*, 2019), positive WOM (Miltgen *et al.*, 2013) and loyalty (Gong *et al.*, 2020; Yuan *et al.*, 2020). Ample research addresses mobile payment acceptance through the lenses of positive theories such as the technology acceptance model (Kalinic *et al.*, 2019; Liébana-Cabanillas *et al.*, 2018; Miltgen *et al.*, 2013), unified theory of acceptance and use of technology (UTAUT) (Al-Saedi *et al.*, 2020; Liébana-Cabanillas *et al.*, 2019; Miltgen *et al.*, 2013), UTAUT2 (Al-Okaily *et al.*, 2020), diffusion of innovation (Johnson *et al.*, 2018; Kalinic *et al.*, 2019; Miltgen *et al.*, 2013; Shao *et al.*, 2019), IS success model (Mouakket, 2020; Talwar *et al.*, 2020; Yuan *et al.*, 2020) and value theory (Cocosila and Trabelsi, 2016; Fan *et al.*, 2018). Despite increasing research on mobile payments, there has been relatively little research on how consumers respond to FRMPS. Our research shed lights on the FRMPS resistance.

Second, our study contributes to the exploration of the inhibitors of FRMPS from an S–S–O perspective. Previous S–S–O studies have shown how stressors drive strain and negative behaviors from social media usage (Malik *et al.*, 2020; Masood *et al.*, 2020). We supplement these studies by taking into account different manifestations of stressors, including information overload, system feature overload, technical uncertainty, perceived risk and privacy concerns. These considerations provide a clearer and more comprehensive understanding of stressors' inhibiting factors and their internal mechanisms when consumers encounter FRMPS. We also show that in the context of FRMPS, users engage in resistance and nWOM as adaptive response strategies to avoid the stressful situations produced by technostress. This research extends previous studies addressing technostress in the context of SNSs (Luqman *et al.*, 2017; Shi *et al.*, 2020) and health applications (Cao *et al.*, 2020), and we illuminate the importance of the specific stressors and strains of FRMPS.

Third, relatively few studies have examined mobile payment authentication methods, specifically biometric authentication. Instead, prior studies have mainly examined fingerprint authentication in a service context, such as fingerprint authentication before ATM transactions (Breward *et al.*, 2017), facial recognition of hotel check-in services (Xu *et al.*, 2021) and fingerprint-authentication-based payment (Ogbanufe and Kim, 2018). Moreover, previous studies on FRPS focus on privacy (Liu *et al.*, 2021), customer characteristics (Zhang *et al.*, 2021) and system characteristics (Zhang, 2021); by contrast, we focus on FRMPS and provide a more comprehensive understanding of resistance behaviors.

Finally, this study contributes to research applying a mixed methods approach to investigate resistance to and nWOM about FRMPS. Previous studies have mainly used a cross-sectional design (Al-Saedi *et al.*, 2020; Chouk and Mani, 2019). We conducted a SEM–ANN analysis to verify the S–S–O framework in the context of FRMPS. Then, we used a deep learning-based ANN analysis as a nonlinear model to reveal the "black box" of technostress and demonstrate accuracy in forecasting technostress, resistance and nWOM. Finally, we retrieved and archived textual information from social media and used machine learning, classification clustering algorithms and sentiment analysis to evaluate comprehensive social discussions among users. Our findings show that a mixed methods approach contributes to a richer explanation of FRMPS resistance.

6.3 Managerial implications

Advanced payment methods have profoundly changed consumers' consumption and payment habits; however, while payment efficiency has improved, security remains a concern. In this study, we found that those who refuse to use FRMPS are mindful of system feature overload, information overload, technology uncertainty, perceived risk and their own privacy. Therefore, practitioners should aim to eliminate these stressors to reduce consumers' fear and prevent resistance or nWOM behaviors.

First, to deal with system feature or information overload, practitioners should provide their payment users with more detailed and easy-to-understand tutorials, such as illustrated manual or instructional videos. Presenting users with an interface in a straightforward and easily comprehensible way is critical to its effectiveness. A second design strategy to avoid system feature or information overload is to drop redundant navigation, a particularly useful suggestion in interfaces that accommodate infrequent users or users who are typically unfamiliar with the content. The payment interfaces on mobiles should be designed in full consideration of user experience and preferences. Moreover, FRMPS designers should take into account usage pattern differences stemming from demographics (e.g. gender, age, education levels). A user-friendly design enables users to improve on the skills they already have without putting in any extra effort. These features should go beyond simple utility by providing access to just-in-time training materials and subject knowledge bases, all of which are crucial for efficient use.

Furthermore, our results from SEM–ANN, text mining and sentiment analyses show that security concerns about new payment methods are one of the major antecedents in users' technostress, resistance and nWOM. Therefore, to resolve users' feelings of uncertainty of the unknown, FRMPS designers should make the information completely open and transparent. For example, instructions and communications should emphasize that FRMPS can efficiently prevent forgeries and ensure account security even if a user attempts to exploit the system using still photographs or recorded videos, which service providers can combine with certain hardware and software advances. Consumers should know that to guard against fraudulent use of biometric information, the system only gathers the minimum necessary information about the user's face for payment verification, the information is algorithmically encrypted to protect user privacy and merchants are unable to access this information. In addition, communications should emphasize that perceived risk and privacy concerns can be discouraged by a well-established payment system that incorporates continuous encryption techniques to enhance digital security and cyber immunity. Therefore, risk prevention and privacy protection will be crucial determinants of success in achieving users' acceptance of FRMPS.

6.4 Limitations and future research

This study has a few flaws and restrictions, which may lead to further research. First, our study conducted text analysis from social media platforms. Future researchers should retrieve and archive text data from other types of platforms. Second, the study uses a mixed methods approach by integrating SEM, ANN, text mining and sentiment analyses. Recent research shows that construal level can affect the choice between security and usability of password use (Kaleta *et al.*, 2019); therefore, future research could use an experimental design method to investigate other aspects of FRMPS resistance. Finally, our study treats technological characteristics as main stressors for resistance. However, prior studies have shown that individual difference such as traditional cultural orientation can influence mobile money transfer adoption (Fall *et al.*, 2021). Future studies could explore how individual differences and design factors of mobile payment affect resistance to FRMPS.

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