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Beyond Intention: Understanding Actual Fintech Usage in Rural Vietnam Through Trust and Social Influence

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ABSTRACT

While digital payment services have expanded rapidly in Vietnam, adoption remains uneven in rural areas, where users often face infrastructural limitations and psychological and social barriers. Existing research has primarily focused on behavioral intention and applied fixed theoretical models, such as the Technology Acceptance Model (TAM) or Unified Theory of Acceptance and Use of Technology (UTAUT), which may not fully capture the realities of technology use in underserved communities. This study addresses these gaps by examining the effects of trust, perceived risk, and social influence on the actual use of digital payment (DP) services among rural users in northern Vietnam. A structural model was developed and tested using survey data collected from 463 individuals across Lang Son and Cao Bang provinces. Using structural equation modeling, the study finds that both trust and social influence are significant positive predictors of behavioral use, whereas perceived risk does not have a statistically significant impact. Furthermore, demographic factors such as age, education, occupation, income, and household size were unrelated to usage behavior, suggesting that perceptual and social variables outweigh structural ones in determining Fintech engagement in rural contexts. These findings underscore the significance of relational trust and community validation in sustaining digital behavior. By focusing on actual usage rather than intention, this study contributes a more grounded understanding of Fintech adoption. It offers a context-sensitive framework that extends prior research and provides actionable insights for promoting inclusive digital finance in marginalized populations.

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1. Introduction

In recent years, the proliferation of financial technology (Fintech) has significantly reshaped the financial services landscape across developing economies. In Vietnam, digital payment systems, including mobile wallets, QR-based transactions, and app-integrated banking, have witnessed rapid growth, driven by government initiatives, the expansion of digital infrastructure, and the private sector's increasing presence in rural markets [1–3]. Despite these advances, digital payment usage remains uneven across regions, particularly in rural and mountainous areas, where financial exclusion, digital illiteracy, and social inertia continue to impede widespread adoption [4–7].

While earlier studies have identified technological access and infrastructural barriers as key limitations to Fintech adoption, more recent research suggests that perceptual and behavioral factors, including trust, perceived risk, and social influence, are dominant explanations, especially among rural populations [4, 5, 8, 9]. In such contexts, where exposure to formal financial institutions is limited, psychological assurance and normative cues often substitute for technical familiarity or institutional trust [10, 11]. For instance, studies have shown that even when access to digital payment platforms is available, rural users may refrain from using them due to concerns over transaction safety, a lack of transparency, or social unfamiliarity with the technology [12–14].

Despite these insights, much of the existing literature focuses on intention to use rather than actual behavioral engagement. This reliance on intention-based models, such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT), may not adequately capture the lived realities of digital behavior in low-infrastructure or community-centered environments. As such, the drivers of real-world usage, particularly among current users in rural areas, remain underexplored. Moreover, studies often rely on pre-defined theoretical frameworks, which may overlook local nuances or context-specific determinants of adoption [12, 15, 16].

This study seeks to address these gaps by examining the extent to which trust, perceived risk, and social influence influence the actual use of digital payments among rural users in Vietnam. Rather than adopting a fixed theoretical model, the study develops a context-driven structural model. It empirically tests it using survey data from 463 users in Lang Son and Cao Bang provinces. Focusing on behavioral use rather than intention, the study aims to provide a more grounded understanding of Fintech engagement in underserved communities.

This research makes three key contributions. First, it shifts the analytical focus from behavioral intention to actual usage, providing a more realistic assessment of Fintech behavior in rural contexts. Second, it validates a context-sensitive model that highlights the central role of trust and social norms, rather than structural access or system features, in shaping digital behavior. Third, it builds upon and extends existing empirical research from Vietnam by integrating findings from several recent studies, many of which have examined similar populations but with differing analytical scopes [12, 17]. In doing so, the study provides both theoretical insights and actionable implications for promoting inclusive digital finance in underrepresented regions.

Accordingly, this study aims to investigate the behavioral use of digital payment services in rural Vietnam, with a particular focus on the influence of trust, perceived risk, and social influence. By analyzing survey data collected from Lang Son and Cao Bang provinces, the study aims to validate a context-sensitive structural model that captures the actual usage behavior of rural users. The objective is to provide empirical evidence that informs both academic understanding and policy design for promoting inclusive Fintech adoption in underserved communities.

2. Theoretical Background

Although previous studies on technology adoption often rely on structured models such as the TAM or the UTAUT, these frameworks do not fully capture the behavioral dynamics observed in rural Fintech users in Vietnam. In particular, perceived usefulness or effort expectancy is less relevant in settings where users may lack prior experience or adequate infrastructure.

Therefore, instead of relying on a single theoretical model, this study adopts a construct-based approach that integrates key determinants commonly found in digital financial service literature: trust, perceived risk, and social influence. These variables are selected based on their demonstrated explanatory power in prior empirical studies, especially those conducted in emerging markets and rural contexts. This approach allows for a more flexible and context-sensitive model that reflects the socio-psychological realities of Fintech usage among rural populations. These constructs are discussed in the following sections, along with the rationale for their inclusion and corresponding hypotheses.

Behavioral use refers to the actual engagement with digital payment systems beyond mere intention. While many studies focus on behavioral intention as an outcome, this research adopts a more behaviorally grounded perspective by examining actual usage patterns. This aligns with calls in recent literature to move beyond intention-based metrics toward real-world usage, especially in rural contexts where behavioral intention may not translate into action[8, 18–20]. In our study, behavioral use (BU) is defined as the actual usage behavior of digital payment services, measured using four observed items on a 5-point Likert scale.

2.1. Trust and Fintech Use

Trust is considered a cornerstone in adopting technology-based financial services, especially in contexts where users may have limited prior exposure to formal financial systems[21]. In the domain of digital payments, trust reflects users' beliefs that the service provider will perform reliably, securely, and ethically[8, 22–24]. It includes perceptions of provider integrity, service accuracy, and personal data protection.

In rural areas where information asymmetry is prevalent, trust can serve as a substitute for technical understanding and act as a psychological enabler for adoption[5, 8, 23, 25]. Prior studies in Vietnam have confirmed that trust significantly influences both the intention and actual use of digital financial services, particularly in regions with low digital literacy and institutional access[22, 26, 27]. Therefore, we propose the following hypothesis:

H1. *Trust positively influences the behavioral use of digital payments.*

2.2. Perceived Risk and Fintech Use

Perceived risk refers to an individual's subjective evaluation of the potential adverse outcomes associated with using digital financial services. These risks include concerns about data breaches, economic loss, transaction failure, and system unreliability[8, 22, 25, 27]. According to perceived risk theory, users who perceive higher levels of uncertainty and potential loss are less likely to adopt or continue using such services.

Although risk perception often deters initial adoption, its effect on actual behavioral use is less conclusive, especially once users gain experience. Prior studies in Vietnam suggest that perceived risk can still reduce the frequency and depth of usage among rural consumers[8, 22, 27]. Therefore, the following hypothesis can be formulated:

H2. *Perceived risk negatively influences behavioral use of digital payments.*

2.3. Social Influence on Technology Adoption

Social influence represents the degree to which individuals perceive that others believe they should use a particular technology[28–30]. This concept is grounded in UTAUT and is particularly relevant in collectivist cultures, where peer norms and community perceptions significantly influence behavior[29, 31].

In rural Vietnamese communities, individuals often rely on family, local leaders, and social media narratives when making decisions related to technology. Previous

studies have confirmed that social influence plays a significant role in shaping behavioral intentions and the adoption of Fintech services [12, 32, 33]. In line with the above argument, we propose the following hypothesis:

H3. *Social influence has a positive effect on the behavioral use of DPs*

The detailed survey items corresponding to the constructs of Behavioral Use (BU), Trust (TR), Perceived Risk (PR), and Social Influence (SI) are provided in **Appendix A**.

2.4. Control Variables

To isolate the effects of psychological and social factors, several demographic variables are included as controls: age, education, occupation, income, and household size. In this study, household size (HH size) refers to the number of individuals living in the same household and is treated as a discrete numerical control variable. Prior studies suggest these may moderate or confound the effects of trust, risk, and social norms. For instance, older individuals or those with lower educational attainment may adopt Fintech differently compared to younger or more educated users [5, 8, 23, 25, 34].

Accordingly, the following hypotheses are proposed:

**H4.** *Age is positively associated with behavioral use of DPs*

H5. *Education level is positively associated with behavioral use of DPs*

H6. *Job status is positively associated with behavioral use of DPs*

H7. *Income level is positively associated with behavioral use of DPs*

H8. *Household size is positively associated with behavioral use of DPs*

The conceptual framework is presented in **Figure 1**.
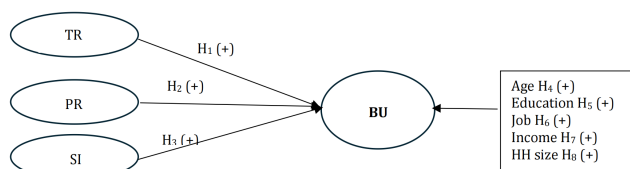
Figure 1. Conceptual framework.

3. Materials and Methods

3.1. Data Collection

This study employed a quantitative survey approach to collect primary data from rural populations in Northern Vietnam, specifically in Lang Son and Cao Bang provinces. These provinces were selected due to their representative characteristics of mountainous regions, such as low population density, limited access to formal financial services, and slower digital transformation. These features provide a meaningful context for investigating the behavioral use of Fintech in underserved rural areas [5, 17].

A total of 463 valid responses were obtained through structured face-to-face interviews with residents between December 2024 and January 2025. Eligible respondents were adults aged 18 and above who had used at least one form of electronic payment, such as mobile wallets, QR code payments, or online banking, within the past six months. Focusing on actual users enables the study to explore behavioral use rather than just behavioral intention, thereby addressing a gap in the existing Fintech adoption literature.

The survey instrument was developed based on validated measurement items from prior research in technology acceptance and Fintech adoption and was modified to reflect the rural Vietnamese context. A pilot study involving 30 rural respondents was conducted to assess the clarity, reliability, and cultural relevance of the items. After refining the questionnaire, trained enumerators, who were familiar with local dialects and customs, conducted the complete survey using face-to-face paper-based interviews to ensure comprehension and data quality.

The number of samples was determined based on the number of constructs in the model, following the guidance of Hair et al. (2019), which recommends a minimum sample size of 20:1 (20 observations per construct). With 4 primary constructs in our model, a minimum of 80 respondents would be required [35]. In practice, we directly surveyed 463 individuals from Lang Son and Cao Bang provinces, exceeding the required number.

Before the survey, we distributed a brief introduction about the study and instructions on voluntary participation. To encourage involvement in remote areas, each respondent who completed the interview received a small appreciation gift equivalent to approximately $2. The final dataset comprised 463 valid responses, all of which met the inclusion criteria and were included in the analysis.

This sampling procedure is consistent with prior studies conducted in similar rural and mountainous contexts in Vietnam [12, 17, 22]. All participants were informed about the voluntary nature of the study and were assured complete confidentiality and anonymity. No personally identifiable data were collected, and ethical standards for social science research involving human subjects were strictly followed.

3.2. Demographic Information

The demographic characteristics of the 463 participants are summarized in **Table 1**. The sample comprised respondents from two northern mountainous provinces: Cao Bang (54.64%) and Lang Son (45.36%). These areas were purposefully selected due to their representative nature of underserved rural populations, particularly in terms of challenges related to digital infrastructure and financial inclusion. Regarding gender, females accounted for 57.88% of the sample, indicating a slightly higher representation of women in Fintech use within rural settings. This aligns with recent findings suggesting that women in rural Vietnam increasingly participate in digital payment activities, particularly through household budgeting and remittance transactions [5, 27, 36].

Table 1. The demographic information of the participants.

Variable	Category	Frequency	Percent
Province	Lang Son	210	45.36
	Cao Bang	253	54.64
Gender	Female	268	57.88
	Male	195	42.12
Age	Under 20	5	1.08
	21–30	86	18.57
	31–40	242	52.27
	41–50	105	22.68
	51–60	140	30.24
	Over 60	5	1.08
Culture	Kinh	80	17.28
	Others	383	82.72
Educational level	None	10	2.16
	Primary school	32	6.91
	Secondary school	17	3.68
	High school	117	25.26
	Vocational School	24	5.18
	College, University	263	56.8
Income (Million VND/month)	Under 1	47	10.15
	2	72	15.55
	3	80	17.28
	4	110	23.76
	≥ 5	154	33.26
Household size (number of people in family)	1	2	0.43
	2	18	3.89
	3	61	13.17
	4	173	37.37
	5	99	21.38
	6	80	17.28
	> 6	30	6.49
Job	Farmer	197	42.55
	Others	266	57.45

Source: Author.

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The age distribution shows a significant concentration in the 31–40 age group (52.27%), followed by the 41–50 and 21–30 age groups. These figures suggest that Fintech adoption is most prevalent among economically active adults, who are likely to be responsible for household financial decisions. The very low representation of older adults highlights potential digital exclusion challenges among the elderly. A notable feature of the sample is its ethnic composition, with 82.72% of respondents belonging to non-Kinh minority groups. This reinforces the study's focus on marginalized rural communities and underlines the importance of culturally sensitive approaches to Fintech implementation. Prior studies have found that ethnic minorities often face higher barriers to digital service adoption, stemming from language differences, lower trust in financial institutions, and limited access to support [17, 26].

The educational profile of participants is relatively high, with 56.8% holding college or university degrees and another 25.26% having completed high school. This may reflect recent educational improvements in rural Vietnam, suggesting a certain level of digital readiness. However, respondents with only primary education (6.91%) or no formal schooling (2.16%) indicate a continued digital divide that could impact Fintech engagement and risk perceptions.

Regarding income, around one-third of respondents reported a monthly household income of 5 million VND or more (33.26%), indicating a relatively stable economic condition among a portion of the sample. Nevertheless, nearly 43.5% earn between 2 and 4 million VND, and 10.15% fall below the 1 million VND threshold, reflecting ongoing income disparities in rural areas. This heterogeneity is particularly relevant when examining perceptions of the cost, trustworthiness, and utility of Fintech platforms. The household size data indicate that most participants live in medium to large families, with 37.37% having four members or more and over 45% having five or more members. Larger households may influence the perceived usefulness and shared use of digital financial tools, especially for inter-household transfers or bill payments.

Regarding occupation, 42.55% of respondents were farmers, while the remaining 57.45% were involved in other types of employment, including retail, services, and public administration. This occupational mix highlights the diversification of income sources in rural regions, suggesting varying needs and risk perceptions in financial service usage. The demographic profile supports the study's aim to investigate actual Fintech use in socially and economically diverse rural communities, where cultural norms, education levels, and livelihood strategies may uniquely influence trust, risk, and social influence.

3.3. Statistical Methods

The analysis was conducted in several stages, utilizing a combination of descriptive statistics, scale validation, and structural equation modeling (SEM). First, the data were screened for completeness and accuracy, and then basic descriptive statistics were generated to summarize the sample characteristics. The reliability of each latent construct was examined using Cronbach's alpha, with a threshold of 0.70 employed to indicate internal consistency.

An Exploratory Factor Analysis (EFA) was performed to explore the underlying factor structure using principal axis factoring with varimax rotation. Items with factor loadings below 0.5 were considered for removal. The Kaiser confirmed the appropriateness of the data for factor analysis, as indicated by the Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. Following EFA, Confirmatory Factor Analysis (CFA) was conducted to assess the validity of the measurement model. The composite reliability (CR) and average variance extracted (AVE) were calculated to assess internal consistency and convergent validity.

The structural relationships among the latent variables were examined using covariance-based SEM, which employed robust maximum likelihood estimation to account for the non-normality of the data, as indicated by Mardia's test. Model fit was evaluated based on several indices, including the chi-square/degrees of freedom ratio (χ^2/df), Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), and Root Mean Square Error of Approximation (RMSEA). Acceptable thresholds were based on guidelines proposed by Hair et al. [35] and Kline [37]. All statistical analyses were performed using

Stata 17.0 and SPSS 26.0, with SEM conducted via the SEM Builder module in Stata.

This study employs covariance-based Structural Equation Modeling (CB-SEM) using Robust Maximum Likelihood Estimation (MLR) to account for the non-normality of Likert-scale data, following the recommendations of Hair et al.[35] and Kline[37]. The following Equation (1) can represent the structural model of this study.

$$BU = \beta_1 * TR + \beta_2 * PR + \beta_3 * SI + \sum_{i=4}^{8} \beta_i * CV_i + \varepsilon \tag{1}$$

Where:

BU = Behavioral use of digital payments (dependent variable)

TR = Trust

PR = Perceived risk

SI = Social influence

CV = Control Variables (Age, Education, Job, Income, Household size)

ε = Error term

4. Empirical Results

4.1. Reliability and Validity Test

To ensure the internal consistency and construct validity of the measurement model, several reliability and EFA tests were performed. The results indicate that the overall measurement model demonstrates high reliability. Specifically, the total Cronbach's alpha was 0.926, which exceeds the commonly accepted threshold of 0.70, indicating strong internal consistency across all scales.

Table 2 shows that all individual constructs also demonstrated high reliability, with Cronbach's alpha coefficients ranging from 0.920 to 0.924. Each construct (BU, TR, PR, and SI) consisted of 4–5 observed indicators showing excellent consistency. This confirms that the items within each latent variable reliably measure the same underlying concept. The EFA was conducted to assess the unidimensionality and factor structure of the observed variables. The KMO measure of sampling adequacy was 0.896, satisfying the recommended threshold of 0.5 < KMO < 1. This suggests that the sample size and data were appropriate for factor analysis. Additionally, Bartlett's test of sphericity was highly significant (χ^2 = 6714.54, p < 0.001), confirming the suitability of the dataset for EFA.

Table 2. The results of Cronbach's alpha and exploratory factor analysis.

Variable	Cronbach's Alpha (CA)	Factor1	Factor2	Factor3	Factor4
BU1	0.923			0.817	
BU2	0.922			0.874	
BU3	0.922			0.810	
BU4	0.922			0.823	
TR1	0.920		0.749		
TR2	0.920		0.778		
TR3	0.920		0.824		
TR4	0.920		0.844		
TR5	0.921		0.764		
PR1	0.924	0.837			
PR2	0.922	0.878			
PR3	0.922	0.876			
PR4	0.921	0.827			
PR5	0.924	0.822			
SI1	0.921				0.834
SI2	0.921				0.852
SI3	0.921				0.667
SI4	0.922				0.670

Note: KMO= 0.896 the Bartlett test χ2 = 6714.54 , p-value = 0.000.
Source: Authors.

The EFA extracted four distinct factors from the 18 observed items, with an eigenvalue greater than 1 (1.292) and a total explained variance of 71.34%, indicating a strong underlying factor structure. All items had factor loadings ranging from 0.667 to 0.878, which exceeded the commonly accepted minimum threshold of 0.5. These loadings support the convergent validity of the measurement model, indicating that each item strongly correlates with its respective construct.

Furthermore, the structure of the extracted components was consistent with prior theoretical frameworks and empirical studies on Fintech adoption [29, 35, 38]. The four constructs (BU, TR, PR, and SI) aligned with the hypothesized measurement model and were retained for further SEM.

To further evaluate the validity and reliability of the measurement model, a confirmatory factor analysis (CFA) was conducted using the maximum likelihood estimation method. The results support a well-fitting and theoretically sound model. All standardized factor loadings were statistically significant at the 1% level, ranging from 0.705 to 0.914, indicating that each observed item strongly reflected its respective latent construct.

Table 3. The results of confirmatory factor analysis.

Items	Coef.	OIM Std. Err	P-Value	Composite Reliability (CR)	Average Variance Extracted (AVE)
Behavioral of Use- BU				0.913	0.725
BU1	0.787	0.019	0.000		
BU2	0.914	0.011	0.000		
BU3	0.827	0.017	0.000		
BU4	0.874	0.014	0.000		
Trust- TR				0.922	0.704
TR1	0.812	0.022	0.000		
TR2	0.828	0.018	0.000		
TR3	0.887	0.014	0.000		
TR4	0.859	0.015	0.000		
TR5	0.767	0.023	0.000		
Perceived of Risk -PR				0.855	0.663
PR1	0.797	0.022	0.000		
PR2	0.864	0.015	0.000		
PR3	0.902	0.012	0.000		
PR4	0.847	0.016	0.000		
PR5	0.789	0.019	0.000		
Social Influence - SI				0.876	0.706
SI1	0.705	0.033	0.000		
SI2	0.705	0.033	0.000		
SI3	0.844	0.030	0.000		
SI4	0.822	0.032	0.000		

Note: LR test of model vs. saturated: chi2 (119) = 390.572   Prob > chi2 = 0.0000.
Source: Authors.

As shown in **Table 3**, the composite reliability (CR) values of the four latent constructs (BU, TR, PR, SI) were above the recommended threshold of 0.70, ranging from 0.855 to 0.922. These results confirm that the internal consistency of the constructs is robust. Moreover, the average variance extracted (AVE) values, which ranged from 0.663 to 0.725, exceed the benchmark of 0.50, suggesting that each construct explains more than half of the variance of its indicators. Together, these indicators confirm the convergent validity of the measurement model.

In addition to reliability and convergence, the model exhibited satisfactory global fit statistics. The chi-

square value divided by degrees of freedom (χ^2/df) was 3.282, within the acceptable range for a moderately fitting model. More importantly, the Comparative Fit Index (CFI) and the Tucker–Lewis Index (TLI) were 0.959 and 0.948, respectively, exceeding the conventional threshold of 0.90. Furthermore, the Root Mean Square Error of Approximation (RMSEA) was 0.07, and the Standardized Root Mean Square Residual (SRMR) was 0.04, both falling within acceptable boundaries[35, 37]. The likelihood ratio (LR) test also yielded a significant result ($\chi^2(119) = 390.572$, $p < 0.001$), confirming the model's goodness of fit compared to a saturated baseline.

Taken together, the results of the CFA provide strong empirical support for the construct validity and reliability of the measurement model. The identified factor structure aligns with theoretical expectations and prior literature, justifying its use in the subsequent structural model analysis.

4.2. Structural Equation Model

Figure 2 and **Table 4** display the estimation results of the model using the SEM method. The overall model demonstrated an acceptable fit to the data, with a χ^2/df ratio of 4.076, a CFI of 0.905, and a TLI of 0.888. Additionally, the RMSEA was 0.08, and the Standardized Root Mean Square Residual (SRMR) was within the acceptable range. These results suggest that the proposed model accurately fits the empirical data.
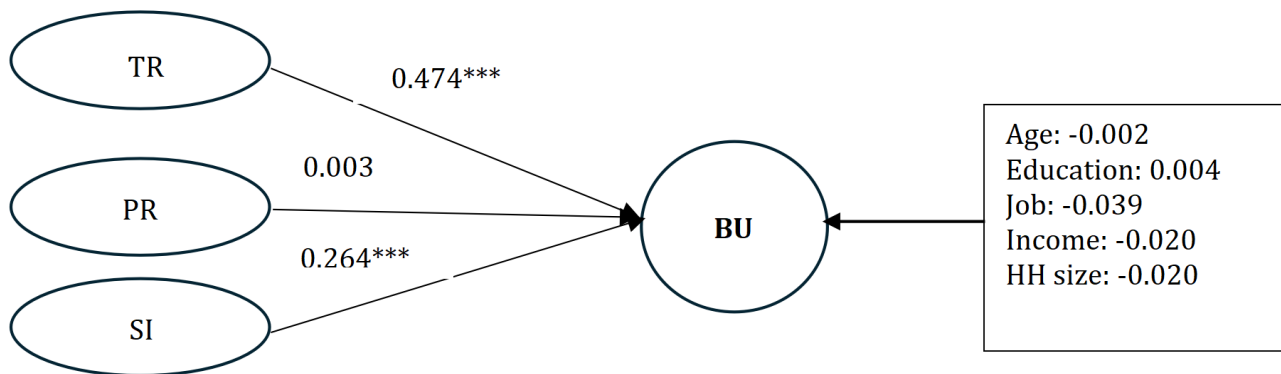
Figure 2. The results of the structural equation model.

Table 4. The results of the structural equation model.

Variable	Coef.	Std. Err	z- Value	p-Value
TR	0.474	0.059	7.98	0.000
PR	0.003	0.039	0.08	0.933
SI	0.264	0.061	4.33	0.000
Age	−0.002	0.004	−0.53	0.599
Education	0.004	0.009	0.47	0.638
Job	−0.039	0.085	−0.46	0.646
Income	−0.020	0.032	−0.63	0.526
HHsize	−0.020	0.022	−0.90	0.368

Note: LR test of model vs. saturated: chi2 (207) = 843.765   Prob > chi2 = 0.0000.
Source: Authors.

As shown in **Table 4**, TR was found to have a strong and statistically significant positive influence on BU at a 1% level, confirming the relevance of trust in determining individuals' continued engagement with Fintech services. SI also exhibited a positive and significant effect at 1% on BU, indicating that social norms and peer pressure are meaningful contributors to Fintech usage among rural users. In contrast, the relationship between PR and BU was not statistically significant, suggesting that perceived risk may not directly shape actual usage behavior in the sample population.

The analysis also incorporated several control variables: age, education level, occupation, income, and household size. However, none of these covariates

showed statistically significant effects on behavioral use. This implies that the main predictors in the model–trust and social influence—have greater explanatory power in this context than socio-demographic characteristics. The model's goodness-of-fit was further supported by the likelihood ratio (LR) test, which compared the structural model to a saturated model and yielded a statistically significant chi-square value ($\chi^2(207) = 843.765$, p < 0.001). This confirms the appropriateness of the model structure and its adequacy for explaining variance in the observed data.

4.3. Additional Analysis

Multivariate normality was evaluated using Mardia's tests for skewness and kurtosis. The results showed significant deviations from normality, with a multivariate skewness value of 95.744 ($\chi^2(1140) = 7441.198$, p < 0.001) and a multivariate kurtosis value of 660.624 ($\chi^2(1) = 14529.000$, p < 0.001). These results indicate that the dataset does not fully meet the assumption of multivariate normality. However, given the robustness of the estimation technique, the model remained appropriate for SEM. In line with prior studies using similar survey-based data, the analysis used robust maximum likelihood estimation to mitigate potential biases associated with non-normality. This approach ensures the stability of the parameter estimates and the validity of the model's overall fit despite statistical deviations from a normal distribution.

Mardia mSkewness = 95.744	chi2(1140) = 7441.198	Prob>chi2 = 0.0000
Mardia mKurtosis = 660.624	chi2(1) =14529.000	Prob>chi2 = 0.0000

5. Discussion

5.1. The Main Findings

The findings from the structural model offer valuable insights into the behavioral use of digital payment systems among rural users in Vietnam. Among the hypothesized relationships, trust was found to have a substantial and statistically significant positive effect on behavioral use (BU), thereby confirming Hypothesis 1. This result aligns with the literature that emphasizes the role of trust in environments characterized by low digital literacy and limited institutional safeguards. In such settings, trust in the reliability, accuracy, and safety of service providers is a key enabler of technology use. This finding is consistent with prior studies conducted in Vietnam [8, 22, 27], which highlight that trust can substitute for users' lack of technical understanding and mitigate concerns about uncertainty. The substantial magnitude of the effect also underscores the practical importance of trust-building mechanisms in expanding Fintech adoption in rural contexts.

Contrary to our expectations, the effect of perceived risk on behavioral use was not statistically significant, providing no support for Hypothesis 2. Although perceived risk is often cited as a barrier to the adoption of technology, especially in financial contexts, its influence appears to diminish once users have experienced the service. This outcome suggests that while risk perceptions may initially deter adoption, they do not significantly impact continued usage behavior among those already engaged in digital payments. Similar findings have been reported in recent studies [5, 25, 27, 39], which suggests that actual users tend to adjust their perception of risk over time, particularly when usage is reinforced by social trust or institutional legitimacy.

The relationship between social influence and behavioral use was also statistically significant and positive, supporting Hypothesis 3. This confirms that the opinions and encouragement of family members, peers, and local authorities play a meaningful role in shaping the usage behavior of rural users. In collectivist societies such as Vietnam, community validation can often substitute for institutional trust, and users tend to follow the behaviors and experiences of those around them. These results are in line with the core arguments of the UTAUT model [28]. They are consistent with recent empirical studies conducted in Northern Vietnam [12, 17], which shows that social norms and perceived expectations strongly influence Fintech behavior.

In terms of control variables, none of the demographic factors included in the model, such as age, education, job, income, and household size, were found

to have a statistically significant relationship with behavioral use. This suggests that once trust and social influence are accounted for, socio-demographic characteristics do not directly influence actual usage behavior. The finding contrasts with studies that highlight the digital divide in Fintech adoption. Still, it supports the argument that simplified access through mobile platforms and local promotion efforts may have lowered traditional barriers to use. In other words, behavioral use of DP services may be increasingly shaped by perceptual and social factors rather than by users' structural conditions.

The structural model provides empirical support for two of the three primary constructs hypothesized to influence the behavioral use of digital payment services. Specifically, trust and social influence were significant and positive predictors, underscoring their central roles in shaping user behavior in rural contexts. In contrast, the perceived risk did not significantly affect actual usage, suggesting that concerns about security and uncertainty may diminish once individuals have adopted the service. Additionally, demographic factors such as age, education, job, income, and household size were not found to have a meaningful impact, highlighting the predominance of perceptual and social variables over structural ones in explaining Fintech use in underserved communities.

5.2. Theoretical Implications

The findings of this study offer several essential contributions to the theoretical understanding of Fintech adoption in underserved contexts. First, the study addresses a critical gap in the adoption literature by focusing on actual behavioral use rather than intention. While much of the existing research in Fintech and technology acceptance has centered on intention-based models, such as TAM or UTAUT, this study emphasizes real-world usage behavior, thereby enhancing the external validity of prior models. The observed divergence between perceived risk and behavioral use is particularly noteworthy. It suggests that constructs traditionally influential at the intention stage may lose explanatory power once users transition to active usage. This finding aligns with calls in the literature to distinguish more clearly between the drivers of intention and those of behavior, and it encourages future models to consider stage-specific effects in Fintech adoption.

Second, the study demonstrates the explanatory power of a construct-based model that integrates trust, perceived risk, and social influence without relying on a predefined theoretical framework. By doing so, it highlights the flexibility and contextual adaptability of these constructs, particularly in settings where classical assumptions, such as rational utility maximization or technical ease of use, may not be applicable. This approach enables the model to capture context-specific factors that shape usage, such as relational trust or communal decision-making, which are particularly salient in rural and collectivist environments. The significance of trust and social influence further reinforces the notion that perceptual and social mechanisms often override structural barriers in digital inclusion.

Finally, the lack of significance for demographic variables challenges long-standing assumptions about the digital divide and the role of structural determinants in technology use. While previous theories have often emphasized the influence of age, education, and income, the present findings suggest that these variables may be less predictive in inclusive, mobile-first Fintech ecosystems. This theoretical shift invites future research to revisit the foundational assumptions of user segmentation and explore how perceptual and social variables may offer more explanatory power in emerging markets and digitally underserved populations.

5.3. Practical Implications

The results of this study offer several practical insights for Fintech providers, policymakers, and local development actors aiming to promote digital financial inclusion in rural areas. First, the central role of trust in driving behavioral use suggests that service providers should prioritize building and maintaining user confidence. This extends beyond ensuring technical security to include visible commitments to reliability, responsiveness, and transparency. In rural settings, where users often rely on informal networks and word-of-mouth information, minor service disruptions or opaque fee structures can quickly erode public confidence. Providers

should, therefore, invest in localized customer service, clear communication about risks and safeguards, and user education tailored to low-literacy audiences.

Second, the significant influence of social norms underscores the need for community-based approaches to promoting Fintech. Rather than relying solely on top-down campaigns, interventions should leverage existing social networks such as village leaders, peer groups, or women's associations to disseminate trust-based information and model usage behavior. In collectivist environments, such as rural Vietnam, the decision to adopt and maintain usage is often socially mediated, and visible endorsement from respected figures can help overcome hesitation. Programs involving trusted community actors in education and implementation are more likely to gain traction than impersonal digital outreach alone.

The findings also suggest that lowering perceived risk may not be sufficient to sustain usage, particularly once users have become accustomed to the service. Instead, efforts should focus on reinforcing positive user experiences, reducing transaction friction, and offering consistent incentives that normalize digital behavior over time. For example, integrating digital payments into routine activities, such as agricultural subsidies, school fees, or healthcare payments, can help embed the technology into everyday life. Moreover, government and donor-backed programs should shift from awareness-building to habit-formation strategies, ensuring that digital usage becomes not only acceptable but also convenient and habitual.

Lastly, the non-significant effects of demographic variables imply that Fintech services in these areas have achieved a degree of accessibility across age, education, and income groups. This is an encouraging sign for financial inclusion. Still, it also places greater responsibility on providers and regulators to ensure equitable service quality and protection for all users, especially the most vulnerable. Targeted safeguards against fraud, grievance redressal mechanisms, and digital literacy support should be designed with attention to the unique needs of first-time or infrequent users.

These findings provide actionable insights for both Fintech designers and rural policymakers, particularly in establishing community trust channels and promoting peer-led adoption behaviors.

5.4. Limitations and Future Directions

While the findings of this study offer meaningful insights into the drivers of digital payment usage in rural Vietnam, several limitations should be acknowledged. First, the data were collected using a cross-sectional design, which restricts the ability to make causal inferences or observe behavioral changes over time. Future studies could employ longitudinal or panel designs to capture the dynamic evolution of trust, risk perception, and social influence as users become more experienced with digital financial services.

Second, the study focused exclusively on actual users of digital payments, which may have introduced a self-selection bias. Individuals who had never used such services were not represented in the sample, which limited the ability to generalize the findings to the broader rural population. Comparative studies that incorporate both users and non-users would provide a more comprehensive understanding of adoption barriers and motivational differences across user segments.

Third, although the study employed robust estimation methods and tested a well-grounded structural model, the set of explanatory variables was necessarily limited. Constructs such as digital literacy, habit, technology anxiety, or government support, each of which may play a significant role in rural adoption contexts, were beyond the scope of the current model. Future research could explore these dimensions or expand the model to capture interactions between psychological and infrastructural factors.

Lastly, the study was conducted in two northern mountainous provinces of Vietnam, which, although representative of rural conditions, may differ from other regions in terms of socio-cultural or economic characteristics. Replication studies in other rural or semi-urban settings would strengthen the generalizability of the findings and enable regional comparisons.

Despite these limitations, this study provides meaningful theoretical and practical contributions. It demonstrates how behavioral use in rural settings is driven by social trust and influence and suggests pathways for inclusive Fintech diffusion strategies.

6. Conclusion

This study contributes to the growing body of literature on digital financial services by examining the behavioral use of digital payment systems in a rural Vietnamese context. By focusing on actual usage behavior rather than mere intention, the study provides a more grounded understanding of what drives technology adoption in underserved communities. The findings reveal that trust and social influence are key determinants of usage, underscoring the importance of psychological assurance and community validation in promoting digital payment behavior. In contrast, the perceived risk does not deter continued use, suggesting that once users overcome initial concerns, their engagement is sustained by trust and social reinforcement.

Notably, the results show that demographic factors, such as age, education, occupation, and income, do not significantly influence usage behavior, indicating a diminishing role for traditional digital divides in contexts where Fintech platforms have become more accessible and inclusive. The study's construct-based approach centered on trust, risk, and social norms, offers a flexible and context-sensitive alternative to classical adoption models, especially in environments where standard theoretical assumptions may not hold.

These insights inform academic discourse and practical efforts to promote inclusive digital finance. The study provides a foundation for future research and policy interventions to close the last-mile gap in financial access by identifying the core perceptual and social mechanisms that drive usage.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data are available upon request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflict of interest.

Appendix A

Table A1. The survey.

	Items	Question	Source
Behavior of Use- BU	BU1	I have used digital payment (DP) services in the past month	Adapted from Oliveira et al. (2016); modified; Adapted from Venkatesh et al. (2003); modified for actual use context; Adapted from Zhou (2011); modified
	BU2	I use DP frequently in my daily transactions.	
	BU3	Using DP is part of my regular shopping behavior.	
	BU4	I feel confident when using DP instead of cash.	

Table A1. *Cont.*

Items		Question	Source
Trust- TR	TR1	I believe that the service provider always provides accurate DP services.	Gefen et al. (2003); Gefen et al. (2003); McKnight et al. (2002); Gefen et al. (2003); Zhou (2011); McKnight et al. (2002); Newly developed based on contextual insights
	TR2	I believe that DP service providers are professional and transparent in their operations.	
	TR3	I believe that the service provider always provides reliable DP services..	
	TR4	I believe that the service provider always provides safe DP services..	
	TR5	I believe that DPs are very safe and secure.	
Perceived of Risk -PR	PR1	I believe that using DP is riskier than paying with cash	Featherman & Pavlou (2003); Featherman & Pavlou (2003); Oliveira et al. (2016); Zhou (2011); Zhou (2011); modified
	PR2	I believe that DP may involve risks related to transaction execution and information security.	
	PR3	I believe that my personal information might be leaked or stolen when using DP.	
	PR4	I believe that using DP may encounter technical problems and system errors.	
	PR5	I believe that it is difficult to control and manage potential risks when using DP.	
Social Influence - SI	SI1	Encouragement from my family and relatives influenced my decision to use DP.	Adapted from Chen & Li (2020); context-specific; Adapted from Hajli (2014); modified; Venkatesh et al. (2003); Venkatesh et al. (2003); Taylor & Todd (1995)
	SI2	Positive feedback from friends and colleagues encourages me to use DP.	
	SI3	I follow the recommendations of local authorities when deciding to use DP.	
	SI4	How media and social networks portray DP affects my decision to use it.	

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