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Influential Factors Impacting Users' Behavioral Intentions Regarding Facial Recognition Payment Systems of Mobile Payment Platforms in Wuhan, China

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Abstract

Purpose: This study aims to investigate the possible factors that drive customers' willingness to utilize facial recognition payment and provide information that companies can refer to spread the face recognition payment service successfully. **Research design, data, and methodology:** Data was collected from 500 Chinese mobile payment users using quantitative research methodology, employing a questionnaire as the data collection tool. The sampling methods used in this research included judgmental, quota, and convenience sampling. To ensure the questionnaire's validity and reliability, a pilot test was conducted with 50 participants, using the Item-Objective Congruence (IOC) index and Cronbach's alpha for reliability assessment. Data obtained from the study were analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM). **Results:** The results show that privacy control significantly affects privacy concerns. Behavioral intention is significantly affected by privacy concerns, perceived usefulness, perceived ease of use, and personal innovativeness but not by facilitating conditions. In addition, perceived privacy risk has no significant effect on privacy concerns. Security has no significant effect on perceived usefulness. **Conclusions:** The results of this study will be of value to various groups associated with E-payment services, such as mobile network operators, financial institutions, and payment service providers.

Keywords : Privacy Control, Privacy Concerns, Behavioral Intention, Personal Innovativeness, Face Recognition Payment

JEL Classification Code: E44, F31, F37, G15

1. Introduction

China has made significant strides in the research and development of new technologies and industrial applications within artificial intelligence, with a continued increase in related patent applications (Wipo, 2021). Li et al. (2020) also mentioned that in the field of face recognition, Baidu, Ali, Tencent, and other companies have developed highly accurate and fast face recognition technology that has repeatedly achieved leading results in world-class competitions. As a representative of the cutting-edge development in China's new digital economy, mobile payment has become a research hotspot in academic circles in recent years. The user acceptance behavior towards mobile payment has become a focal point for experts and scholars.

The providers of e-payment, mobile payment, and banking services consistently offer innovative features such as convenience, flexibility, creative design, and an effective payment process that influence customers preference for innovative QR code or biometric payment systems, Liébana-Cabanillas et al. (2022) attributed that as one of the novel, innovative payment methods, facial recognition payment (FRP) has garnered widespread attention for its ability to provide an efficient and convenient payment process. The application of facial recognition technology in areas such as

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customs, attendance, and payment has significantly enhanced convenience. Today, the financial industry has ushered in a new era of payment services by implementing cutting-edge face recognition technology.

Burt (2020) announced that the maturation of biometric technology provides a robust technical foundation for the global proliferation of cashless payments. Consumers are increasingly familiarizing themselves with mobile applications that utilize biometric technology to unlock and verify payments. This indicates a growing trend toward adopting such solutions (i.e., facial recognition, fingerprints, iris scans, or voice). It was reported that during the COVID-19 outbreak, the heightened awareness of health concerns among individuals has led to a surge in the adoption of various digital payment methods (Lin et al., 2023).

Mobile payment integrates mobile technology and online payment systems, enabling users to initiate, authorize, and complete financial transactions for goods and services through wireless communication or mobile networks (Qasim & Abu-Shanab, 2015). Loh et al. (2021) defined Mobile payment as a wireless-based electronic payment method for mobile commerce that enables customers to conduct payment transactions using their mobile devices. Furthermore, Zhou (2013) stated that There exist two distinct categories of mobile payment, namely proximity mobile payment (PMP) and remote mobile payment (RMP). Qasim and Abu-Shanab (2015) conceptualized proximity mobile payment as a proximity-based mobile payment method that utilizes technologies such as barcode scanning, radio-frequency identification (RFID), or near field communication (NFC) to facilitate transactions within a limited range between users and merchants.

Few studies have investigated consumers' inclination toward facial recognition payment. With the continuous advancement of facial recognition technology, it is imperative to examine the factors that influence users' behavioral intention and willingness to adopt this mode of payment as a primary method in the future. Therefore, this study aims to investigate the factors that drive customers' willingness to utilize facial recognition payment and provide information that companies can refer to to spread face recognition payment service successfully. The results of this study will be of value to various groups associated with E-payment services, such as mobile network operators, financial institutions, and payment service providers.

2. Literature Review

2.1 Perceived Privacy Risk

Perceived privacy risk refers to users' perception that personal information may exposed without the user's knowledge or permission, such as exposure to direct markets, third-party companies, and criminal uses (Aldás-Manzano et al., 2009; Martins et al., 2014). Pons and Polak (2008) argued that sensitive biometric information could increase users' perceived risks and decrease the use intention. Furthermore, users' perceived risks have been found to negatively affect the intention to accept a biometric system (Miltgen et al., 2013).

Aldás-Manzano et al. (2009) pointed out that the unique privacy risk of biometrics and the widespread applications in the retail industry have elicited users' fear of privacy leaks. Thus, causing them to resist the use of facial recognition payment technology. Zhang and Kang (2019) also stated that biometric technology requires collecting large amounts of personal data, which increases consumers' concerns about the leakage of private information. Facial recognition payment, being a new technology, to eliminate consumers' worries and privacy concerns about information disclosure is a relatively important issue. Accordingly, the study proposes the following hypothesis:

H1: Perceived privacy risk has a significant effect on privacy concerns.

2.2 Privacy Control

Privacy Control is the degree to which a user believes that she/he can perform a recommended response to a privacy threat (Boss et al., 2015). Privacy control and the perceived effectiveness of privacy policy are often considered separate but vital variables concerning attitudes when individuals are engaged in trade-off decisions and have thus been included in privacy-related models (Zhang & Kang, 2019). Facial recognition payment platforms in China offer a personal control enhancing mechanism, giving users the choice of autonomous control over using facial information by providing the function of turning off or turning on the facial payment. This strategy lets users deal directly with their information privacy issues and take proactive steps to reduce their privacy concerns (Wang & Herrando, 2019).

Perceived privacy risk and privacy control are significant factors distinct from privacy concerns but closely related to them (Ba & Pavlou, 2002). Empirical evidence shows that control and risk are the key factors in explaining privacy concerns (Sheehan & Hoy, 2000). Previous studies show decreased perceived control will lead to a higher perception of privacy intrusion (Hoadley et al., 2016). On the other hand, once the users perceive higher control over their personal information, the perceived security will increase, their worries concerning privacy will be alleviated (Malhotra et al., 2004), and they will be more willing to share information (Hajli & Lin, 2016). Therefore, the following hypotheses are proposed:

H2: Privacy control has a significant effect on privacy concerns.

2.3 Security

Security is the degree of personal information or financial transaction-related information system management using financial technology payment service processes without leakage (Zhang & Kang, 2019). It defines how people believe personal or financial information will be protected without leakage while using new technology. Security is one of the most important factors influencing the intent to use mobile pay; similarly, many scholars regard safety as the main research factor when studying mobile payment (Pham & Ho, 2015) and use the technology acceptance model (TAM) to research consumer's intent to use of new technologies.

The relationship between security and perceived usefulness is a complex and significant aspect of various technological systems, products, and services. It is crucial in influencing user adoption, satisfaction, and overall success (Pham & Ho, 2015). This relationship is particularly relevant in information technology, cybersecurity, e-commerce, and digital communication. Security has a profound impact on the perceived usefulness of facial recognition technology, particularly in today's digital age, where concerns about privacy, data breaches, and unauthorized access are paramount. Facial recognition technology, which identifies individuals based on their unique facial features, has gained widespread attention and adoption in various sectors, from law enforcement to consumer electronics (Zhang & Kang, 2019). Thus, a hypothesis is developed:
H3: Security has a significant effect on perceived usefulness.

2.4 Privacy Concerns

Privacy concerns pertain to the apprehensions of individuals regarding their privacy on the Internet (Hui et al., 2007). Privacy concerns associated with adopting facial payment technology are expressed as perceived risks, which involve threat appraisal (perceived severity and vulnerability) and coping appraisals (response efficacy and self-efficacy). The negative impact of threat appraisals on individuals' intention to adopt facial payment technology is counteracted by the positive influence of coping appraisals (Li et al., 2020).

Users' perception of privacy concerns might impede their adoption of facial recognition payment, which may further lead to the failure of facial recognition payment. It is important to investigate both the underlying drivers of users' adoption of facial recognition payment and their privacy concerns in facial recognition payment usage to get a comprehensive understanding of users' adoption of facial recognition payment. (Pons & Polak, 2008). As an automatic method of individual recognition based on biometric information, facial recognition payment can identify and track people without consumers' consent, which may raise greater privacy concerns than other payment methods (Prabhakar et al., 2003). Based on these definitions, this study proposes the following hypothesis:
H4: Privacy concerns have a significant effect on behavioral intention.

2.5 Perceived Usefulness

Perceived usefulness refers to the extent to which an individual believes utilizing a specific technology can enhance task performance (Madan & Yadav, 2018). Perceived usefulness of adopting Facial Recognition Technology is defined as the extent to which an individual believes that using this technology will enhance task performance. This factor is crucial because consumers are more likely to adopt Facial Recognition Technology when they perceive cloud services as improving organizational productivity, profitability, and efficiency (Min et al., 2022).

The Technology Acceptance Model posits that perceived usefulness and ease of use are determinants of attitude, while perceived usefulness and attitude act as determinants of behavioral intention. Previously, Taj and Morosan (2011) discovered a significant indirect impact of perceived ease of use and usefulness on the adoption intention of biometric technology in restaurants through attitude towards biometric technology. Later, Feng et al. (2022) discovered a statistically significant influence of perceived usefulness on the intention to utilize e-learning in China. Consequently, a hypothesis is developed:
H5: Perceived usefulness has a significant effect on behavioral intention.

2.6 Perceived Ease of Use

Perceived ease of use refers to the extent to which an individual perceives a particular system as effortless. Users must investigate the response of information technology, as it has been demonstrated to impact the utilization and motivation toward specific technical purposes (Min et al., 2022). Perceived ease of use refers to how an individual perceives that interacting with a system would be effortless. (Davis, 1989).

Customers' attitudes and intentions toward adopting new technology are influenced by their perceptions of its usefulness and ease of use (Davis, 1989). If customers perceive technology as useful, easy to use, and aligned with their values and lifestyle, they are more likely to hold positive attitudes toward its adoption (Min et al., 2022). Several studies have demonstrated that perceived ease of use and usefulness are significant predictors of online purchase and usage of smartphone technology (Zhong et al., 2021).

Lee et al. (2007) studied the determinants of mobile financial services adoption. They found that consumers' cognitive factors, including perceived usefulness and ease of use, and demographic variables such as gender, age, and business type significantly influence their intention to adopt these services. Zhong et al. (2021) have demonstrated that positive factors, such as perceived enjoyment, facilitating conditions, coupon availability, and perceived ease of use, can significantly influence users' decisions to adopt facial recognition payment based on the TAM. Thus, the following hypotheses are indicated:

H6: Perceived ease of use has a significant effect on perceived usefulness.

H7: Perceived ease of use has a significant effect on behavioral intention.

2.7 Personal Innovativeness

Personal innovativeness refers to the willingness of the user to try new technology or things (Yi et al., 2006). Kim et al. (2018) mentioned that innovativeness will be important to determine. Aroean and Michaelidou (2014) stated that personal innovativeness is critical for marketing practitioners. Acceptance of innovation changes the existing way of life and is accompanied by negative feelings such as fear, uncertainty, doubts, and expectations for the changes that innovation will bring (Shin & Lee, 2016).

Taj and Morosan (2011) tested and proved the direct and indirect effect of personal innovativeness towards information technology on behavioral intention to use biometric technologies in hotels, at security checkpoints in airports (Taj & Morosan, 2011), for access to a bank account through ATM, and a library account (Miltgen et al., 2013). Also, Zhong et al. (2021) found that customers' perceived innovativeness towards information technology influences customers' intention to use biometric technology in restaurants. Thus, perceived innovativeness towards information technology may also affect QRS customers' intention to use facial recognition. Therefore, this study hypothesizes that:

H8: Personal innovativeness has a significant effect on behavioral intention.

2.8 Facilitating Conditions

Facilitating conditions can be defined as a customer's perception of the availability of essential resources and support to perform a particular task (Venkatesh et al., 2003). Facilitating conditions, which was taken from the unified theory of acceptance and use of technology (UTAUT) model of Venkatesh et al. (2003), is considered one of the decisive factors that can positively affect both usefulness and ease of use (Yuan et al., 2023). Makanyeza (2017) stated that facilitating conditions make it easier for users to adopt a new innovative system. If the user's facilitating conditions match the innovative system, users will likely adopt a new innovative technology.

Madan and Yadav (2018) studied mobile wallets; the result indicated that facilitating conditions significantly impacted behavioral intention. Nysveen et al. (2005) stated that facilitating conditions directly and positively influenced innovative technology usage. Conversely, Makanyeza (2017) studied consumers' intention to adopt mobile banking in Zimbabwe; the result of the study revealed that facilitating conditions had no significant influence on behavioral intention to adopt mobile banking. Accordingly, this study can put forward a hypothesis that:

H9: Facilitating conditions have a significant effect on behavioral intention.

2.9 Behavioral Intention

Behavioral intention is a probability or a measurement of the strength of an individual's intention to perform a particular behavior or usage (Fishbein & Ajzen, 1975). High behavioral intention represents a high tendency for technology adoption, which is the critical measurement of successful adoption (Fishbein & Ajzen, 1975; Yi et al., 2006). Hassan et al. (2014) stated that there is a gap between behavioral intention and actual behavior. Moreover, Zarmpou et al. (2012) refer to behavioral intention as an individual's subjective probability of using mobile payment services. de Sena Abrahão et al. (2016) stated that behavioral intention refers to the intention of effective use by the users of a future mobile payment system. Furthermore, Lai Ying et al. (2013) stated that individuals with high intentions to use a product or service will likely become adopters.

3. Research Methods and Materials

3.1 Research Framework

Figure 1 outlines four major theories related to the acceptance and use of Facial Recognition Payment (FRP) systems to contruct a conceptual model. Dong and Hai (2019) explored factors like behavioral intention, perceived ease of use, perceived usefulness, privacy concerns, subjective norms, and perceived enjoyment in relation to FRP acceptance. Zhang and Kang (2019) investigated factors affecting the intention to use FRP in China, incorporating elements such as security, social image, surrounding environment, and user personality. Liu et al. (2021) considered variables developed from perceived risk theory, privacy concerns, and innovation resistance to understand the factors causing resistance to FRP. Zhong et al. (2021)

looked into how industry 4.0 affects the acceptance of FRP through an extended Technology Acceptance Model. These theories collectively contribute to a comprehensive understanding of the various factors influencing the adoption and use of FRP systems in China.

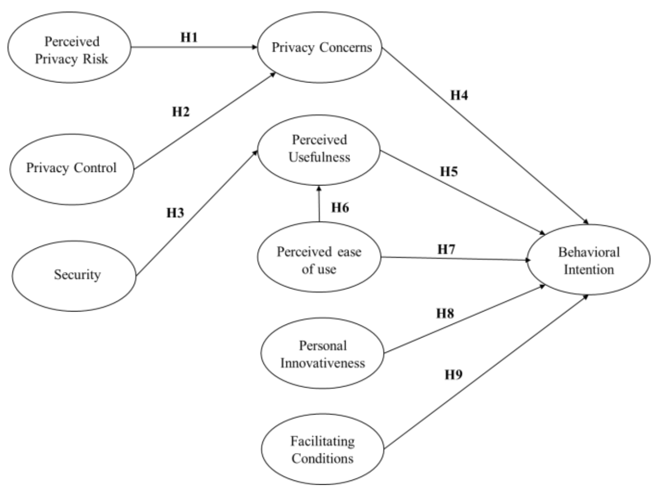

Figure 1: Conceptual Framework

H1: Perceived privacy risk has a significant effect on privacy concerns.
H2: Privacy control has a significant effect on privacy concerns.
H3: Security has a significant effect on perceived usefulness.
H4: Privacy concerns have a significant effect on behavioral intention.
H5: Perceived usefulness has a significant effect on behavioral intention.
H6: Perceived ease of use has a significant effect on perceived usefulness.
H7: Perceived ease of use has a significant effect on behavioral intention.
H8: Personal innovativeness has a significant effect on behavioral intention.
H9: Facilitating conditions have a significant effect on behavioral intention.

3.2 Research Methodology

This research uses quantitative research methodology, employing a questionnaire as the data collection tool. The questionnaire consisted of four parts. The first part was screening questions. The second part measured independent variables: perceived usefulness, perceived ease of use, security, privacy concerns, perceived privacy risk, perceived privacy control, facilitating conditions, and personal innovativeness. In this study, the researcher applied a five-point Likert scale. The third part measured the dependent variable, which is behavioral intention. The last part of the questionnaire is about the demographic factors of the respondents. Data obtained from the study were analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM).

To ensure the questionnaire's validity and reliability, a pilot test was conducted with 50 participants, using the Item-Objective Congruence (IOC) index and Cronbach's alpha for reliability assessment. During the IOC approach, three experts will be asked to evaluate each item by rating the item with 1,0 and -1. If an expert gives 1, the item can measure its objective. The highest rating for nine constructs with 34 items was equal to 1. The lowest rating was equal to 0.66, which was greater than 0.5. the researcher then assigned questionnaires to 50 participants, or 10% from the main study, with similar attributes to the target population. The results are that the Cronbach's Alpha coefficient of each construct was equal to or above 0.60, and it is the accepted value (Nunnally & Bernstein, 1994).

3.3 Population and Sample Size

The population is 18 years old or over, Chinese living in Wuhan, and has experienced the use of Facial Recognition (FR) payment through mobile payment platforms/applications (including mobile applications or face-scan devices). Based on Soper (2023), the recommended minimum sample size is 460. Therefore, the researcher aimed to collect 500 samples for each online or mobile payment companies for a better statistical result.

3.4 Sampling Technique

The sampling methods used in this research included judgmental, quota, and convenience sampling. In order to fulfill the objective of this study, the researcher applies judgmental sampling to examine the behavioral intention of FR payment via mobile payment platforms of Wuhan users, who must have experience using the top rankings of FR payment via mobile payment platforms in purchasing products or services. The researcher considered applying a quota sampling method to allocate respondents in each top-ranking application to equal the total sample size of 500 respondents, as shown in Table 1. In addition, the researcher applied convenience sampling to distribute the online questionnaire to people who are 18 years old and above.

Table 1: Quota Sampling

Application Name	Number of questionnaires per application company	Percentage Allocation (%)
Alipay	250	50%
Wechat pay	200	40%

Application Name	Number of questionnaires per application company	Percentage Allocation (%)
Other pay apps	50	10%
Total	500	100%

4. Results and Discussion

4.1 Demographic Information

According to Table 2, the analysis of the demographic data for the 500 participants reveals key insights into their gender, age, educational background, occupation, and monthly income levels in RMB. The study includes 212 male participants, constituting 42.4% of the total sample. Female participants are more predominant, with 288 individuals, making up 57.6% of the total sample. The gender distribution in the study demonstrates a relatively balanced representation of both males and females, which is crucial for ensuring diverse perspectives in the research. The age group of 20 to 40 is the largest, with 36.6% of participants falling within this range. The majority, 56.2%, have attained a bachelor's degree. A substantial 28.8% work as employees in private companies. A significant portion, 24.2%, consists of government officers. The largest proportion, 37.0%, earns a monthly income between RMB 5000 and RMB 8000%.

Table 2: Demographic Profile

Demographic and General Data (N=500)		Frequency	Percentage
Gender	Male	212	42.4%
	Female	288	57.6%
Age	18-20	95	19.0%
	20-40	183	36.6%
	41-60	130	26.0%
	Above 60	92	18.4%
Education	Secondary School or equivalent	23	4.6%
	Diploma	65	13.0%
	Bachelor’s Degree	281	56.2%
	Master’s Degree	85	17.0%
	Doctor’s Degree	31	6.2%
	Others	15	3.0%
Occupation	Student	89	17.8%
	Government Officer	121	24.2%
	Self-Employed	78	15.6%
	Private Company Employee	144	28.8%
	State Enterprise officer	45	9.0%
	Others	23	4.6%
Level of Income (Monthly in RMB)	RMB 3000 or less	31	6.2%
	RMB 3000 – 5000	99	19.8%
	RMB 5000 – 8000	185	37.0%
	RMB 8000 – 10,000	120	24.0%
	Above RMB 10,000	65	13.0%

4.2 Confirmatory Factor Analysis (CFA)

CFA begins with the specification of a measurement model, which defines the relationships between latent constructs (factors) and their observed indicators (items or variables). Researchers hypothesize how the observed variables reflect the underlying constructs (Hair et al., 2010). The results are that the Cronbach’s Alpha coefficient of each construct was equal or above 0.60 and it is the accepted value (Nunnally & Bernstein, 1994). According to established guidelines, factor loadings exceeding 0.50 are considered substantial (Hair et al., 2006). These loadings suggest that the observed variables (items) are indeed relevant and significant in measuring the intended latent constructs. Additionally, the p-value associated with each factor loading should be below 0.05, further affirming the statistical significance of the relationships. To establish the convergent validity of the constructs, researchers look at two critical statistics. First, the Composite Reliability (CR) should exceed the threshold of 0.6, indicating that the latent constructs have internal consistency and reliability. Second, the Average Variance Extracted (AVE) should surpass the 0.4 cutoff point. This signifies that the variance captured by the latent construct through its indicators is substantial and justifies the construct's existence (Fornell & Larcker, 1981).

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Perceived Privacy Risk (PPR)	Liu et al. (2021)	4	0.793	0.678-0.723	0.794	0.491
Privacy Control (PC)	Liu et al. (2021)	3	0.894	0.846-0.879	0.894	0.738
Privacy Concerns (PCO)	Liu et al. (2021)	4	0.778	0.585-0.804	0.780	0.473
Security (S)	Zhang and Kang (2019)	4	0.898	0.810-0.865	0.899	0.689
Perceived Usefulness (PU)	Zhong et al. (2021)	3	0.889	0.819-0.905	0.888	0.725
Perceived Ease of Use (PEU)	Zhong et al. (2021)	4	0.787	0.614-0.776	0.793	0.491
Personal Innovativeness (PI)	Zhong et al. (2021)	4	0.782	0.668-0.723	0.783	0.475
Facilitating Conditions (FC)	Zhong et al. (2021)	3	0.862	0.768-0.881	0.865	0.681
Behavioral Intention (BI)	Zhong et al. (2021)	5	0.835	0.690-0.734	0.836	0.505

As per the findings presented in Table 4, the statistical values derived from the measurement model exhibit an acceptable level of fit. Specifically, the model demonstrates the following fit indices: CMIN/DF=1.228, GFI=0.936, AGFI=0.922, NFI=0.930, CFI=0.986, TLI=0.984, and RMSEA=0.021. These values collectively affirm that the measurement model effectively aligns with the observed data, meeting the criteria for an acceptable fit.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 3.00 (Hair et al., 2006)	602.790/491 = 1.228
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.936
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.922
NFI	≥ 0.80 (Wu & Wang, 2006)	0.930
CFI	≥ 0.80 (Bentler, 1990)	0.986
TLI	≥ 0.80 (Sharma et al., 2005)	0.984
RMSEA	< 0.08 (Pedroso et al., 2016)	0.021
Model summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI, normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, and RMSEA = root mean square error of approximation.

Discriminant validity is a critical aspect of construct validation, ensuring that a measurement instrument effectively distinguishes between the construct of interest and other unrelated constructs. It aims to establish that the indicators or items used to measure one construct have a stronger association with each other than with indicators from distinct constructs. This assessment is fundamental for confirming that the instrument indeed measures the intended construct and not others (Fornell & Larcker, 1981).

As presented in Table 5, the values derived from the analysis indicated that the correlations between the construct of interest and unrelated constructs were consistently weaker than the correlations among items within the same construct. This observation confirms the discriminant validity of the measurement instrument, supporting the notion that it effectively distinguishes the construct of interest from unrelated constructs.

Table 5: Discriminant Validity

	PPR	PC	PCO	S	PU	PEU	PI	FC	BI
PPR	**0.701**								
PC	0.406	**0.859**							
PCO	0.177	0.284	**0.688**						
S	-0.057	-0.088	0.016	**0.830**					
PU	0.440	0.756	0.313	-0.072	**0.852**				
PEU	0.471	0.502	0.245	-0.040	0.580	**0.701**			
PI	0.633	0.617	0.302	-0.114	0.683	0.629	**0.689**		
FC	0.023	0.011	0.062	0.390	0.048	-0.081	0.011	**0.825**	
BI	0.301	0.529	0.282	-0.054	0.544	0.561	0.540	0.028	**0.711**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

The structural model explores the relationships between latent constructs and examines how they affect each other directly or indirectly. It includes path coefficients that quantify the strength and direction of these relationships. SEM employs various fit indices, such as the Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR), to assess how well the hypothesized model aligns with the observed data. Adequate fit indices indicate that the model is a good representation of the data. The accepted statistical results after the adjustment were CMIN/DF =2.902, GFI = 0.852, AGFI = 0.826, NFI=0.828, CFI = 0.880, TLI = 0.867, RMSEA = 0.062, as shown in Table 6.

Table 6: Goodness of Fit for Structural Model

Index	Acceptable Values	Statistical Values	
		Before Adjustment	**After Adjustment**
CMIN/DF	< 3.00 (Hair et al., 2006)	1558.854/518 = 3.009	1477.105/509 = 2.902
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.845	0.852
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.822	0.826
NFI	≥ 0.80 (Wu & Wang, 2006)	0.819	0.828
CFI	≥ 0.80 (Bentler, 1990)	0.871	0.880
TLI	≥ 0.80 (Sharma et al., 2005)	0.860	0.867
RMSEA	< 0.08 (Pedroso et al., 2016)	0.063	0.062
Model summary		**Unacceptable Model Fit**	**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI, normalized fit index, CFI = comparative fit index, TLI = Tucker-Lewis index, and RMSEA = root mean square error of approximation.

4.4 Research Hypothesis Testing Result

In the context of statistical analysis, particularly in structural equation modeling (SEM), assessing hypotheses is a crucial step to determine whether the proposed relationships between independent and dependent variables hold true. This study employed regression coefficients, standardized path coefficients, and t-values as statistical tools to evaluate these relationships. The outcomes of this evaluation, as presented in Table 7, confirmed the hypotheses with a significant level set at $p<0.05$.

Table 6: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Testing result
H1: Perceived privacy risk has a significant effect on privacy concerns.	0.085	1.545	Not Supported
H2: Privacy control has a significant effect on privacy concerns.	0.261	4.880*	Supported
H3: Security has a significant effect on perceived usefulness.	-0.045	-1.033	Not Supported
H4: Privacy concerns have a significant effect on behavioral intention.	0.119	2.413*	Supported
H5: Perceived usefulness has a significant effect on behavioral intention.	0.260	4.288*	Supported
H6: Perceived ease of use has a significant effect on perceived usefulness.	0.564	9.592*	Supported
H7: Perceived ease of use has a significant effect on behavioral intention.	0.317	4.829*	Supported
H8: Personal innovativeness has a significant effect on behavioral intention.	0.207	4.050*	Supported
H9: Facilitating conditions have a significant effect on behavioral intention.	-0.037	-0.802	Not Supported

Note: * $p<0.05$
Source: Created by the author

According to Table 5.10, the results can be discussed as follows:

H1: The data results indicate that the standardized path coefficient (β) for this relationship is 0.085, and the t-value is 1.545. The result suggests that there is no significant effect of perceived privacy risk on privacy concerns ($p>0.05$). Therefore, H1 is not supported. This implies that, in this study, perceived privacy risk does not appear to have a substantial influence on individuals' privacy concerns.

H2: The data results show a substantial effect of privacy control on privacy concerns with a standardized path coefficient (β) of 0.261 and a t-value of 4.880. This result is statistically significant ($p<0.05$), supporting H2. It suggests that the level of control individuals have over their privacy significantly influences their privacy concerns. In other words, when individuals have more control over their personal information, their concerns about privacy tend to be lower.

H3: The data indicates a standardized path coefficient (β) of -0.045 and a t-value of -1.033 for the relationship between security and perceived usefulness. The result suggests that there is no significant effect of security on perceived usefulness ($p>0.05$). Therefore, H3 is not supported, indicating that security does not appear to significantly impact individuals' perceptions of the usefulness of a system or service in this context.

H4: The data results show a significant effect of privacy concerns on behavioral intention with a standardized path coefficient (β) of 0.119 and a t-value of 2.413. This result is statistically significant ($p<0.05$), supporting H4. It suggests that individuals' concerns about privacy play a significant role in shaping their behavioral intentions related to a system or service. Higher privacy concerns may lead to certain behavioral intentions or actions.

H5: The data indicates a substantial effect of perceived usefulness on behavioral intention with a standardized path coefficient (β) of 0.260 and a t-value of 4.288. This result is statistically significant ($p<0.05$), supporting H5. It implies that individuals' perceptions of the usefulness of a system or service significantly influence their behavioral intentions. When individuals perceive a system as useful, they are more likely to exhibit certain behavioral intentions related to that system.

H6: The data results demonstrate a significant effect of perceived ease of use on perceived usefulness with a standardized path coefficient (β) of 0.564 and a t-value of 9.592. This result is statistically significant ($p<0.05$), supporting H6. It suggests that the ease with which individuals can use a system or service significantly affects their perceptions of its usefulness. When a system is easy to use, individuals are more likely to find it useful.

H7: The data indicates a significant effect of perceived ease of use on behavioral intention with a standardized path coefficient (β) of 0.317 and a t-value of 4.829. This result is statistically significant ($p<0.05$), supporting H7. It implies that the ease of use of a system or service significantly influences individuals' behavioral intentions. When a system is easy to use, individuals are more likely to exhibit certain behavioral intentions related to that system.

H8: The data results demonstrate a significant effect of personal innovativeness on behavioral intention with a standardized path coefficient (β) of 0.207 and a t-value of 4.050. This result is statistically significant ($p<0.05$), supporting H8. It suggests that individuals' personal innovativeness significantly influences their behavioral intentions related to a system or service. Those who are more innovative tend to exhibit certain behavioral intentions.

H9: The data indicates a standardized path coefficient (β) of -0.037 and a t-value of -0.802 for the relationship between facilitating conditions and behavioral intention. The result suggests that there is no significant effect of facilitating conditions on behavioral intention ($p>0.05$). Therefore, H9 is not supported, indicating that in this study, facilitating conditions do not appear to have a substantial impact on individuals' behavioral intentions.

5. Conclusion and Recommendation

5.1 Conclusion and Discussion

The study explores the factors that influence customers' willingness to adopt facial recognition payment systems. The research provides valuable insights that companies can utilize to promote the adoption of facial recognition payment services successfully. The study analyzes data collected from 500 Chinese mobile payment users, employing structural equation modeling to draw meaningful conclusions.

The research findings reveal that privacy control plays a pivotal role in influencing privacy concerns. This implies that users who perceive a higher degree of control over their privacy are less likely to have concerns regarding the use of facial recognition payment systems. This result underscores the importance of implementing robust privacy control mechanisms in facial recognition payment platforms to address users' apprehensions effectively.

The study demonstrates that several factors significantly impact users' behavioral intention to adopt facial recognition payment systems. These factors include privacy concerns, perceived usefulness, perceived ease of use, and personal innovativeness. Users who express greater privacy concerns are more likely to exhibit reservations towards adopting this technology. On the other hand, those who perceive facial recognition payment systems as useful and easy to use, as well as individuals characterized by personal innovativeness, are more inclined to embrace this payment method. Companies looking to promote facial recognition payment should focus on emphasizing the convenience and utility of their systems, while also addressing privacy concerns.

Surprisingly, the study found that facilitating conditions did not have a significant effect on users' behavioral intention. This suggests that the ease of access and availability of necessary resources may not be the primary drivers for adopting facial recognition payment systems among the surveyed users. Further research may be needed to explore this unexpected finding and understand the role of facilitating conditions in more depth.

The study also examined the effects of perceived privacy risk and security on users' perceptions. Interestingly, perceived privacy risk did not significantly impact privacy concerns, and security had no significant effect on perceived usefulness. These results emphasize the need for companies to address users' privacy concerns directly and highlight the security measures in place to build trust in facial recognition payment systems.

In conclusion, this research provides valuable insights into the factors influencing the adoption of facial recognition payment systems in Wuhan, China. It highlights the importance of privacy control, perceived usefulness, ease of use, and personal innovativeness in shaping users' behavioral intention. The study suggests that companies should focus on addressing privacy concerns and emphasizing the convenience and utility of their systems to encourage widespread adoption. Additionally, further investigation is needed to understand the role of facilitating conditions better.

5.2 Recommendation

Based on the findings of this study on factors affecting the behavioral intention towards facial recognition payment systems among users in Wuhan, China, the following recommendations are made:

Enhance Privacy Control Features: Companies developing facial recognition payment systems should prioritize the development of robust privacy control features. Users clearly value their privacy, and providing them with easy-to-use tools to manage their personal data and control who has access to it can help alleviate concerns.

Education and Awareness Campaigns: To address privacy concerns and increase perceived usefulness, service providers should launch educational campaigns to inform users about the benefits and security measures of facial recognition payment systems. Highlighting the convenience, security, and advantages of the technology can positively influence users' perceptions.

Simplify User Experience: Perceived ease of use is a significant driver of behavioral intention. Companies should continually work on simplifying the user interface and ensuring that the facial recognition payment process is intuitive and straightforward. User-friendly interfaces can encourage adoption.

Target Personal Innovators: Personal innovativeness has a positive impact on behavioral intention. Identifying and targeting early adopters and innovators who are open to trying new technologies can help drive initial adoption and generate positive word-of-mouth recommendations.

Consider Regulatory Compliance: As regulatory frameworks surrounding facial recognition and data privacy evolve, companies must stay compliant with local and national laws. Engaging in responsible data handling practices can build trust among users concerned about privacy.

Further Research on Facilitating Conditions: While this study did not find facilitating conditions to significantly impact behavioral intention, further research can explore the specific conditions or external factors that may influence adoption. Understanding what facilitates or hinders usage can guide service providers in improving the ecosystem around their technology.

Continuous User Feedback: Companies should establish feedback mechanisms to collect user opinions and concerns continually. This feedback can inform iterative improvements and updates to the facial recognition payment system, making it more aligned with user expectations.

Cross-Cultural Adaptation: If expanding services beyond Wuhan or internationally, companies should conduct cross-cultural studies to understand how cultural factors influence adoption. Tailoring marketing and user experiences to different cultural preferences is crucial.

Longitudinal Studies: To assess the long-term impact and sustainability of facial recognition payment system adoption, conduct longitudinal studies that track users over time. This will provide insights into how initial intentions translate into prolonged usage.

Ethical Considerations: Prioritize ethical considerations in the development and deployment of facial recognition payment systems. Implement clear guidelines and practices for data handling, consent, and security to build user trust and mitigate ethical concerns.

These recommendations aim to assist companies and policymakers in promoting the successful adoption of facial recognition payment systems while addressing user concerns and privacy considerations. By implementing these suggestions, stakeholders can contribute to the responsible and widespread use of this innovative technology.

5.3 Limitation and Further Study

While this study provides valuable insights into the factors influencing the behavioral intention towards facial recognition payment systems among users in Wuhan, China, several limitations should be acknowledged for future research:

The study focused exclusively on users in Wuhan, China. To enhance the generalizability of findings, future research should consider conducting similar studies in different regions and countries with varying cultural and regulatory contexts. This will help determine whether the factors influencing adoption are consistent or context-dependent.

Cultural factors can significantly influence technology adoption behaviors. Future research should explore how cultural differences impact the adoption of facial recognition payment systems. Comparative studies across multiple cultural contexts can provide a more comprehensive understanding.

The study employed a quantitative survey method. Future research could complement these findings with qualitative insights gained from interviews or focus groups to provide a deeper understanding of users' motivations, concerns, and experiences.

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