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Factors Impacting Students' Behavioral Intention to Use Facial Recognition Payment on Campus in Sichuan

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Abstract

This study aims to explore the factors influencing undergraduate students in Sichuan, China, in their use of facial recognition payments on campus. The researchers utilized the TAM combined with the UTAUT2 to design a theoretical model centered on analyzing undergraduate students' behavioral intentions to use facial recognition payments. Considering the millennials' openness to new technologies, concerns about financial services, and the widespread application of facial recognition payments in China, the researchers introduced variables such as perceived risk and habit. Through a questionnaire survey, the study selected 500 undergraduates with knowledge of computer science and experience using facial recognition technology for the investigation. This study employed CFA to examine the reliability and validity of the variables. Using SEM, the researchers assessed the model's fitness and the relationships between variables. The findings confirmed that trust, habit, perceived risk, and attitude significantly influence behavioral intention, with trust exerting the strongest positive effect, followed by attitude and habit, while perceived risk negatively influences behavioral intention. Moreover, perceived ease of use and perceived usefulness indirectly affect behavioral intention through attitude. To help operators of facial recognition payment systems understand the factors influencing customer usage, the researchers recommend that operators enhance the feasibility of their products and adopt practical measures to increase user convenience, thereby fostering more positive user attitudes toward the product. This study also validates the effectiveness of UTAUT2 in the field of facial recognition payment.

Keywords: Facial recognition payment, TAM, UTAUT2, Attitude, Behavioral intention

Introduction

Biometric technology identifies individuals by capturing unique physical characteristics such as voice, fingerprints, facial features, irises, and veins (Unar et al., 2014). This technology is increasingly being integrated into various aspects of society. For example, some companies utilize fingerprint recognition for employee attendance tracking (Rahman et al., 2017), while security agencies employ iris and palm print recognition for personnel identification and access control (Gusain et al., 2018; Sujatha & Chilambuchelvan, 2018). Facial recognition, due to its unobtrusive nature and convenience, has become increasingly common in everyday applications. It is widely used for personal device unlocking (Sati et al., 2018), facial recognition payments (FRP) (Li et al., 2019), hotel check-ins (Morosan, 2020), and social security management (Brey, 2004), among others.

Banks and financial institutions have implemented various biometric methods for payment activities using biometric authentication technologies. Consumers, particularly younger individuals, have accumulated significant experience with biometric techniques such as fingerprint, facial, iris, and voice recognition for mobile unlocking and authentication (Vince, 2023). As more users adopt biometric applications, institutions predict that biometric payments will shape a new future of business (Jordan, 2022).

FRP is considered one of the key methods for completing consumer transactions. Traditional transaction passwords, due to security requirements, must be composed of random strings of numbers, which can be easily forgotten if not used for a period. On the other hand, using password-free payments introduces the risk of unauthorized transactions (Akdemir & Yenal, 2020). Facial features, however, are difficult to imitate or duplicate and do not change significantly over short periods of time (Parmar & Mehta, 2014), and therefore are increasingly being used. The initial facial recognition payment system was launched by Alibaba Group in China. After years of development, Alipay's FRP system has evolved from using special Face ID cameras to utilizing standard cameras for facial recognition, with applications extending to self-service vending machines, supermarket checkout terminals. Its accuracy rate has reached 99.99% (Alipay, 2023). With the growth of Alipay and WeChat in China, facial recognition has become a convenient, efficient, and seamless method of payment.

The outbreak of the COVID-19 pandemic has also presented new opportunities for the development of facial recognition technology. During the pandemic, many countries worldwide advocated for minimizing direct contact with others (Nadanovsky & Santos, 2020). FRP offers a simpler alternative, eliminating the need for cash or credit card transactions, which involve physical contact. In addition to providing consumers with a quicker and more seamless transaction experience, this method also reduces the risk of virus transmission (Nasution et al., 2020). With advancements in artificial intelligence and sensor technology, the efficiency of FRP systems has continually improved, and the range of use cases has expanded (Zhong et al., 2021). As a result, FRP has become an increasingly popular method of transaction.

Although facial recognition has enhanced productivity and work efficiency, it also raises concerns regarding privacy and data security. Since the information stored in facial recognition systems consists of publicly familiar facial data, the potential for data breaches has led to user concerns about the protection of personal information. For instance, various face-swapping applications currently pose ethical and legal challenges for ordinary individuals (Whittaker et al., 2020). The digitalization of consumers' biometric data brings up issues related to rights and interests, and if such data is leaked or misused, it could lead to serious security risks. Unlike other methods, facial features are hard to be changed, making it impossible to implement protective measures like those used for different forms of security (Liu & Yang, 2021). Driven by profit, new black-market industries on the dark web have emerged, engaging in the illegal trade of personal information. Data leaks can spread quickly and be exploited, causing significant harm to individuals. For example, Sense Nets, a company specializing in AI security, experienced a large-scale data breach due to insufficient password protection in their facial recognition database, exposing highly sensitive consumer data (Alfred, 2019).

In summary, while facial recognition has contributed to various fields and greatly reduced the additional burdens in transactions, whether users support FRP by smaller institutions with less robust data protection remains a topic of debate. University students with computer science backgrounds have a deeper understanding of information systems, making them an important group for study. This paper investigates the factors influencing university students' use of FRP technology. A survey was designed and developed based on existing literature to reflect the actual acceptance of facial recognition technology among university students. To obtain objective and reliable results, quantitative research methods are employed to explore the factors influencing the willingness of university students with computer knowledge in Sichuan, China, to use FRPs on campus. This study identifies six key potential variables in this mechanism.

Literature Review

Perceived Ease of Use (PEOU)

PEOU is defined as the degree to which a user believes that using a system requires minimal effort (Davis, 1989). In the TAM framework, simpler technologies are more likely to be accepted. PEOU reflects perceptions of simplicity and convenience, such as ease of operation and accessibility. Prior studies show that when users realize they can complete payments with minimal effort, their perceived ease of use increases (Al Mamun et al., 2023).

Perceived Usefulness (PU)

PU refers to the extent to which users believe new technology improves performance (Davis, 1989). Empirical evidence shows that technology perceived as useful significantly shapes user attitudes and adoption (Norfolk & O'Regan, 2020). PU is also linked to trust and risk, with research confirming its role in directly and indirectly influencing behavioral intention.

Habit (HAB)

Habit describes the extent to which behavior is performed automatically based on prior experience (Venkatesh et al., 2012). It reflects both learned behaviors and unconscious repetition (Limayem et al., 2007). Studies show that habit is instrumental in technology adoption and is a key driver of behavioral intention in mobile and online payment contexts (Gupta & Arora, 2020).

Trust (TR)

Trust reflects user perceptions of competence, credibility, and integrity (Mayer et al., 1995). It reduces uncertainty and strengthens confidence in using new technologies (Hengstler et al., 2016). In financial technology, trust is a decisive factor that encourages adoption and mitigates perceived risk (Chen et al., 2023).

Perceived Risk (PR)

PR refers to users' expectations about potential negative outcomes when adopting new products or services (Grewal et al., 2007). Higher risk perceptions discourage repeated use and hinder adoption of biometric authentication (Yi et al., 2020). PR has been consistently identified as a significant obstacle to financial technology acceptance.

Attitude (ATT)

Attitude denotes an individual's positive or negative evaluation of a behavior (Fishbein & Ajzen, 1977). In TAM-based studies, attitude is both a predictor and mediator of behavioral intention (Rehman & Shaikh, 2020). It reflects emotional and cognitive appraisals that translate into willingness to adopt technology.

Behavioral Intention (BI)

BI represents a user's likelihood of adopting or continuing to use a technology (Ajzen, 1991). It is shaped by both cognitive appraisals (usefulness, ease of use) and experiential factors (trust, risk, habit). As the ultimate dependent variable, BI is frequently used to assess acceptance of payment innovations (Abedi et al., 2020).

Based on the theoretical background, this study developed six hypotheses:

H1: Perceived ease of use has a significant positive impact on attitude.

H2: Perceived usefulness has a significant positive impact on attitude.

H3: Habit has a significant positive impact on behavioral intention.

H4: Trust has a significant positive impact on behavioral intention.

H5: Perceived risk has a significant negative impact on behavioral intention.

H6: Attitude has a significant positive impact on behavioral intention.

Drawing upon the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), this study integrates perceived ease of use, perceived usefulness, trust, perceived risk, habit, and attitude as predictors of behavioral intention to adopt FRP. The six hypotheses developed provide the foundation for the conceptual framework illustrated in Figure 1. To empirically test these hypotheses, the following section describes the research design, sampling strategy, instrument development, and analytical procedures employed.

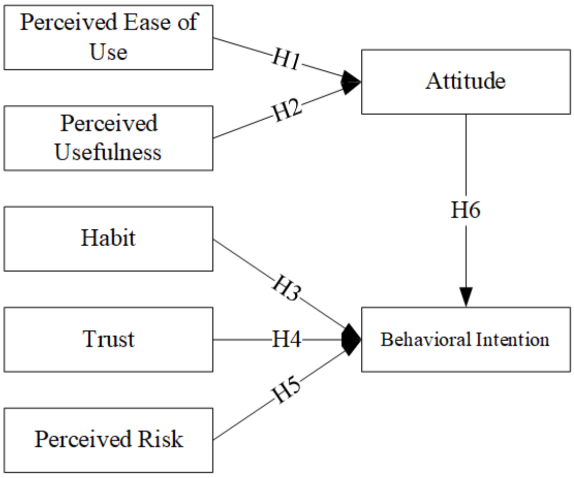
Research Methodology

Research Framework

This study establishes a framework to analyze the factors influencing college students' acceptance of facial recognition technology on campus by synthesizing previous academic findings. It relies on the TAM and the UTAUT2. Li et al. (2019) employed the UTAUT2 model to explore the willingness of Chinese users to adopt online payments, highlighting the interrelationships between PEOU, PU, and ATT in the payment context. Nguyen et al. (2020) investigated the intention to use online banking, revealing the relationships among HAB, TR, and BI. Lastly, Kaur and Arora (2020) demonstrated that perceived risk influences behavioral intention in their study. Figure 1 illustrates the conceptual framework underpinning this investigation.

Figure 1

Conceptual framework



Note: Created by the author.

This study aims to analyze and explore the impact of various potential variables (e.g., PEOU, PU, ATT, HAB, TR, and PR) on the BI to use FRP on campus. The research subjects are university students with a background in the computer industry from a university in Sichuan, China. Additionally, to identify the factors influencing behavioral intention, this research project also examines the interrelationship pathways among the various variables.

Research Methodology

According to Israel (2014), quantitative research methods involve the interpretation of objective phenomena, while Creswell and Guetterman (2019) state that one of the primary objectives of quantitative research is to assess the strength and nature of relationships between measurable variables. The authors argue that quantitative methods ensure the collected results are objective and free from researcher bias. Based on the objectives and characteristics of the research subjects, in this study, a quantitative research methodology is utilized, facilitating a comprehensive examination of the research goals and enabling a more objective assessment of variable relationships.

To objectively analyze college students' attitudes toward using facial recognition technology for payments, this study employed a multi-stage sampling method, selecting 500 respondents from students majoring in computer-related fields. The questionnaire consists of three parts. The first part ensures that the participants have specific characteristics (Kervin, 1992). The second part collects demographic information such as gender, age, and usage experience (Polonsky & Waller, 2018). A five-point Likert scale was used, ranging from 1 =

strongly disagree to 5 = strongly agree, adapted for all constructs to ensure consistency across items (Zikmund et al., 2003).

To establish the reliability and validity of the proposed methodology, a panel of three researchers with doctoral degree expertise was assembled following the guidelines of the American Educational Research Association. This panel was responsible for evaluating and providing feedback to ensure the questionnaire accurately measures the relevant variables. The experts independently assessed the questionnaire items to ensure unbiased analysis (Rovinelli & Hambleton, 1976). Additionally, the pilot study was conducted with a sample of 50 respondents, and the pilot study was conducted with 50 respondents. Cronbach's alpha values for each construct exceeded the 0.70 threshold (ranging from 0.82 to 0.89), confirming internal consistency. Items with alpha values below the acceptable threshold were revised or removed based on expert panel feedback.

Millennials are exposed to the internet at a younger age and are more willing to adopt new technologies (Aref & Okasha, 2019). Internet technology provides advanced enhancement tools, making electronic online questionnaires more efficient for data processing and analysis (Lavrakas, 2008). Compared to other collection methods, online surveys are more cost-effective, can overcome geographical limitations, and allow for broader data collection (Khan & Qudrat-Ullah, 2021).

After confirming the dependability and validity of the survey instrument, it was distributed to respondents from the target institution through both online and paper-based methods. Finally, AMOS software was used for evaluation, analyzing the data collected. Structural Equation Modeling (SEM) was employed to test the proposed hypotheses and to examine both the direct and indirect relationships among the variables.

Population and Sample Size

Based on the recommendations of Singh and Masuku (2014), the final sample size for this study was determined to be 500. The target population consists of sophomore, junior, and senior students with knowledge of computer science and experience using facial recognition technology. These students are majoring in Software Engineering, Computer Science and Technology, Network Engineering, and IoT Engineering.

Sampling Strategy

To achieve accurate, effective, and representative conclusions, the selected sample needs to cover as broad a range as possible. This approach minimizes the influence of specific relationships within the sample on the overall population, accurately reflecting the intrinsic relationships among the sample and yielding valid conclusions. Therefore, the researchers adopted a multi-stage sampling method comprising two parts. Initially, judgment sampling was used to select 2,191 students from the sophomore to senior years at a university in Sichuan for the survey. The questionnaire was distributed through both online (university WeChat and email) and paper-based methods during classes. A total of 500 valid responses were collected from 650 distributed questionnaires, yielding a response rate of 77%. Finally, questionnaires were distributed to students from each major based on the sample proportions calculated in the table below.

Table 1

Sample Unit and Sample Size

Major Name	Population Size	Proportional Sample Size
Software Engineering major	567	129
Computer Science and Technology major	898	205
Network Engineering major	390	89
Internet of Things Engineering major	336	77
Total	2191	500

Note: Created by the Author

Results and Discussion

Demographic Information

Table 2 presents a comprehensive overview of the demographic characteristics of the respondents. Among the respondents, 305 were male, accounting for 61%, and 195 were female, accounting for 39%. Based on the different majors surveyed, 26% of the respondents were from Computer Science and Technology, 42% from Software Engineering, 18% from Network Engineering, and 15% from Internet of Things Engineering. Regarding academic year classification, 20% of the respondents were sophomores, 53% were juniors, and 27% were seniors.

Table 2

Demographic Information

Demographic Information (N=500)		Frequency	Percentage
Gender	Male	305	61%
	Female	195	39%
Major	Software Engineering major	209	42%

Demographic Information (N=500)		Frequency	Percentage
	Computer Science and Technology major	129	26%
	Network Engineering major	89	18%
	IoT Engineering major	73	15%
Grade	Sophomore	100	20%
	Junior	267	53%
	Senior	133	27%

Note: Created by the Author

Confirmatory Factor Analysis (CFA)

CFA is a statistical technique used to validate and evaluate the measurement model by analyzing the associations between observed variables and their corresponding latent constru cts; it serves as a critical preliminary step in SEM (Hair et al., 2010). CFA estimates every par ameter of the model, including factor loadings, average variance extracted, Pearson correlatio n coefficients, and composite reliability(Kline, 2023; Unar et al., 2014). To determine whethe r the number of components and loadings of each observed variable proposed in this study ali gns with the expected hypothesized results, the study conducted a confirmatory factor analysi s. As shown in Table 3, all results indicate that the research matrix has a good fit, thus, all the fit indices in this study are deemed appropriate.

Table 3

GoF for CFA

Index	Criterion	Source	Practical Values
CMIN/DF	<3	(Hair et al., 2013)	1.319
GFI	>0.9	(Hair et al., 2013)	0.947
AGFI	>0.9	(Hair et al., 2013)	0.934
CFI	>0.9	(Bentler, 1990)	0.986
NFI	>0.9	(Bentler & Bonett, 1980)	0.946
TLI	>0.9	(Bentler & Bonett, 1980)	0.984
RMSEA	<0.08	(Pedroso et al., 2016)	0.024

Note: Created by the Author

Table 4

CFA Result, Composite Reliability, and Average Variance Extracted

Variables	Source of Questionnaire (Measurement Indicator)	Items Amount	Cronbach's Alpha	Factors Loading	CR	AVE
PEOU	(Li et al., 2019)	3	0.846	0.800~0.808	0.847	0.648

Variables	Source of Questionnaire (Measurement Indicator)	Items Amount	Cronbach's Alpha	Factors Loading	CR	AVE
PU	(Li et al., 2019)	3	0.851	0.791~0.822	0.851	0.656
HAB	(Nguyen et al., 2020)	3	0.845	0.772~0.864	0.847	0.649
TR	(Nguyen et al., 2020)	5	0.865	0.721~0.793	0.867	0.565
PR	(Kaur & Arora, 2020)	5	0.876	0.71~0.804	0.877	0.589
ATT	(Li et al., 2019)	3	0.859	0.763~0.861	0.861	0.673
BI	(Kaur & Arora, 2020)	6	0.885	0.723~0.765	0.885	0.562

Note: Created by the Author

As presented in Table 4, the CA values for all constructs exceed 0.8, indicating high internal consistency. All factor loadings are above 0.5, while the CR values for all constructs surpass 0.8, and the AVE values are all greater than 0.5, confirming convergent validity. In Table 5, the diagonal elements represent the square roots of the AVE. The correlation coefficients between any two latent constructs are all below 0.7, providing evidence of satisfactory discriminant validity. Therefore, these quantitative indicators demonstrate effective discriminant validity.

Table 5

Discriminate Validity

	PEOU	PU	HAB	TR	PR	ATT	BI
PEOU	0.805						
PU	0.435	0.81					
HAB	0.177	0.118	0.806				
TR	0.21	0.163	0.35	0.752			
PR	-0.167	-0.161	-0.106	-0.188	0.767		
ATT	0.37	0.309	0.24	0.41	-0.157	0.82	
BI	0.385	0.388	0.371	0.542	-0.367	0.507	0.75

Note: Created by the Author

Structural Equation Model (SEM)

After performing CFA on the data of this study, SEM was applied as planned for model validation. SEM is one of the most widely applied statistical techniques in quantitative research, particularly within the domain of multivariate statistics, as it leverages covariance structures to examine complex relationships among observed and latent variables (Byrne, 2010). SEM integrates factor analysis and path analysis, providing an in-depth analysis of explicit, latent, and disturbance variables within the analyzed model (Hoyle, 1995). SEM helps determine the model's fit and the relationships between model variables, as well as the impact of the studied population's behavioral intentions towards using FRP technology (Baumgartner & Homburg, 1996; Kaplan, 2008). With Table 6's result, after adjusting the model, the values for CMIN/DF, GFI, AGFI, CFI, NFI, TLI, and RMSEA all exceeded the standard thresholds. For this reason, the researchers conclude that the SEM fit is great.

Table 6

GoF for SEM

Index	Criterion	Source	Practical Values
CMIN/DF	<3	(Hair et al., 2013)	2.142
GFI	>0.9	(Hair et al., 2013)	0.901
AGFI	>0.8	(Hair et al., 2013)	0.882
CFI	>0.9	(Bentler, 1990)	0.944
NFI	>0.9	(Bentler & Bonett, 1980)	0.901
TLI	>0.9	(Bentler & Bonett, 1980)	0.939
RMSEA	<0.08	(Pedroso et al., 2016)	0.048

Note: Created by the Author

Hypothesis Testing Results

Table 7 presents the results of the hypothesis testing. From the results, it can be seen that trust has the highest direct impact on BI, with a Standardized Path Coefficient (β) of 0.412 (t-Value = 8.374***). In addition, attitude has the second-largest impact on BI, β value is 0.406 (t-Value = 8.549***). The next variable is perceived risk, β value is -0.307 (t-Value = -6.765***). The research results indicate that risk is an important factor influencing users' choice of technology; the stronger the PR, the more difficult it is for users to choose products based on this technology.

Table 7

Hypothesis Result of the SEM

Hypothesis	Paths	Standardized Path Coefficient (β)	t-Value	Testing Result
H1	ATT←PEOU	0.377	7.326***	Supported
H2	ATT←PU	0.223	4.519***	Supported
H3	BI←HAB	0.206	4.697***	Supported
H4	BI←TR	0.412	8.374***	Supported
H5	BI←PR	-0.307	-6.765***	Supported
H6	BI←ATT	0.406	8.549***	Supported

Note: *** $p<0.001$, ** $p<0.01$, * $p<0.05$
Note: Created by the Author

From the findings presented in Table 7, the researchers propose the following extensions:

H1: The conclusion indicates that PEOU is a major factor influencing user attitude, with a Standardized Path Coefficient of 0.377. Li et al. (2019) also found in their study that user-friendly operation can promote users' attitudes toward a product.

H2: The conclusion shows that perceived usefulness is also an important factor influencing user attitude, with β value of 0.223. This is consistent with the findings of Li et al. (2019), who concluded that when users believe a product can provide them with assistance, they tend to develop a more positive attitude toward the product.

H3: The results show that user BI has some impact on BI, but compared to other factors, HAB has the least influence on BI, with a Standardized Path Coefficient of 0.206. Nguyen et al. (2020) research further revealed a strong and significant connection between user HAB and the adoption of financial services.

H4: The conclusion reveals that trust has the most significant impact on users' intention to use facial recognition for payments, with a Standardized Path Coefficient of 0.412. This is consistent with the research conclusion of Nguyen et al. (2020), TR significantly and positively affects the uptake of online banking and payment services.

H5: The results demonstrate that PR results in a significant negative consequence for users' BI to use a product, with β value is -0.307 in this study. Kaur and Arora (2020) also found in their research that increasing PR hinders users' choice of payment products.

H6: The results show that users' attitudes have a very significant impact on BI, with a Standardized Path Coefficient of 0.406. Li et al. (2019) also found that a positive ATT significantly influences users' choice of a specific financial payment product.

Direct, Indirect, and Total Effects

The results of SEM confirmed that four variables—trust, attitude, perceived risk, and habit—directly affect behavioral intention, while perceived ease of use and perceived usefulness indirectly influence intention through attitude.

Trust exerted the strongest positive influence on behavioral intention ($\beta = 0.412$, $p < 0.001$). This underscores privacy protection and transparent data management are critical for encouraging adoption of FRP systems. Attitude also significantly influenced intention ($\beta = 0.406$, $p < 0.001$), aligning with TAM's prediction that favorable evaluations of technology drive behavioral outcomes.

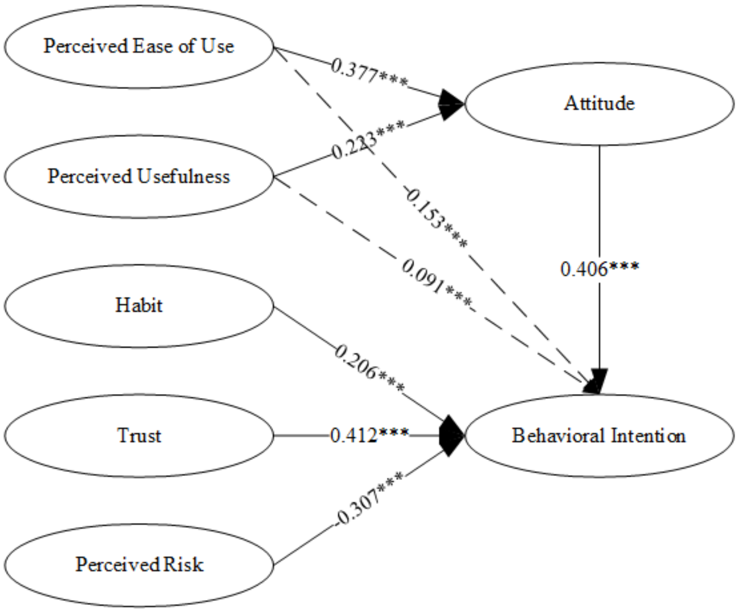
Perceived risk negatively impacted intention ($\beta = -0.307$, $p < 0.001$), highlighting persistent concerns regarding security and misuse of biometric data. Habit had a positive but comparatively weaker effect ($\beta = 0.206$, $p < 0.001$), suggesting that while repetitive use reinforces adoption, it is less decisive than trust or attitude.

Indirect effects further revealed that perceived ease of use (β = 0.377) and perceived usefulness (β = 0.223) significantly shaped attitudes, which in turn mediated their influence on behavioral intention. These findings emphasize the mediating role of attitude within TAM and the contextual relevance of trust and perceived risk within UTAUT2.

Compared with demographic variables, psychological and experiential constructs sho wed greater explanatory power, accounting for 47.1% of variance in behavioral intention.

Figure 2

Path Diagram Analysis



Note: *** p<0.001, ** p<0.01, * p<0.05
Note: Created by the Author

Conclusions and Recommendations

Conclusions

This study contributes to understanding the determinants of FRP adoption among university students in China by integrating TAM and UTAUT2. Trust emerged as the most influential predictor of behavioral intention, followed closely by attitude, while perceived risk negatively affected adoption. Habit also played a supporting role. Perceived ease of use and perceived usefulness indirectly influenced intention through attitude, confirming TAM's mediating framework.

From a theoretical perspective, these results extend UTAUT2 by demonstrating that, in the FRP context, trust and perceived risk are more salient than other constructs such as social influence or price value. Practically, the findings suggest that FRP operators should strengthen privacy protections, communicate security measures transparently, and ensure usability to enhance trust and reduce risk perceptions.

Overall, this study affirms the adaptability of TAM and UTAUT2 in explaining emerging payment technologies and provides both empirical evidence and actionable guidance for the sustainable implementation of FRP systems in educational and broader societal contexts.

Recommendations for Practice

This study investigates the factors influencing the BI of university learners with a background in computer science in Sichuan, China, regarding FRP on campus. Based on the quantitative survey results, the researcher recommends that when promoting and implementing FRP systems, careful consideration should be given to the interactions between PEOU, PU, HAB, TR, PR, ATT, and BI. To develop a more reasonable application strategy for FRP products, the following recommendations are made:

Trust: Operators of FRP products must ensure that the process is controllable and perceivable by users. Additionally, operators should prioritize protecting users' facial data and inform users about the measures taken to safeguard their privacy. Furthermore, the government must establish sound legal frameworks to regulate how operators use and protect users' facial data, thereby enhancing users' trust in the technology.

PU and PEOU: Operators should set up FRP methods in complex scenarios to improve users' perceptions of the convenience and usefulness of this payment option. It is essential to ensure that users perceive the system as saving time and reducing the difficulty of payment.

PR: Since PR significantly negatively affects users' BI to use FRP, operators must enhance the product's reliability, reduce unexpected incidents, and strive to build a strong and healthy brand image. This will reduce users' concerns about using such financial products.

From a theoretical perspective, the results reveal that PEOU and PU exert an indirect influence on BI through ATT, thereby providing further empirical support for the TAM proposition that ATT serves as a critical mediating variable. The significant impact of HAB on BI in the context of facial recognition technology use also aligns with the UTAUT2 assertion that HAB facilitates technology adoption. Furthermore, the findings suggest that, in comparison to other UTAUT2 constructs such as PV and SI, TR and PR exhibit greater relevance within the specific domain of FRP. Accordingly, it is posited that the UTAUT2 model can and should be tailored to fit particular application contexts. Overall, the study affirms the robustness and adaptability of the UTAUT2 theoretical framework when applied to novel technological settings.

Limitations and Further Exploration

This study has several limitations, including the fact that it only analyzed users with a background in the computer science industry and selected only a few potential variables in the conceptual framework. To further explore users' BI towards FRP, future research can be improved in the following ways:

Expanding the survey population to include individuals without a background in computer science or even those with limited educational backgrounds. Considering additional theoretical models, such as the Theory of Planned Behavior or the Theory of Reasoned Action, to construct a broader conceptual framework.

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