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The Impact of Social Influence, Perceived Risk, and Trust on Mobile Payment Usage Intention and Behavior among Vietnamese Consumers: The Moderating Role of Generation and Usage Experience

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ABSTRACT: *Mobile payment is now integral to daily life in Vietnam, yet rising fraud concerns heighten the importance of perceived risk and trust. This study examines how social influence, perceived risk, and provider trust shape usage intention and actual usage behavior, and whether these relationships vary by generation and usage experience. Survey data from 156 Vietnamese mobile payment users were analyzed using bootstrapped mediation and multi-group moderation tests. Trust is the strongest determinant of intention (β = 0.54) and substantially reduces perceived risk (β = −0.75). Perceived risk retains an independent negative effect on intention (β = −0.29), and intention strongly predicts usage behavior (β = 0.56). Social influence has no significant direct effect on intention, but its total effect is substantial (B = 0.90), fully mediated by trust. Moderating effects of usage experience and generation were not supported. Given the convenience sample, cross-sectional design, and possible common method bias, findings are preliminary.*

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I. INTRODUCTION

Mobile payment has evolved from a novel option into an integral part of daily transactions in Vietnam. Interbank QR code payments, e-wallets (such as MoMo, ZaloPay, VNPay, and Viettel Money), bank-app embedded wallets, and device-native wallets (Apple Pay, Google Pay, Samsung Pay) coexist. Data from the National Payment Corporation of Vietnam (NAPAS) illustrates this scale: in 2024, the system processed 9.56 billion transactions valued at approximately 61 quadrillion VND (Vietstock, 2025), and in 2025, transaction volume increased by 24% while total value rose by 8% (Government News Portal, 2026). Specifically, VietQR code transfers during the first 10 months of 2025 surged by over 52% in volume (reaching 3.6 billion transactions) and 85% in value compared to the same period in 2024 (Journal of Economics and Finance, 2025), with nearly 90 million banking app accounts utilizing VietQR code scanning (Dan Tri, 2025). This infrastructure has established cross-border QR payment connectivity with Thailand, Laos, Cambodia, and unidirectional connectivity with China (Government News Portal, 2026).

This expansion is accompanied by two key shifts. First, user concerns have shifted from technological risk (system glitches, card data leaks) to scam and fraud risk (impersonation of authorities, account takeover, malicious QR codes, and social engineering to install malware). Second, regulatory and technical frameworks have tightened: effective July 1, 2024, under Decision No. 2345/QD-NHNN of the State Bank of Vietnam, individual electronic funds transfers exceeding 10 million VND per transaction or a cumulative daily value exceeding 20 million VND require biometric authentication (State Bank of Vietnam, 2023). These transformations render traditional three-variable models from previous literature (social influence, risk, intention) insufficient to fully explain contemporary behavior.

The research questions are:

RQ1: How does social influence affect perceived risk, trust, and mobile payment usage intention?

RQ2: Do perceived risk and trust mediate the effect of social influence on usage intention?

RQ3: How does intention translate into actual usage behavior, and do these relationships vary across generational cohorts and experience levels?

II. THEORETICAL FRAMEWORK

2.1. Mobile Payment

Mobile payment is defined as the use of mobile devices (smartphones, wearables) in conjunction with wireless connection technologies or QR code scanning to authenticate, authorize, and finalize financial transactions (Antovski & Gusev, 2003; Dahlberg et al., 2015; Al-Saedi et al., 2020). In this study, mobile

payment encompasses an omnichannel ecosystem, including QR code payments, e-wallets, mobile banking applications, and contactless (NFC/Tap-to-pay) payments, across both point-of-sale (POS) and online transactions (Kapoor et al., 2022).

2.2. Social Influence

Social influence refers to the degree to which an individual perceives that important others (e.g., family, peers, colleagues) believe they should adopt mobile payments (Karahanna et al., 1999; Venkatesh et al., 2003). In today's digital ecosystem, sources of influence extend to social media influencers (KOLs/KOCs), online communities, and promotional spillover effects from digital campaigns (Busalim et al., 2021). This study explicitly distinguishes among subjective norms, social image, and social proof, as they exert distinct impacts on user behavior.

2.3. Multidimensional Perceived Risk

Perceived risk is defined as a user's subjective expectation of loss when executing a financial transaction (Bauer, 1967; Peter & Ryan, 1976; Mitchell, 1999). Featherman & Pavlou (2003) conceptualize this construct across four dimensions: financial risk, security/fraud risk, privacy risk, and time/performance risk. Based on empirical scale validation (Section 4.3), time/performance risk was omitted due to low reliability; thus, perceived risk is analyzed as a multidimensional construct comprising financial risk, online fraud/security risk, and data privacy risk (Widyanto et al., 2022; Bland et al., 2024).

2.4. Trust

Trust is defined as the willingness of a party to be vulnerable to the actions of another based on the expectation that the trustee possesses ability, benevolence, and integrity (Mayer et al., 1995). In mobile payments, trust targets both service providers (banks, e-wallet platforms) and the underlying payment infrastructure (Alrawad et al., 2023). Trust acts as a critical mechanism that directly enhances usage intention while mitigating perceived risk (Gefen et al., 2003; Shao et al., 2019).

2.5. Empirical Studies in Vietnam (2021-2025)

Empirical findings in Vietnam between 2021 and 2025 reveal directional inconsistencies across studies, particularly regarding two focal constructs: perceived risk and trust:

- To and Trinh (2021): Examining a sample of 332 users, they extended the Technology Acceptance Model (TAM) by incorporating trust and perceived enjoyment. Findings confirmed that perceived ease of use, perceived usefulness, and perceived enjoyment positively influence mobile wallet usage intention, whereas trust exhibits no direct effect.
- Nguyen and Nguyen (2021): Surveying 320 mobile wallet users, they demonstrated that perceived risk, personal innovativeness, perceived ease of use, and long-term orientation significantly impact perceived value, which in turn drives commitment and word-of-mouth behavior.
- Nguyen (2024): Investigating Apple Pay adoption among Generation Z, this study indicated that perceived risk and social image have no statistically significant impact on behavioral intention.
- Truong (2025): Measuring actual usage behavior among 463 rural residents in Lang Son and Cao Bang provinces, the results identified trust and social influence as positive predictors of behavior, while perceived risk was statistically insignificant, and demographic variables were unrelated to behavior.
- Truong and Nguyen (2025): Conducted among 509 users in the Northern mountainous region, this study identified trust as a key determinant influencing perceived usefulness and subjective norms; notably, it revealed an unexpected negative relationship between perceived usefulness and attitude.
- Ngo and Pham (2024): Proposed a theoretical framework shaping mobile payment acceptance behavior based on the joint determination of social influence and trust, though it remains empirically unverified.

In the broader research context, Ramayanti et al. (2024) conducted a systematic literature review (SLR) on the intention–behavior gap in digital payments, Siagian et al. (2022) and Giang et al. (2024) analyzed the mediating role of trust in financial technology acceptance models, and Al-Qudah et al. (2024) focused on clarifying the determinants of digital payment adoption specifically among Generation Z.

III. RESEARCH MODEL AND HYPOTHESES

3.1. Research Model

The proposed research model provides a comprehensive analytical framework to explain the formation of mobile payment usage behavior (UB) by integrating direct effects, parallel mediation mechanisms, and multi-group moderation effects:

- Direct and Parallel Mediating Effects: Social Influence (SI) serves as a primary antecedent directly affecting Behavioral Intention (BI). Simultaneously, SI exerts indirect effects on BI through dual parallel mediators:

Perceived Risk (PR) and Trust (TR). Specifically, social signals are hypothesized to attenuate perceived risk and reinforce consumer trust, thereby indirectly strengthening usage intention.
- Intention–Behavior Link: Behavioral Intention (BI) acts as the central mechanism linking users' social and cognitive perceptions to actual Usage Behavior (UB), exerting a direct predictive impact on UB.
- Moderating Mechanisms: The framework incorporates Generation (GEN) and Usage Experience (EXP) as key contextual moderators. These variables are posited to moderate the magnitude of structural paths within the model (including SI → PR/TR/BI, PR/TR → BI, and BI → UB), capturing behavioral disparities across generational cohorts and varying levels of user experience.

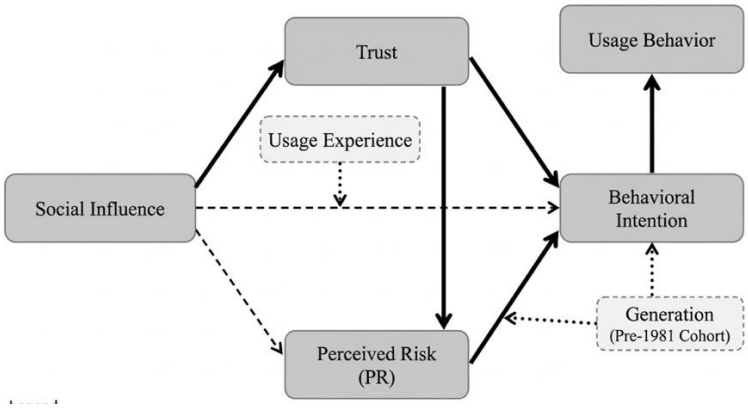


Fig. 1, Research Model

3.2. Hypotheses

Direct Effects:
- H1 (+): Social influence has a positive effect on mobile payment usage intention.
- H2 (-): Social influence has a negative effect on perceived risk.
- H3 (+): Social influence has a positive effect on trust in the provider.
- H4 (-): Perceived risk has a negative effect on usage intention.
- H5 (+): Trust has a positive effect on usage intention.
- H6 (-): Trust has a negative effect on perceived risk.
- H7 (+): Behavioral intention has a positive effect on actual usage behavior.

Mediating Effects:
- H8a: Perceived risk mediates the effect of social influence on behavioral intention.
- H8b: Trust mediates the effect of social influence on behavioral intention.
- H8c: The trust-perceived risk chain mediates the effect of social influence on behavioral intention.

Moderating Effects:
- H9: The effect of social influence on intention is stronger for the group with less usage experience compared to the group with more usage experience
- H10: The effect of perceived risk on intention is stronger (more negative) for the older group compared to the Gen Z and Millennials group.

IV. RESEARCH METHODOLOGY

4.1. Data Collection

The target population comprised individuals aged 18 and older who own a smartphone and possess awareness of mobile payment services. A total of 170 responses were collected, consisting of 88 online and 82 paper-based questionnaires.

During the initial screening phase, 14 respondents were excluded due to a lack of awareness regarding mobile payments. No questionnaires were disqualified based on age criteria (<18 years), lack of consent, non-ownership of a smartphone, failure on attention-check items, or straight-lining responses across the main Likert scales. Consequently, the final analytical sample comprised 156 valid responses (81 online and 75 paper-based). Given that all 156 respondents had prior experience with mobile payment systems, the empirical framework specifically captures post-adoption continued usage intention and actual usage behavior among existing users, rather than initial adoption among non-users.

Data collection was executed using a non-probability convenience sampling strategy. Geographic demographic indicators (such as specific provinces, administrative regions, or urban versus rural classifications) were not recorded, thereby constraining the evaluation of geographic representativeness.

4.2. Sample size and Statistical Analysis

To evaluate sample size adequacy, this study applied the benchmark formula $n \geq 50 + 8m$ proposed by Tabachnick and Fidell (1996), where m represents the number of main predictor variables. For m = 3 main structural predictors, the minimum required sample size is 74. The final sample size of N = 156 substantially exceeds this threshold.

Furthermore, considering a maximum of eight predictors (three main predictors and five control variables) at a significance level of $\alpha = 0.05$, a statistical analysis reveals that the sample size of N = 156 yields a statistical power of approximately 0.79 for a small-to-medium effect size ($f^2 = 0.05$) and exceeds 0.99 for a medium effect size ($f^2 = 0.15$). However, the statistical power drops to approximately 0.42 for a small effect size ($f^2 = 0.02$). Subgroup and multi-group analyses similarly exhibit lower statistical power, particularly for the pre-1981 age cohort (n = 25).

4.3. Measurement

All primary constructs within the proposed research framework were operationalized using multi-item scales measured on a 7-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). To preserve measurement validity while reflecting the specific contextual characteristics of mobile payment adoption, all indicators were adapted from established academic literature.

First, preliminary reliability analysis revealed an anomaly among the time/performance risk items (PRT1–PRT3). Specifically, item PRT3 was negatively correlated with PRT1 (r = -0.66) and PRT2 (r = -0.58), whereas PRT1 and PRT2 exhibited a strong positive correlation (r = 0.91), yielding a negative Cronbach's alpha (-0.91). This pattern indicates a potential reverse-coding error or respondent misinterpretation. Upon reverse-coding PRT3, the subscale achieved high internal consistency (α = 0.87), and the main structural conclusions remained unchanged.

Second, item PRP1 was removed due to an insufficient factor loading of 0.23. The remaining dimensions (financial, security/fraud, and privacy risks) displayed high inter-construct correlations (r = 0.68 to 0.85). Furthermore, a three-factor structure yielded negligible improvement in overall model fit compared to a unidimensional representation (CFI = 0.714 vs. CFI = 0.713). Consequently, following the principle of parsimony, Perceived Risk (PR) was operationalized as a single-factor overall construct comprising eight items.

Finally, Usage Behavior (UB) was operationalized as a composite index calculated from the mean score of three standardized indicators, demonstrating high internal consistency reliability (α = 0.93).

4.4. Data Analysis

Data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS version, which is suitable for prediction-oriented research, relatively small samples, and models with mediation and multi-group analysis (Hair et al., 2019, 2022). Significance was assessed using 5,000 bootstrap resamples. Model fit was evaluated using the standardized root mean square residual (SRMR; Henseler et al., 2014).

V. RESULTS

5.1. Sample Characteristics

The final analytical sample comprised 156 respondents (Table 1). The mean age was 35.7 years (SD = 9.7, ranging from 21 to 68). The sample skewed toward a younger and highly educated demographic, with 84.0% belonging to Gen Z or Millennials and 78.8% holding a bachelor's degree or higher. Regarding usage patterns, 100% of respondents utilized QR code scanning, 65.4% used e-wallets, 58.3% engaged in contactless mobile payments, and 53.2% conducted in-app transactions. Furthermore, 48.1% transacted more than 10 times per week, and 52.6% spent 10 million VND or more monthly via mobile payment channels.

Table 1. Sample Characteristics (n = 156)

Characteristic	Category, (%)
Data Colection	Online 81 (51.9%); Paper-base 75 (48.1%)
Gender	Male 77 (49.4%); Female 77 (49.4%); Other 2 (1.3%)
Generation	Gen Z 48 (30.8%); Millennials 83 (53.2%); Gen X 21 (13.5%); Born before 1965 4 (2.6%)
Education	Below high school (0.6%); High school 10 (6.4%); Vocational / Associate degree 22 (14.1%); Bachelor's degree 86 (55.1%); Postgraduate degree 37 (23.7%)
Occupation	Students 2 (1.3%); Office workers /Civil servants 68 (43.6%); Business owners /Entrepreneurs 50 (32.1%); Manual laborers 20 (12.8%); Agriculture, forestry, and fisheries 6 (3.8%); Retired /Household 10 (6.4%)
Monthly Income (million VND)	Below 5 2 (1.3%); 5 to under 10 20 (12.8%); 10 to under 20 52 (33.3%); 20 million VND and above (26.9%); Undisclosed 40 (25.6%)
Usage Duration on Mobile Payment	Under 6 months 18 (11.5%); 6 months to under 1 year 58 (37.2%); 1 to under 3 years 31 (19.9%); 3 years or more 49 (31.4%)
Fraud Exposure Experience	Personally lost money 12 (7.7%); Near-miss fraud attempts 45 (28.8%); Relatives / Acquaintances defrauded 74 (47.4%); No fraud exposure 25 (16%)

5.2. Measurement Model Assessment

Table 2. Scale Reliability and Convergent Validity

Construct	Factor Loadings	Cronbach's alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Social Influence (5 items)	0.54 – 0.86	0.84	0.86	0.55
Trust (4 items)	0.68 – 0.93	0.90	0.92	0.74
Perceived Risk (8 items)	0.59 – 0.93	0.93	0.94	0.65
Behavioral Intention (3 items)	0.68 – 0.99	0.77	0.87	0.70

The initial four-factor confirmatory factor analysis (CFA) indicated that global model fit indices did not meet recommended benchmarks ($X^2 = 1200.7$, df = 164, CFI = 0.713, TLI = 0.667, RMSEA = 0.202) (Hair et al., 2019; Kline, 2023). Regarding construct reliability and convergent validity, all latent variables exceeded standard empirical thresholds (Cronbach's alpha ≥ 0.70, CR ≥ 0.70, AVE ≥ 0.50) (Hair et al., 2022). However, item-level inspection revealed minor anomalies: indicator SI3 demonstrated a relatively low loading (0.54), whereas indicator BI2 exhibited an extremely high loading (0.99), suggesting a potential Heywood case. Because PLS-SEM does not rely on covariance-based global fit indices, the measurement model was assessed through indicator loadings, reliability, convergent validity, and discriminant validity. For transparency, a covariance-based CFA yielded poor global fit (CFI = 0.713, RMSEA = 0.202); this is discussed as a limitation.

Discriminant validity was established at an acceptable, albeit cautious, level (Table 3). All Heterotrait-Monotrait (HTMT) ratios remained below the 0.90 threshold (Franke & Sarstedt, 2019; Henseler et al., 2015). The HTMT ratio between Trust and Behavioral Intention (0.893) exceeds the conservative 0.85 threshold but remains below the 0.90 criterion for conceptually similar constructs (Henseler et al., 2015); its bootstrap 95% confidence interval [lower, upper] does not include 1.00, supporting discriminant validity. The Social Influence–Trust pair (HTMT = 0.846) was close to, but below, the 0.85 threshold.

Table 3. HTMT Ratios and Inter-Construct Correlations

Construct Pair	HTMT Ratio	Correlation (r)
SI – TR	0,846	0,732
SI – PR	0,612	−0,530
SI – BI	0,734	0,635
TR – PR	0,789	−0,749
TR – BI	0,893	0,831
PR – BI	0,785	−0,750

5.3. Structural Model Assessment and Hypothesis Testing

Table 4. Structural Path Coefficients and Hypothesis Testing Results (5,000 Bootstrap Resamples)

Hypothesis	Structural Path	Unstandardized (B)	Standardized (β)	95% CI for B	Outcome
H1 (+)	SI → BI	0.12	0.08	[−0.03; 0.25]	Not Supported
H2 (−)	SI → PR	0.02	0.01	[−0.16; 0.21]	Not Supported
H3 (+)	SI → TR	0.81	0.71	[0.68; 0.94]	Supported
H4 (−)	PR → BI	−0.32	−0.29	[−0.51; −0.15]	Supported
H5 (+)	TR → BI	0.69	0.54	[0.46; 0.89]	Supported
H6 (−)	TR → PR	−0.88	−0.75	[−1.07; −0.70]	Supported
H7 (+)	BI → UB	0.51	0.56	[0.39; 0.65]	Supported

The structural model accounted for 58.1% of the variance in Trust (R^2 = 0.581), 57.8% in Perceived Risk (R^2 = 0.578), 73.3% in Behavioral Intention (R^2 = 0.733), and 80.6% in Usage Behavior (R^2 = 0.806). These coefficient of determination values signify moderate-to-substantial explanatory power according to established statistical thresholds (Cohen, 1988; Hair et al., 2022).

Regarding effect sizes (f^2), Trust exerted a medium effect on Behavioral Intention (f^2= 0.30), Perceived Risk showed a small-to-medium effect on Intention (f^2 = 0.14), whereas the direct effect of Social Influence on Intention was negligible (f^2 = 0.01). Furthermore, Social Influence demonstrated a substantial effect on Trust (f^2= 1.17), Trust had a large effect on Perceived Risk (f^2 = 0.56), and Intention exhibited a strong effect on actual Usage Behavior (f^2 = 1.06). Multicollinearity diagnostic checks revealed predictor Variance Inflation Factors (VIF) for Intention of 2.16 (SI), 3.53 (TR), and 2.28 (PR), all below the conservative threshold of 5.0 (Hair et al., 2022), although elevated bivariate correlations between SI–TR (r = 0.73) and TR–BI (r = 0.83) reflect strong underlying indirect mechanisms.

Direct hypotheses H1 and H2 were not supported when Trust was specified in the structural system. However, the total effect of Social Influence on Behavioral Intention remained highly significant (B = 0.90, 95% CI [0.74, 1.04]), and its total effect on Perceived Risk was significantly negative (B = -0.70, 95% CI [-0.86, -0.57]), confirming that the influence of social factors is fully channeled through Trust.

5.4. Mediating Effect Analysis

Table 5. Direct, Indirect and Total Effects Analysis (5,000 Bootstrap Resamples)

Mediation Path	Coefficient (B)	95% CI for B	Statistical Decision
Direct Effect: SI → BI	0.12	[−0.03; 0.25]	Non-Significant
H8a: SI → PR → BI	−0.01	[−0.07; 0.05]	Non-Significant
H8b: SI → TR → BI	0.56	[0.35; 0.77]	Significant
H8c: SI → TR → PR → BI	0.23	[0.10; 0.38]	Significant
Total Indirect Effect	0.78	[0.63; 0.95]	Significant
Total Effect (SI → BI)	0.90	[0.74; 1.04]	Significant

As detailed in Table 5, the results demonstrate a pattern of indirect-only (full) mediation through Trust (Zhao et al., 2010). Specifically, the simple indirect path through Trust (H8b: B = 0.56, 95% CI [0.35, 0.77]) and the sequential indirect path through Trust and Perceived Risk (H8c: B = 0.23, 95% CI [0.10, 0.38]) were statistically significant, as their 95% bias-corrected bootstrap confidence intervals excluded zero (Preacher & Hayes, 2008). Conversely, the isolated indirect path through Perceived Risk (H8a: B = -0.01) was non-significant.

5.5. Moderating Effect Analysis

Testing Hypothesis H9 (Usage Experience):

To evaluate the moderating role of usage experience (H9), the dataset was bifurcated based on adoption duration: low-experience users (< 1 year; n = 76) and high-experience users (≥ 1 year; n = 80). A two-stage moderated regression analysis revealed that the interaction term (SI x Low Experience) was statistically non-significant (B = 0.003, 95% CI [-0.34, 0.37]). Conversely, partial least squares multi-group analysis (PLS-MGA; Cheah et al., 2020; Henseler et al., 2016) indicated an unexpected directional contrast: the direct path from Social Influence to Behavioral Intention was negative in the low-experience cohort (B = -0.21) but positive in the high-experience cohort (B = 0.23), yielding a significant path difference of -0.44 (95% CI [-0.88, -0.07]). This implies that social influence exerts a stronger influence among more experienced users, opposite to theoretical expectations.

The divergence between the interaction model and PLS-MGA is attributable to structural parameter constraints: the interaction model imposes equality constraints across remaining model parameters, whereas MGA allows unconstrained estimation of all structural paths across subgroups (e.g., the path from Trust to Intention was B = 0.96 for low-experience vs. B = 0.50 for high-experience users; difference = 0.47, 95% CI [-0.06, 0.99]). Consequently, *Hypothesis H9 was not supported.*

Testing Hypothesis H10 (Generational Cohort):

Hypothesis H10 posited that the negative relationship between Perceived Risk and Behavioral Intention is amplified among older consumers. When isolating the pre-1981 age cohort (n = 25), the interaction coefficient PR x Older Cohort) was positive (B = 0.27, 95% CI [0.02, 0.52]), indicating that the inverse effect of perceived risk on intention was attenuated (weaker) rather than strengthened in this demographic.

To mitigate information loss associated with artificial categorization (Dawson, 2014), a supplementary robustness check modeled age as a continuous moderator, yielding a non-significant interaction term (B = 0.06, 95% CI [-0.04, 0.18]). Given the small sample size of the older sub-segment (n = 25), the empirical test suffered from constrained statistical power, increasing the risk of Type II errors (Hair et al., 2022; Matthews, 2017). Therefore, these exploratory findings must be interpreted with caution; *Hypothesis H10 was not supported* and warrants further validation with larger, representative samples of older adopters.

VI. DISCUSSION

Trust in the mobile payment provider emerged as the most dominant determinant of behavioral intention (β = 0.54) while substantially attenuating perceived risk (β = -0.75, $p < 0.001$). These findings align with foundational e-commerce literature (Gefen et al., 2003) and recent empirical evidence in Vietnam (Truong, 2025; Truong & Nguyen, 2025), underscoring trust as an essential condition in digital financial transactions. Conversely, this result diverges from To and Trinh (2021), who observed no direct linkage between trust and mobile wallet behavioral intention. Such divergence may be attributed to sampling variations, differences in measurement operationalization, or the high bivariate correlation between Trust and Intention (r = 0.83), warranting cautious construct discrimination in future studies.

Although Social Influence exerted a substantial total effect on behavioral intention (B = 0.90, p < 0.001), its direct effect was statistically non-significant. Instead, interpersonal social pressure strongly reinforced institutional trust (β = 0.71, p < 0.001), which in turn fully transmitted the effect to behavioral intention. This mechanism contrasts with traditional technology acceptance models assuming that social influence directly mitigates perceived risk (Karahanna et al., 1999; Yang et al., 2012). In the Vietnamese emerging market, word-of-mouth recommendations serve mainly vouch for the provider's credibility rather than technical risk reducers. Although collectivistic cultural dynamics (Hofstede, 2001) might explain this reliance on social cues, individual-level cultural traits were not explicitly measured, precluding definitive cultural attributions.

Even after controlling for provider trust, Perceived Risk retained an independent negative effect on behavioral intention (B = -0.32, β = -0.29, p < 0.001), displaying stability across multiple measurement specifications. This contrasts with Nguyen (2024) and Truong (2025), where risk effects became non-significant. Among the reliable risk dimensions, privacy concerns (M = 5.46) and security/fraud anxiety (M = 4.94) outweighed financial loss fears (M = 4.13). This pattern closely reflects the current threat environment, as 84% of respondents reported personal or peer exposure to digital fraud (36.5% experienced actual financial loss or near-miss incidents).

Behavioral intention strongly predicted actual usage behavior (β = 0.56, p < 0.001). However, because both variables were self-reported within the same cross-sectional instrument, common method variance may artificially inflate this path coefficient. Furthermore, as the analytical sample comprised existing users, intention operationalizes post-adoption continued usage rather than initial service trial.

Neither usage experience (H9) nor generational cohort (H10) received empirical support. Multi-group analysis revealed a counter-intuitive pattern, with social influence demonstrating stronger effects among experienced adopters. Finally, the restricted sample size of the pre-1981 cohort (n = 25) resulted in low statistical power, precluding firm generalizations regarding generational behavioral disparities.

IV. CONCLUSION

This study evaluates the structural relationships among social influence, perceived risk, and provider trust in predicting behavioral intention and actual usage behavior of mobile payments, drawing upon an empirical sample of 156 users in Vietnam. The structural results indicate that trust in the provider serves as the most potent determinant of behavioral intention (β = 0.54) while substantially mitigating perceived risk. Even after controlling for provider trust, perceived risk exerts a persistent negative direct effect on behavioral intention (β = -0.29). Behavioral intention strongly predicts actual usage behavior (β = 0.56).

Notably, social influence demonstrates no statistically significant direct effect on either behavioral intention or perceived risk when trust is specified in the structural system; however, its total effect remains substantial (B = 0.90), operating almost entirely through full mediation via trust. Moderating hypotheses regarding usage experience and generational cohort were not empirically supported.

Given the sub-optimal covariance-based measurement model fit, uneliminated potential for common method bias (CMB), and a sample restricted to post-adoption existing users, these findings should be interpreted as preliminary empirical evidence. Future research should deploy larger and more geographically diverse samples alongside refined measurement scales to enhance generalizability and statistical robustness.

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