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How Technology Readiness Shapes Facial Recognition Payment Adoption: An Integrated Structural Model of Cognitive, Trust, and Risk Beliefs

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ABSTRACT

Facial recognition payments are gaining widespread adoption, yet the psychological underpinnings of their acceptance remain unclear. This study introduces technological readiness as a second-order formative construct to explain how users' latent attitudes influence their perceptions of usability, usefulness, trust, and risk toward facial recognition payment systems. Data from 398 participants were analyzed using partial least squares structural equation modeling. Results indicate that this second-order construct significantly influences all perceived beliefs, highlighting its central role in user evaluations. Usability, trust, and perceived risk emerge as strong predictors of usage intention, while perceived ease of use exerts an indirect effect. Importance-performance analysis underscores that enhancing usability and trust should be strategic priorities for boosting user adoption. This study enriches theoretical understanding of biometric payment acceptance and provides practical guidance for improving system design and user communication.

Keywords: Facial Recognition Payment, Technology Readiness, Trust-Risk Perception, Behavioral Intention
JEL Classifications: D12, M31, O33

1. INTRODUCTION

In recent years, facial recognition payment (FRP) has emerged as one of the most prominent biometric authentication applications in the consumer market. It enables users to complete transactions through automated facial verification, offering a streamlined payment experience while reducing reliance on physical cards or mobile devices. An increasing number of retailers and service providers are integrating FRP into their digital transformation strategies to enhance convenience and minimize transaction friction (Yu et al., 2024). However, public acceptance of FRP has not kept pace with technological advancements, with many consumers remaining cautious. This stems primarily from privacy concerns, perceptions of surveillance, and uncertainty about the reliability of biometric systems (Li and Li, 2023; Lee et al., 2024).

To date, research on the adoption of facial recognition technology (FRT) has primarily been grounded in the technology acceptance model (TAM), which emphasizes perceived usefulness and perceived ease of use as key determinants of technology acceptance (Davis, 1989). More recently, research emphasizes that in biometric payment contexts, risk and trust perceptions are particularly salient because misused facial information can produce serious social and individual consequences (Lee et al., 2024; Liébana-Cabanillas et al., 2025). While these studies deepen our understanding of how individuals assess facial recognition perceived risk (FRP), they primarily focus on downstream cognitive and affective beliefs without addressing why individuals initially form these beliefs.

Technological readiness (TR) is defined as an individual's propensity to adopt and use new technologies, providing a theoretical basis for such variations (Parasuraman and Colby, 2015). Comprising facilitating factors (optimism, innovativeness) and inhibiting factors (discomfort, insecurity), TR has been shown to influence users' perceptions of system complexity, usefulness, and potential risks across diverse digital environments (Roy et al., 2017). Surprisingly, despite the close relationship between facial recognition payment (FRP) and individuals' attitudes toward technological innovation and biometric technologies, TR has rarely been incorporated into FRP adoption models. Existing research often treats all users as a homogeneous group, overlooking the impact of individual dispositions on trust formation, risk assessment, and perceptions of system usability.

- RQ1. What is the relationship between technology readiness and the key belief constructs, including perceived ease of use, perceived usefulness, perceived trust, and perceived risk in the context of facial recognition payment?
- RQ2. What is the relationship between perceived ease of use and perceived usefulness when consumers evaluate facial recognition payment?
- RQ3. What is the relationship between perceived usefulness, perceived trust, perceived risk and users' behavioral intention to use facial recognition payment?
- RQ4. To what extent does technology readiness indirectly shape behavioral intention through these belief constructs?

To address this gap, the present study develops an integrated model combining technology readiness, TAM, and risk–trust perspectives to explain intention to use facial recognition payment. In this model, TR is conceptualized as a second-order formative construct comprising optimism, innovativeness, discomfort, and insecurity. These dimensions are proposed to influence four central belief constructs, perceived ease of use, perceived usefulness, perceived trust, and perceived risk, which in turn predict behavioral intention. By linking individual differences with FRP-specific cognitive evaluations, this study provides a more complete account of FRP adoption. The findings are expected to enrich theoretical understanding of biometric payment acceptance and offer practical guidance for enhancing user trust, reducing perceived risks, and improving system design in commercial FRP applications.

2. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

2.1. Integration of Technology Readiness and Acceptance Model (TRAM) with Risk–Trust Perspectives

Combining technology readiness (TR), the technology acceptance model (TAM), and the risk-trust perspective provides a more comprehensive understanding of facial recognition payment (FRP) adoption. TAM emphasizes perceived usefulness and perceived ease of use as cognitive beliefs guiding technology evaluation (Davis, 1989; Venkatesh and Davis, 2000). Risk-trust research adds that biometric systems also trigger judgments about potential harms and system reliability, which strongly influence acceptance in sensitive data environments (Lee et al., 2024; Liébana-Cabanillas et al., 2025). TR complements these models by capturing individual dispositions, optimism, innovativeness, discomfort, and insecurity, that shape how users interpret new technologies before forming specific beliefs (Parasuraman and Colby, 2015). Integrating these perspectives allows the adoption of FRP to be understood as a process where individual technological orientations shape key beliefs about usability, trust, and risk, which in turn guide behavioral intentions (Figure 1).

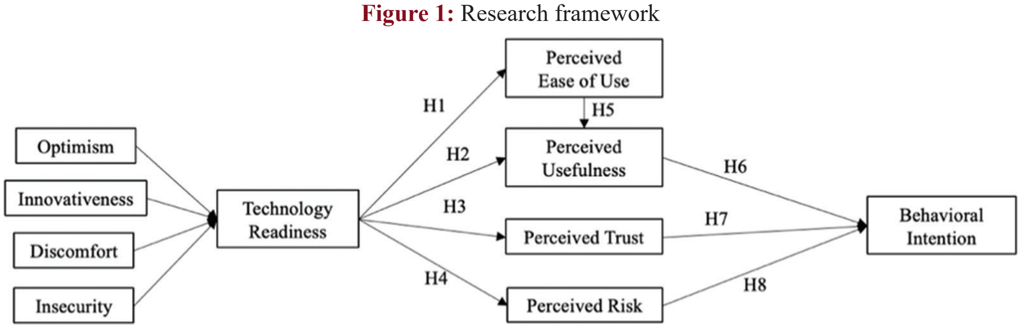
2.2. Technology Readiness

Technological readiness (TR) refers to an individual's tendency to accept or resist new technologies and is widely regarded as a key indicator for predicting technology-related cognition and behavior (Parasuraman and Colby, 2015). Contemporary literature continues to conceptualize TR as a multidimensional construct comprising two facilitating factors (optimism and innovativeness) and two inhibiting factors (discomfort and insecurity). Optimism denotes an individual's positive belief that technology can enhance efficiency and improve quality of life, while innovativeness reflects willingness to experiment with emerging technologies. Conversely, discomfort manifests as an individual's sense of being overwhelmed by technological complexity, and insecurity relates to concerns about data security and system reliability.

In digital service environments, TR has been shown to influence users' assessments of system usability, benefits, trustworthiness, and potential risks. Optimistic or innovative individuals tend to perceive technology as easier to use and more valuable, while those experiencing discomfort or insecurity often express greater concerns about privacy and security (Roy et al., 2017). Recent studies on mobile payments, e-wallets, and cashless systems also indicate that users with high technology acceptance rate evaluate digital payments more favorably and express greater confidence in system performance, even when confronted with unfamiliar or complex authentication processes (Leong et al., 2021; Rahardja et al., 2023; Zhang and Zhang, 2024).

Therefore, TR is modeled in this study as a second-order formative construct, with each first-order dimension contributing uniquely to the formation of users' overall readiness toward FRP.

Figure 1: Research framework



H_1: Technology Readiness positively influences perceived ease of use of facial recognition payment.
H_2: Technology Readiness positively influences perceived usefulness of facial recognition payment.
H_3: Technology readiness positively influences perceived trust in facial recognition payment.
H_4: Technology readiness negatively influences perceived risk associated with facial recognition payment.

2.3. Perceived Ease of Use and Perceived Usefulness

The technology acceptance model (TAM) posits that perceived ease of use (PEOU) and perceived usefulness (PU) are core predictors of technology adoption (Davis, 1989). PEOU refers to the extent to which users perceive interacting with a system as effortless, while PU reflects the degree to which the system enhances task performance. TAM has been widely applied across various digital service scenarios, including biometric authentication and technology-enhanced online shopping, demonstrating its versatility in explaining user adoption decisions (Li and Li, 2023; Lai et al., 2025). Recent empirical studies continue to validate the positive role of PEOU and PU in the adoption process: For instance, a 2024 study on mobile payment adoption found that PEOU significantly enhanced PU and usage intention (Tian and Chan, 2024); while another 2024 study indicated that PEOU and PU remain key predictors of e-wallet usage even in the presence of perceived risk (Chong et al., 2024).

In the field of facial recognition payment (FRP), perceived ease of use (PEOU) reflects users' perceptions of whether facial scanning is smooth, intuitive, and convenient, while perceived usefulness (PU) reflects users' perceived benefits of FRP, such as faster checkout speeds, contactless authentication, and reduced reliance on physical cards or devices (Kim et al., 2025). Previous research indicates that users perceive systems as more useful when they are easier to use, and such systems are more readily adopted (Venkatesh and Davis, 2000). Therefore, this study proposes that PEOU positively influences PU, and PU in turn enhances users' willingness to adopt FRP.
H_5: Perceived ease of use positively influences perceived usefulness of facial recognition payment.
H_6: Perceived Usefulness positively influences behavioral intention to use facial recognition payment.

2.4. Perceived Trust and Perceived Risk

Biometric payment systems involve sensitive facial data, making trust and risk perception particularly influential in users' adoption decisions. Perceived trust refers to users' confidence in the system's reliability, security, and the service provider's responsible handling of the system (Li and Li, 2023). High levels of trust encourage users to believe that facial recognition algorithms operate accurately and that their biometric data will be processed ethically with appropriate safeguards. Recent studies on facial recognition payment (FRP) adoption also indicate that trust can reduce users' privacy concerns and enhance consumers' willingness to use biometric authentication (Lim et al., 2024; Gao et al., 2024).

In contrast, perceived risk encompasses concerns about privacy violations, unauthorized facial data collection, identity theft, data misuse, or algorithmic errors (Liébana-Cabanillas et al., 2025). Since biometric identifiers cannot be changed once exposed, perceived risk tends to be more pronounced in FRP than in other digital payment scenarios. Recent empirical research indicates that user anxiety regarding biometric surveillance remains high, with significant concerns about how companies store, analyze, and share facial data (Yu et al., 2024). Even when users acknowledge the convenience or ease of use of biometric technology, these concerns substantially reduce their acceptance.

Prior empirical work consistently finds that trust strengthens users' willingness to adopt biometric or mobile payment technologies, while perceived risk undermines such adoption decisions (Li and Li, 2023; Lee et al., 2024). Recent studies reinforce this pattern: For instance, a Malaysian study on facial recognition payments (FRP) found trust to be one of the strongest predictors of adoption intent, while data-related risks remained a primary barrier (Lim et al., 2024). Similarly, research on the adoption of mobile and contactless payments indicates that for risk-averse users, perceived risks, particularly privacy and performance risks, may outweigh perceived utility (Lee et al., 2024). Given the limited transparency in biometric data processing, these effects are expected to be more pronounced in the field of facial recognition payments.
H_7: Perceived Trust positively influences Behavioural Intention to use facial recognition payment.
H_8: Perceived risk negatively influences behavioural intention to use facial recognition payment.

3. RESEARCH METHODOLOGY

3.1. Research Design and Data Collection

This study employs a quantitative research design to investigate consumers' willingness to adopt facial recognition payment (FRP). Data collection spanned 6 weeks using judgmental sampling, with questionnaires distributed online via mainstream social media platforms. The majority of responses were gathered through WeChat, supplemented by QQ, Weibo, Xiaohongshu, and Douyin. The fully online survey method enabled broader coverage, faster data collection, and greater convenience for potential participants. A total of 403 valid questionnaires were retrieved. After screening, 5 questionnaires containing patterned or invalid responses (e.g., identical answers selected for all options) were excluded. The final valid dataset comprised 398 valid questionnaires. Among all participants, 56.7% were male and 43.2% were female. Students (39.6%) and employees (37.6%) comprised the majority of respondents. Regarding educational attainment, 44.9% held a bachelor's degree, followed by postgraduate qualifications (22.6%) and technical diplomas (22.3%). All respondents had used FRP, with the majority indicating they had used it 1-2 times (35.6%) or 3-5 times (33.6%). Table 1 provides a complete summary of demographic characteristics.

3.2. Measurement Scales

All conceptions and their corresponding measuring scales were based on validated instruments in earlier research. For TR, optimism, innovativeness, discomfort and insecurity, were each assessed using 4 items, adapted from previous studies by Celik and Kocaman (2017). Perceived ease of use was assessed through

Table 1: Respondent demographics

Variables	Descriptions	Percentage
Gender	Male	56.7
	Female	43.2
Age	18-25	38.1
	26-30	30.6
	31-35	19.5
	36-40	6.7
	More than 40	4.7
Occupation	Student	39.6
	Employee	37.6
	Businessman	7.2
	Freelance	5.5
	Civil servants	4.7
	Others	5.0
Monthly income	Less than RMB2,500	19.3
	RMB2,501-RMB5,000	29.8
	RMB5,001-RMB7,500	22.6
	RMB7,501-RMB10,000	15.3
	RMB10,501-RMB12,500	8.5
	More than RMB12,500	4.2
Education level	Secondary	6.2
	Technical	22.3
	Undergraduate	44.9
	Graduate	22.6
	Doctorate or above	3.7
Experience (times)	Once or twice	35.6
	Three to 5 times	33.6
	Five or more	15.8
	Lots of experiences	14.8

5 items based on Davis (1989). Three items capturing perceived usefulness were sourced from Davis (1989). To evaluate perceived risk, 4 items referenced Belanche et al. (2012). And perceived trust was evaluated via 5 items from Pavlou (2003). Behavioral intention to use facial recognition payment was gauged using 5 indicators derived from Sharma et al. (2020) and Almaiah et al. (2022). All measurement tools were selected due to their frequent application in previous studies and their proven psychometric soundness.

Following Brislin's (1970) translation and back-translation methodology, measurement items were first translated into Simplified Chinese and then back into English to ensure semantic consistency. Prior to formal data collection, we conducted a pilot test of the draft questionnaire using convenience sampling with a small sample to assess wording clarity and identify any linguistic issues that might affect respondent comprehension. To determine the required sample size, Hair et al. (2010) recommended a minimum of ten respondents per measurement item. This study comprised 38 items and obtained over 380 valid responses, meeting the sample size criteria for reliable statistical analysis. All constructs were assessed using a seven-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree").

3.3. Common Method Variance

To examine the presence of common method variance (CMV), this study followed the procedure recommended by Malhotra et al. (2006). Two diagnostic techniques were employed: Harman's single-factor analysis and comparison with a constrained single-factor model. Malhotra et al. (2006) indicated that CMV may be problematic if the first unrotated factor explains over 40% of the total variance or if the single-factor model demonstrates acceptable fit. The unrotated principal component analysis revealed that the first factor explained only 17.33% of the variance, well below the recommended threshold. This indicates that CMV is unlikely to pose a substantive threat. Furthermore, the poor fit of the single-factor model further supports the conclusion that CMV has no substantive impact on the findings of this study.

4. DATA ANALYSIS AND RESULTS

4.1. Respondent Demographics

This study employed SmartPLS 4.1 software for data analysis and examined the reliability and validity of all latent constructs according to established methodological guidelines for PLS-SEM research. To assess internal consistency, Cronbach's alpha coefficients were first calculated for each construct. This metric is widely recognized for evaluating whether items within the same construct measure the same latent concept. Consistent with the recommended benchmark of 0.70 proposed by Nunnally (1978), all Cronbach's alpha coefficients in this study significantly exceeded this threshold.

Specifically, Cronbach's alpha coefficients ranged from 0.857 to 0.904 across structures, indicating acceptable and stable reliability for all measurement modules. These findings suggest robust item structure and consistent respondent comprehension. Furthermore, this reliability pattern aligns with prior empirical studies employing similar constructs, further validating the methodological soundness of the instruments used in this research.

To establish convergent validity, this study conducted a comprehensive assessment encompassing item loadings, average variance extracted (AVE), and composite reliability (CR), metrics that collectively form the core indicators for evaluating construct convergence in PLS-SEM. Following the criteria proposed by Hair et al. (2006), factor loadings above 0.70, composite reliability (CR) values above 0.80, and average variance extracted (AVE) values above 0.50 serve as acceptable benchmarks for determining whether observed indicators adequately represent their underlying constructs.

Empirical results indicate that all constructs exhibit high convergent validity. Specifically, factor loadings ranged from 0.740 to 0.906, with all items exceeding the recommended threshold. These high loadings demonstrate that each item shares a substantial portion of variance with its corresponding construct, reflecting high reliability and conceptual consistency of the measures. Combined reliability values also fell within the ideal range, spanning from 0.883 to 0.932. This confirms that items within each construct collectively exhibit strong internal consistency, far exceeding the level captured by Cronbach's alpha coefficients.

In addition, the AVE values ranged from 0.723 to 0.778, considerably above the minimum requirement of 0.50, signifying that the latent constructs explained more than half of the variance in their indicators. This further reinforces the conclusion that the measurement items meaningfully and consistently reflect the underlying theoretical constructs. Importantly, no construct failed

Table 2: Item loadings and reliability measures

Constructs	Items	Loadings	CR	AVE	Cronbach's α
Optimism	OPT1	0.861	0.925	0.756	0.893
	OPT2	0.880			
	OPT3	0.866			
	OPT4	0.871			
Innovativeness	INN1	0.869	0.931	0.771	0.901
	INN2	0.861			
	INN3	0.876			
	INN4	0.906			
Discomfort	DISC1	0.844	0.913	0.723	0.873
	DISC2	0.869			
	DSIC3	0.841			
	DSIC4	0.848			
Insecurity	INSC1	0.849	0.924	0.753	0.892
	INSC2	0.871			
	INSC3	0.850			
	INSC4	0.902			
Perceived Usefulness	PU1	0.879	0.913	0.778	0.857
	PU2	0.871			
	PU3	0.895			
Perceived Ease of use	PEOU1	0.860	0.929	0.723	0.904
	PEOU2	0.859			
	PEOU3	0.839			
	PEOU4	0.832			
	PEOU5	0.860			
Perceived risk	RIS1	0.876	0.927	0.760	0.895
	RIS2	0.874			
	RIS3	0.885			
	RIS4	0.853			
Perceived trust	TRU1	0.847	0.932	0.734	0.910
	TRU2	0.883			
	TRU3	0.849			
	TRU4	0.854			
	TRU5	0.850			
Behavioral intention	BI1	0.867	0.932	0.734	0.909
	BI2	0.852			
	BI3	0.856			
	BI4	0.839			
	BI5	0.868			

to meet any of the reliability or validity benchmarks, underscoring the robustness of the measurement quality. Furthermore, AVE values ranged from 0.723 to 0.778, significantly exceeding the minimum requirement of 0.50, indicating that the latent constructs explained over half of the variance in their respective indicators. This further reinforces the conclusion that measurement items meaningfully and consistently reflect the underlying theoretical constructs. Importantly, all constructs met all reliability and validity benchmarks, highlighting the robustness of measurement quality. The corresponding measurement results are shown in Table 2.

4.2. Measurement Model Assessment

This study employs the Heterotrait-Monotrait (HTMT) ratio to assess discriminant validity, adhering to the guidelines proposed by Henseler et al. (2015). They emphasize that HTMT represents a more rigorous and sensitive indicator compared to traditional correlation-based techniques. As shown in Table 3, all HTMT coefficients in this study ranged between 0.035 and 0.323, well below the conservative threshold of 0.85 and the lenient upper limit of 0.90. These values indicate that the theoretical association levels between distinct constructs remain sufficiently low to ensure empirical separability of latent variables. The findings reinforce the theoretical assumption that each construct captures a unique domain of consumer perception without overlapping with other dimensions. This consistent pattern provides strong evidence that discriminant validity has been satisfactorily established.

Discriminant validity was further validated using the Fornell-Larcker criteria, following the classic methodology proposed by Fornell and Larcker (1981). Table 4 shows that the square root of the AVE (bolded on the diagonal) consistently exceeds the corresponding inter-construct correlations. This result was observed for all constructs (BI, DICS, INN, INSC, OPT, PEOU, RIS, TRU, and PU), indicating that each latent variable shares a significantly higher proportion of variance with its own indicators than with any other construct. This pattern supports the assertion that the constructs are conceptually distinct and do not overlap. In summary, the results from the HTMT ratio (Henseler et al., 2015) and the Fornell-Larcker criteria (Fornell and Larcker, 1981) provide strong convergent evidence for adequate discriminant validity. The integration of these complementary methods enhances the credibility of the measurement model and confirms that multicollinearity or conceptual redundancy does not compromise the structural assessment. Having established a robust measurement foundation, the analysis will proceed to examine the structural model and empirically test the proposed hypotheses

4.3. Measurement Model of Second Order

In this study, technological readiness (TR) is defined as a second-order formative construct comprised of four first-order reflective dimensions: Optimism (OPT), innovativeness (INN), discomfort (DICS), and insecurity (INSC). This hierarchical structure reflects the theoretical perspective that TR is a broad, high-order disposition manifested through individuals' attitudes toward these four distinct yet interrelated aspects of technology. To assess the measurement quality of this higher-order construct, this study adopted the two-stage approach recommended by Hair et al. (2021) and Sarstedt et al. (2019) (Figure 2). In the first stage, we obtained latent variable scores for the four first-order constructs. In the second stage, these scores served as indicators for formative second-order constructs, and their contribution to TR was assessed through external weights, multicollinearity diagnostics, and significance tests (Becker et al., 2012).

Table 5 presents the formative measurement assessment for the higher-order construct "Technological Readiness" (TR). Four first-order dimensions, DICS, INN, INSC, and OPT, are considered formative indicators of TR. First, we examined variance inflation factor (VIF) values to rule out multicollinearity among dimensions. As shown in Table 5, all VIF values ranged between 1.003 and 1.007, well below the conservative threshold of 3.3 (Diamantopoulos and Siguaw, 2006; Hair et al., 2021). This indicates no redundancy among the four dimensions, with each contributing unique information to the overall TR construct. Second, we examined external weights, t-values, and P-values to assess the relative importance of each dimension. The outer weights for DICS, INN, INSC, and OPT were -0.516, 0.577, −0.221, and 0.551, respectively, all statistically significant (t-values ranging from 2.026 to 4.805, $P < 0.05$). These findings indicate that all four dimensions make significant contributions

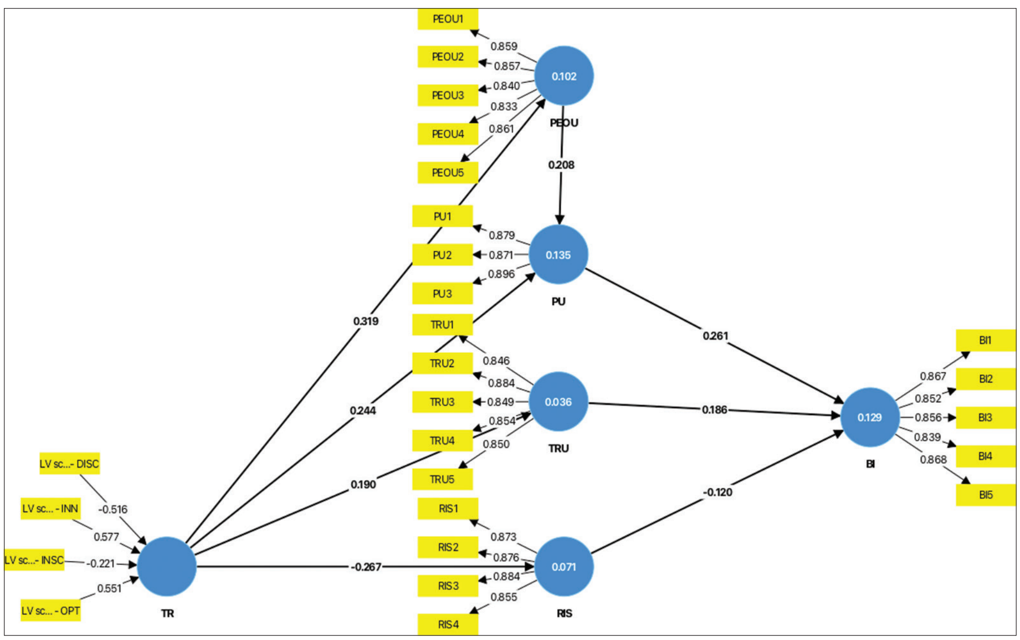
Table 3: Heterotrait-monotrait (HTMT) matrix

	BI	DICS	INN	INSC	OPT	PEOU	RIS	TRU	PU
BI									
DICS	0.122								
INN	0.225	0.056							
INSC	0.069	0.062	0.035						
OPT	0.122	0.042	0.075	0.048					
PEOU	0.288	0.182	0.213	0.129	0.184				
RIS	0.176	0.165	0.193	0.047	0.19	0.094			
TRU	0.212	0.118	0.126	0.074	0.098	0.09	0.081		
PU	0.314	0.174	0.226	0.044	0.223	0.323	0.109	0.044	

Table 4: Fornell-Larcker criterion

	BI	DICS	INN	INSC	OPT	PEOU	RIS	TRU	PU
BI	0.857								
DICS	−0.110	0.851							
INN	0.206	−0.033	0.878						
INSC	−0.058	−0.042	−0.021	0.868					
OPT	0.110	−0.002	0.067	0.044	0.870				
PEOU	0.264	−0.167	0.196	−0.128	0.168	0.850			
RIS	−0.158	0.148	−0.176	−0.024	−0.171	−0.085	0.872		
TRU	0.203	−0.107	0.118	−0.067	0.093	0.086	−0.073	0.857	
PU	0.279	−0.154	0.201	−0.033	0.196	0.286	−0.095	0.033	0.882

Figure 2: Results of path analyze



to the formation of technological readiness (TR). The negative signs for discomfort and insecurity suggest that higher levels of these traits correlate with lower overall TR values, while higher levels of optimism and innovativeness correlate with higher TR values, fully consistent with the original conceptualization of the Technological Readiness Index (Parasuraman, 2000; Parasuraman and Colby, 2015).

In the formative measurement, outer weights reflect each indicator's relative contribution, while outer loadings reflect their absolute association with the higher-order construct. Although not listed in Table 5, all four dimensions' outer loadings exceeded the recommended minimum of 0.70, indicating strong absolute correlations with TR. Following the research of Hair and Alamer (2022) and Diamantopoulos and Winklhofer (2001), even if certain weights are smaller than others, they should be retained as long as they possess theoretical significance, substantial weight, and adequate loadings. Given their substantial weights, acceptable multicollinearity statistics, and robust conceptual justification, all four TR dimensions were retained in the final model, supporting the robustness of the higher-order formative indicator configuration.

4.4. Structural Model and Hypothesis Testing

To evaluate the structural model, this study employed the partial least squares consistency (PLSc) algorithm (Dijkstra and Henseler, 2015), with all computations performed using SmartPLS 4.1

(Ringle et al., 2023). Following the recommendations of Hair et al. (2019), the nonparametric bootstrap method with 5000 resamples was used to test model significance. This method provides bias-corrected confidence intervals and enhances the precision of path coefficient estimates. The evaluation of the structural model focused on the magnitude and direction of standardized path coefficients (β), their statistical significance (P-values), effect size indicators (f^2), and multicollinearity assessed via variance inflation factors (VIF). Figure 2 presents the complete structural framework, including estimated paths, loadings, and R^2 values for all endogenous variables, visually illustrating the model's explanatory power.

Regarding explanatory power, Table 6 shows R^2 values for endogenous variables ranging from 0.034 to 0.131. Specifically, the R^2 value for behavioral intention (BI) is 0.123, while those for perceived usefulness (PU), perceived ease of use (PEOU), perceived risk (RIS), and perceived trust (TRU) are 0.131, 0.102, 0.069, and 0.034, respectively. Although these values fall within the "weak to moderate" range according to Hair et al. (2019) guidelines, they still indicate that the predictive variables in the model account for a substantial portion of variance in each dependent variable. The predictive correlation (Q^2) assessed via blind evaluation further confirms the model's predictive capability. All endogenous variables exhibited positive Q^2 values, BI (0.091), PU (0.100), PEOU (0.070), RIS (0.052), and TRU (0.025), indicating acceptable predictive correlation for each outcome variable. These findings support the robustness of the structural model, as positive values indicate that the model maintains predictive accuracy when reconstructing missing data points.

Table 7 summarizes the significance test results for each hypothesized path, including β coefficients, t-values, P-values, and f^2 effect sizes. Overall, empirical evidence supports all eight proposed hypotheses, indicating coherent and theoretically consistent relationships among technological readiness, cognitive evaluations, and behavioral intentions.

Consistent with theoretical expectations, technological readiness (TR) exerted significant positive effects on all four key cognitive evaluations. TR significantly enhanced perceived ease of use (PEOU) (H_1: β = 0.110, t = 4.346, P < 0.001), indicating that individuals with higher technological readiness tend to experience smoother interactions when using the system. TR also enhanced perceived usefulness (PU) (H_2: β = 0.291, t = 3.900, P < 0.001), indicating that technologically confident users are more likely to perceive the functional benefits of the system. TR also exerted a significant positive effect on perceived trust (TRU) (H_3: β = 0.159, t = 3.329, P = 0.001), underscoring that technological readiness enhances users' confidence in the system's reliability.

Similarly, technological readiness (TR) exerted a significant positive effect on perceived risk (RIS) (H4: β = 0.183, t = 4.234, P < 0.001), indicating that individuals with high technological readiness possess stronger awareness and assessment capabilities regarding potential uncertainties. Regarding the internal cognitive pathway, perceived ease of use (PEOU) significantly influenced perceived usefulness (PU) (H_5: β = 0.093, t = 4.318, P < 0.001). Consistent with technology acceptance model (TAM) literature, this indicates that the convenience of interaction enhances perceived effectiveness. Furthermore, perceived usefulness (PU) significantly and positively influenced behavioral intention (BI) (H_6: β = 0.114, t = 5.363, P < 0.001), indicating that users' functional evaluations strongly influence their willingness to adopt the system.

Moreover, perceived trust exerted a significant positive influence on behavioral intention (BI) (H_7: β = 0.107, t = 4.085, P < 0.001), underscoring the importance of psychological assurance in behavioral outcomes. Finally, perceived risk also significantly influenced behavioral intention (BI) (H_8: β = 0.186, t = 2.461, P = 0.014), indicating that users' risk assessment remains a crucial factor influencing adoption intention.

Table 5: Outer weights of higher-order construct: Technology readiness

Constructs	Items	VIF	Outer weight	t-value	P-value
TR	LV scores-DISC	1.003	−0.516	3.922	0.000***
	LV scores-INN	1.006	0.577	4.805	0.000***
	LV scores-INSC	1.004	−0.221	2.026	0.043*
	LV scores-OPT	1.007	0.551	4.655	0.000***

Significance levels: *P<0.05; **P<0.01; ***P<0.001; two-tailed probabilities

Table 6: R-square and Q-square results

Variable→	R^2	Q^2
BI	0.123	0.091
PEOU	0.1	0.07
RIS	0.069	0.052
TRU	0.034	0.025
PU	0.131	0.1

4.5. Importance–Performance Map Analysis

To complement the PLS-SEM results, we conducted an Importance-Performance Map Analysis (IPMA) by jointly examining the relative importance and performance of antecedent variables influencing behavioral intention. Following the analytical guidelines proposed by Ringle and Sarstedt (2016), IPMA identifies variables with the greatest potential for managerial improvement. As shown in Figure 3, Perceived Usefulness (PU) occupies the farthest right position on the horizontal axis, indicating it is the strongest predictor of behavioral intention among all examined variables. PU also exhibits relatively high-performance levels, suggesting users already perceive its practical functional value. However, sustained improvement in this area could yield significant behavioral impacts.

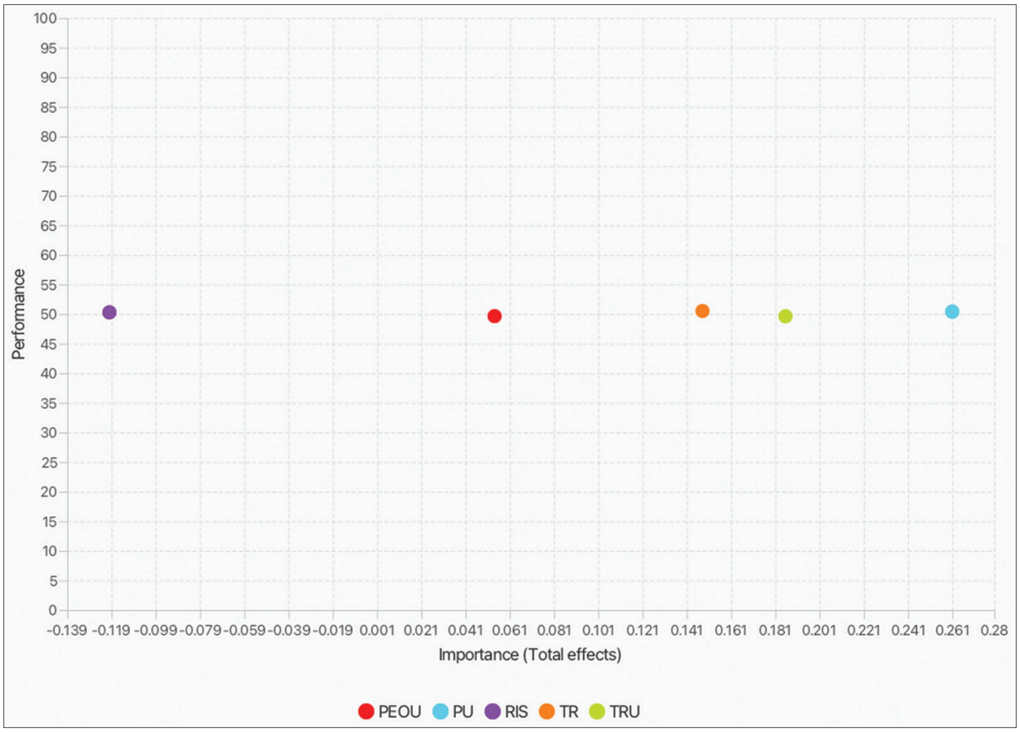
Perceived trust (TRU) ranks second in importance and demonstrates moderate performance. This pattern indicates that enhancing users' confidence in the system remains an effective strategy for improving adoption rates. Technological readiness (TR) holds moderate importance but exhibits relatively high performance. This suggests that while users typically possess sufficient readiness, boosting their technological confidence or familiarity may still yield positive outcomes.

Table 7: Hypothesis testing

Hypothesis	Path→	β	f^2	T-value	P-values	Supported
H1	TR→PEOU	0.110	0.114	4.346	0.000	Yes***
H2	TR→PU	0.291	0.062	3.900	0.000	Yes***
H3	TR→TRU	0.159	0.037	3.329	0.001	Yes**
H4	TR→RIS	0.183	0.077	4.234	0.000	Yes***
H5	PEOU→PU	0.093	0.045	4.318	0.000	Yes***
H6	PU→BI	0.114	0.078	5.363	0.000	Yes***
H7	TRU→BI	0.107	0.039	4.085	0.000	Yes***
H8	RIS→BI	0.186	0.016	2.461	0.014	Yes*

Significance levels: *P<0.05; **P<0.01; ***P<0.001; two-tailed probabilities

Figure 3: Importance–performance map analysis. BI: Behavioral intention, PEOU: Perceived ease of use, RIS: Perceived risk, TRU: Perceived trust, PU: Perceived usefulness, TR: Technology readiness



In contrast, perceived risk (RIS) and perceived ease of use (PEOU) are positioned on the left side of the importance axis, indicating their relatively weaker influence on behavioral intention. Their performance levels are comparable to other constructs, but given their lower importance, they are not urgent targets for optimization from a management perspective. The IPMA findings underscore that practicality (PU) and trustworthiness (TRU) are primary levers for enhancing behavioral intention. Consequently, efforts focused on improving system practicality, transparency, and trust-building capabilities are likely to yield the greatest practical benefits.

5. CONCLUSION AND IMPLICATION

5.1. Conclusion

This study combines the technology readiness (TR) framework with the established technology acceptance model to deepen understanding of behavioral intentions toward facial recognition payment (FRP). Unlike traditional acceptance models primarily focused on system perception, this research emphasizes the foundational role of individual psychological dispositions, optimism, innovativeness, discomfort, and insecurity, which are captured through a constitutive TR model. Empirical findings reveal that TR is not a marginal factor; rather, it systematically shapes users' core evaluations of FRP, significantly influencing perceived ease of use (PEOU), perceived usefulness (PU), perceived trust (TRU), and perceived risk (RIS).

The findings further validate the central role of PU, TRU, and PEOU in predicting behavioral intention (BI), consistent with prior technology adoption literature. Users are more inclined to adopt FRP when they perceive its functionality as practical, operationally easy, and trustworthy. Concurrently, RIS continues to exert a significant negative influence on BI, reminding practitioners that security and privacy concerns remain paramount even within technologically advanced payment environments. Collectively, these findings indicate that FRP adoption is influenced not only by system performance and interface design but also by deeper psychological evaluations and trust-related judgments.

Crucially, modeling TR as a higher-order formative structure provides a more refined theoretical lens for explaining the adoption of biometric payments. This study advances psychometric understanding of FRP acceptance by demonstrating that each dimension of TR contributes meaningfully to the overall construct (albeit to varying degrees). TR does not directly determine BI; instead, it indirectly influences intent by affecting perceptions such as usefulness, trust, and risk. This aligns with contemporary perspectives emphasizing the importance of psychological readiness and affective dispositions in technology adoption processes.

The findings offer actionable recommendations for system designers, service providers, and marketers: enhancing perceived utility, strengthening trust mechanisms, and addressing perceived risks can collectively facilitate a smooth transition from user evaluation to practical adoption in facial recognition payment environments. Importance-performance matrix analysis (IPMA) highlights perceived usefulness and perceived trust as the most critical factors for enhancing behavioral intent. While all constructs demonstrate relatively stable performance levels, these two factors stand out as key strategic targets for enhancement. This indicates that the widespread adoption of FRP (functional recognition payment) requires not only technological optimization but also the creation of a secure, trustworthy, and value-oriented user experience.

5.2. Theoretical Implication

This study makes several contributions to the theoretical understanding of technology adoption in the field of biometric payments. First, it models technological readiness (TR) as a formative second-order construct and integrates it with core technology acceptance beliefs, thereby deepening our understanding of how individual psychological dispositions influence perceptions of facial recognition payments (FRP). Previous studies typically examined optimism, innovativeness, discomfort, or insecurity as independent reflective constructs, rarely treating them as formative dimensions jointly constituting higher-order readiness characteristics (Parasuraman and Colby, 2015; Zhang and Zhang, 2024). This study confirms that TR significantly influences perceived ease of use, perceived usefulness, perceived trust, and perceived risk, indicating readiness is not merely a background trait but a prerequisite shaping critical evaluative judgments. These theoretical contributions collectively enrich current behavioral intention research, demonstrating that psychological readiness, usefulness beliefs, affective trust, and risk assessment interact to shape users' intentions toward facial recognition payments. This multidimensional explanatory structure offers a more realistic and theoretically grounded interpretation of how users evaluate and adopt facial recognition payment technology.

The findings extend traditional technology acceptance frameworks by elucidating how trust-related and risk-related perceptions moderate the influence of readiness on behavioral intention. Although perceived usefulness and perceived ease of use remain core predictors, consistent with the technology acceptance model (TAM) and post-TAM literature (Davis, 1989; Venkatesh et al., 2012), the findings emphasize that perceived trust and perceived risk also serve as critical cognitive mechanisms in biometric payment contexts, particularly regarding privacy sensitivity and security assessments (Soto-Beltrán et al., 2022). The significant influence of TR on both TRU and RIS further indicates that readiness not only affects beliefs about convenience and utility but also impacts the affective and security-oriented evaluations essential for FRP (functional payment) adoption. This finding deepens the theoretical understanding of the psychosocial determinants of trust formation in biometric transactions.

In addition, this study empirically demonstrates that perceived ease of use contributes to perceived usefulness, and that usefulness, trust, and risk jointly predict behavioral intention. Specifically, the joint significance of perceived usefulness (PU), technological usefulness (TRU), and risk information systems (RIS) reinforces the multidimensionality of payment technology intention formation. Findings suggest that future facial recognition payment adoption models should treat utility, security, and affective trust as intertwined rather than isolated predictors.

Moreover, applying a two-stage approach to assess formative second-order structures contributes to methodological clarity in technological readiness (TR) research. Although technological readiness has long been theorized as a comprehensive readiness profile, empirical assessments often employ retrospective operationalization methods, leading to conceptual inconsistencies (Blut and Wang, 2020). By validating TR through formative indicators with significant external weight and theoretical support, this study provides a methodological foundation for future biometric payment research, treating readiness as a composite construct to capture distinct psychological dispositions.

5.3. Practical Implication

Empirical findings provide several actionable insights for organizations developing or promoting facial recognition payment (FRP) systems. Since behavioral intentions in this study are jointly influenced by perceived usefulness, perceived trust, and perceived risk, all of which are further shaped by users' technological readiness and perceived ease of use. Practitioners should adopt multi-layered strategies to align technological design with the psychological acceptance patterns observed in the data.

First, the significant influence of technological readiness (TR) on perceived usefulness, perceived ease of use, trust, and risk indicates that FRP adoption largely depends on users' psychological preparedness for digital technologies. This suggests system deployment should be supplemented with structured education and familiarization programs. Practical operational guidance, scenario demonstrations, and transparent communication about system functionality help reduce user discomfort and insecurity, two readiness factors known to hinder facial recognition payment adoption. Enhancing psychological readiness before or during biometric technology adoption can simultaneously boost positive perceptions across multiple cognitive dimensions, thereby strengthening subsequent behavioral intentions (Zhang and Zhang, 2024).

Given that perceived ease of use (PEOU) significantly influences perceived usefulness (PU), developers must prioritize intuitive interface design. Payment interfaces should minimize operational steps, reduce cognitive load, and ensure hardware/software stability, particularly in high-traffic or time-sensitive transaction environments. Past research consistently indicates that intuitive biometric systems reduce learning costs and enhance perceived performance benefits (Moriuchi, 2021). Therefore, service providers should improve recognition accuracy, shorten processing times, and maintain consistent scanning experiences to translate ease of use into stronger perceived utility.

Perceived trust (TRU) emerges as a significant predictor of behavioral intent, underscoring the importance of credibility cues in biometric payment adoption. Businesses must invest in visible and verifiable trust-building mechanisms, such as independent security certifications, clear data storage policy disclosures, and third-party audits. Previous research on biometric authentication emphasizes that transparent handling of personal data significantly enhances user trust, particularly when sensitive facial features are involved (Meden et al., 2021; Gavrilova et al., 2022). Communicating these measures in a concise and understandable manner helps align users' subjective assessments of security with the system's actual safeguards.

The negative impact of perceived risk (RIS) on user willingness underscores the necessity of addressing concerns related to privacy, misuse of biometric data, and potential identity vulnerabilities. Organizations should adopt proactive communication strategies that directly address these concerns rather than assuming users will infer security from system quality. Implementing opt-in consent options, allowing users to view their biometric data rights, and providing assurances regarding data deletion or encrypted storage can effectively reduce perceived risk. Evidence from digital payment research indicates that risk perception typically diminishes with repeated exposure and accumulated experience (Featherman and Pavlou, 2003; Mahler and Murphy, 2025), making pilot trials or phased rollouts beneficial for users to gradually internalize security cues.

Given that perceived usefulness (PU) and perceived trust (TRU) exert the strongest positive influence on behavioral intent in your model, marketing strategies should simultaneously emphasize functional and psychological value propositions. Messaging should combine performance-oriented claims, such as speed, convenience, and efficiency, with assurances of transparency, fairness, and responsible data governance. This dual emphasis enables businesses to appeal simultaneously to users' rational evaluations and emotional trust, both of which are critical for the widespread adoption of facial recognition payment ecosystems.

5.4. Limitations and Future Directions

Although this study offers a more nuanced perspective on how technological readiness, cognitive evaluation, and risk trust beliefs influence the intention to use facial recognition payment (FRP), certain limitations exist. These limitations should be considered when interpreting the findings and may also guide future research. Data were collected through a cross-sectional survey limited to a single country, with relatively homogeneous FRP usage scenarios. While judgment sampling is common in technology adoption studies, it may skew the sample toward younger, more digitally literate users or those already interested in innovative payment methods. Future research should prioritize probability sampling to broaden sample coverage, incorporate underrepresented groups (e.g., seniors, rural users, small merchant customers), and conduct cross-national comparisons to examine cultural factors influencing FRP adoption. Second, all constructs were measured using Likert-scale self-report questionnaires, relying solely on responses from the same respondents at a single point in time. Although common method variance was statistically assessed and found within acceptable limits, self-report scales may still overstate association strengths or underestimate nuanced behavioral characteristics (Podsakoff et al., 2024). Future research could qualitative interviews capturing contextual details often overlooked by structured questionnaires.

Furthermore, while concise, this theoretical model covers only a subset of factors potentially influencing FRP adoption. Fctors such as social influence, perceived security, institutional trust, price-value judgments, and concerns about algorithmic transparency or fairness also shape user responses to biometric and AI-driven payment systems (Yu et al., 2024; Hasan et al., 2021). Future models could refine these variable branches further, integrate them, or explore alternative configurations using other research methodologies to examine how different belief combinations collectively drive high intent or persistence.

Beyond this, technological readiness is operationally defined using four formative dimensions, following the TRI 2.0 tradition. While this offers richer psychological layers than many models, other traits and affective states, such as general technology anxiety, privacy concerns, trust propensity, or habit formation, remain unaccounted for. Furthermore, multigroup analyses could investigate whether the effects of readiness, trust, and risk vary across age, gender, or income groups, informing more nuanced targeting strategies.

Lastly, this study examines intentions rather than long-term post-adoption behaviors. Future research could employ panel designs tracking users to link early perceptions of usefulness, risk, and trust to later metrics like FRP usage frequency, wallet share, or recommendation intent. Such designs would not only strengthen causal inference but also illuminate how the relationship between users and technology evolves as biometric payment systems become more deeply integrated into daily life. By addressing these limitations, subsequent work can establish a more comprehensive theoretical and empirical foundation for understanding FRP and the broader ecosystem of biometric and AI-powered payment services.

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