Anusandhanvallari
Vol 2024, No.1
December 2024
ISSN 2229-3388

Consumer Trust, Security Perception, and Resistance toward Cashless Payment Systems: Evidence from Madurai District

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Abstract

The rapid proliferation of cashless payment systems in India has transformed the financial landscape, yet adoption remains uneven across urban and semi-urban populations. This study investigates the interplay among consumer trust, security perception, and resistance toward cashless payment systems among residents of Madurai District, Tamil Nadu. Grounded in the Technology Acceptance Model (TAM), Innovation Resistance Theory (IRT), and the Trust-Risk framework, the study employs a quantitative cross-sectional research design with data collected from 400 respondents selected through stratified random sampling. Primary data were gathered using a structured questionnaire comprising five-point Likert-scale items validated for reliability (Cronbach's alpha > 0.80) and construct validity. Statistical techniques including descriptive statistics, exploratory factor analysis (EFA), Pearson correlation, multiple regression analysis, and structural equation modeling (SEM) were applied using SPSS 26.0 and AMOS 24.0. The findings reveal that consumer trust exerts a significant positive influence on cashless payment adoption, while security perception mediates the relationship between trust and adoption intention. Innovation resistance, driven largely by usage barriers and value barriers, significantly inhibits cashless payment uptake. Demographic variables including age, education, and income level moderate these relationships. The study contributes to the understanding of behavioral determinants in digital payment ecosystems within the South Indian context, offering actionable insights for fintech providers, commercial banks, and policymakers seeking to enhance digital financial inclusion.

Keywords: Cashless payments, consumer trust, security perception, innovation resistance, Technology Acceptance Model, digital financial inclusion, Madurai District

1. Introduction

The global financial ecosystem has witnessed an unprecedented shift from cash-based transactions to digital and cashless payment modalities over the past decade. In India, this transformation accelerated substantially following the demonetization policy of November 2016, the launch of the Unified Payments Interface (UPI) by the National Payments Corporation of India (NPCI), and more recently, the COVID-19 pandemic that further discouraged physical currency handling. Mobile wallets, internet banking, point-of-sale (POS) terminals, and QR code-based payments have collectively redefined how consumers engage with financial services (Dahlberg et al., 2015; Mishra & Bisht, 2019).

Despite considerable policy impetus and infrastructure development, the adoption of cashless payment systems in India remains heterogeneous. While metropolitan cities such as Chennai, Mumbai, and Bengaluru demonstrate relatively high digital payment penetration, semi-urban and tier-II cities continue to exhibit measurable resistance to the complete abandonment of cash. Madurai District, a historically and culturally significant urban center in Tamil Nadu with a mixed demographic profile encompassing traders, students, government employees, and agricultural laborers, presents an instructive case study for examining the socio-psychological determinants of cashless payment behavior.

Consumer trust and security perception have emerged as two of the most critical antecedents of technology adoption in financial services (Gefen et al., 2003; Kim et al., 2009). Trust represents a consumer's willingness to rely on a technology-mediated transaction partner despite inherent vulnerabilities, while security perception refers to the subjective assessment of the degree to which a payment system is free from unauthorized access, data breaches, and fraudulent activities. When these constructs are deficient, innovation resistance defined as the opposition or reluctance of consumers to accept new technologies that require behavioral change (Ram & Sheth, 1989) intensifies and delays or prevents adoption.

This study addresses an important lacuna in the digital payment adoption literature by examining how trust and security perception jointly shape resistance behavior in the specific socio-economic context of Madurai District. While extant research has explored digital payment adoption in urban India broadly, empirical investigations focusing on tier-II cities and incorporating the mediating role of security perception between trust and resistance remain sparse. Understanding these dynamics is crucial for designing targeted interventions that can accelerate digital financial inclusion in similar geographic contexts across South India and beyond.

The remainder of this manuscript is structured as follows: Section 2 presents a review of the relevant literature; Section 3 identifies the research gap; Section 4 articulates the study's objectives; Section 5 describes the research design and methodology; Section 6 presents statistical analysis and interpretation of findings; Section 7 offers conclusions and practical implications; and the final section provides a comprehensive list of references.

2. Review of Literature

2.1 Cashless Payment Systems and Adoption

Cashless payment systems encompass a broad spectrum of digital financial instruments including debit and credit cards, mobile payments, electronic funds transfers, internet banking, and more recently, cryptocurrency-based transactions. The Technology Acceptance Model (TAM) originally proposed by Davis (1989) remains the most widely applied theoretical framework for understanding adoption of information systems, positing that perceived usefulness and perceived ease of use are the principal determinants of behavioral intention to use a technology. Subsequent modifications, including TAM2 (Venkatesh & Davis, 2000) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), incorporated social influence, facilitating conditions, and hedonic motivation as additional predictors.

Srivastava et al. (2010) examined mobile payment adoption in India and found that perceived usefulness, ease of use, and social influence collectively explained approximately 62% of variance in adoption intention. Singh et al. (2020) extended this finding by demonstrating that government regulatory support and digital literacy moderated the adoption-intention relationship among rural consumers in Uttar Pradesh. Ozturk et al. (2017) and Oliveira et al. (2016) reported consistent patterns in hotel and retail contexts respectively, reinforcing the robustness of TAM-derived models across service industries.

In the South Indian context, Thakur (2013) and Krishnan and Teo (2012) found that mobile payment adoption was significantly influenced by perceived security and prior experience with digital banking. Consumers with higher digital literacy demonstrated lower activation inertia, a finding that has important implications for Madurai where educational attainment varies considerably across demographic segments.

2.2 Consumer Trust in Digital Payments

Trust is a foundational construct in electronic commerce and digital financial services (Pavlou, 2003). Mayer et al. (1995) conceptualized trust as encompassing three dimensions: ability (competence of the trustee), benevolence (positive intentions of the trustee toward the trustor), and integrity (adherence to acceptable principles). In the context of digital payments, trust extends to the technology infrastructure, the service provider, and the regulatory environment.

Gefen et al. (2003) demonstrated that institutional trust defined as the perception that structural conditions such as laws, regulations, and guarantees exist to safeguard the consumer was a stronger predictor of online purchase intention than cognitive trust in e-commerce platforms. Kim et al. (2009) further decomposed payment-specific trust into trust in the payment service provider and trust in the underlying technology, finding that both dimensions independently predicted adoption.

In India-specific research, Chawla and Joshi (2019) examined 384 consumers in Jaipur and found that interpersonal trust norms and institutional trust significantly influenced mobile payment adoption, particularly among first-time users. Roy and Sinha (2014) identified that prior positive experience with digital banking was the strongest predictor of trust, followed by provider reputation. Kesharwani and Bisht (2012) reported that trust-building mechanisms such as digital certificates, two-factor authentication, and consumer grievance redressal systems positively moderated the trust-adoption relationship.

Beldad et al. (2010) systematically reviewed 67 empirical studies and concluded that trust is universally and positively associated with online service adoption, irrespective of cultural context. More recently, Cham et al. (2022) found that trust-related factors were particularly salient in emerging market contexts where regulatory frameworks for digital commerce are still maturing, a condition that aptly characterizes India's digital payments ecosystem.

2.3 Security Perception and Digital Financial Behavior

Security perception occupies a central position in models of digital payment adoption and resistance. Defined as the subjective belief that a payment system provides adequate protection against unauthorized access and financial loss, security perception is distinct from objective security but often has a stronger influence on behavioral outcomes (Featherman & Pavlou, 2003). The Privacy-Trust-Behavioral Intention (PTB) model proposed by Malhotra et al. (2004) situates security perception as a mediating construct between informational privacy concerns and adoption behavior.

Luo et al. (2010) examined mobile banking adoption in the United States and China and found that perceived security risk, operationalized as the consumer's expectation of loss due to fraudulent transactions, was the strongest barrier to adoption in both cultural contexts, overriding the positive effects of usefulness and ease of use. Shaikh and Karjaluoto (2015), in a meta-analysis of 55 mobile banking studies, confirmed that security and privacy concerns consistently emerged among the top three inhibitors of adoption across studies conducted in Asia, Europe, and Africa.

Sharma et al. (2022) investigated security perception in the context of UPI payments among consumers in Tier-II Indian cities and found that personal data misuse concerns, phishing awareness, and SIM swap fraud experiences significantly depressed adoption intention even among technologically literate consumers. Raza et al. (2017) showed that in developing market contexts, where consumer financial protection laws are perceived as weak, security concerns have an amplified negative effect on trust, creating a compounding barrier to adoption.

Within Tamil Nadu specifically, Anbalagan and Krishnan (2020) surveyed 310 consumers in

Coimbatore and found that 67% of non-adopters cited data security concerns as their primary reason for avoiding digital payments, underscoring the need for region-specific interventions. Muthuvelayutham and Karuppasamy (2021) further demonstrated that security perception mediated the relationship between awareness of digital frauds and adoption resistance, a finding that motivates the mediation analysis central to the present study.

2.4 Innovation Resistance Theory

The Innovation Resistance Theory (IRT) developed by Ram (1987) and subsequently refined by Ram and Sheth (1989) provides a demand-side perspective on technology non-adoption by explicating the cognitive and behavioral mechanisms through which consumers resist change. IRT identifies two categories of barriers: functional barriers (usage, value, and risk barriers arising from performance-related concerns) and psychological barriers (tradition and image barriers arising from cultural norms and identity concerns).

Laukkanen et al. (2007) applied IRT to mobile banking adoption in Finland and found that usage barriers, particularly the complexity of transactions and poor user interface design, were the primary functional barriers, while tradition barriers related to habitual cash use were the most significant psychological barriers. Laukkanen et al. (2008) replicated these findings across five European countries, confirming the cross-cultural applicability of IRT in digital financial services.

In the Indian context, Madan and Yadav (2016) applied IRT to mobile wallet adoption among millennials in Delhi and found that risk barriers and usage barriers jointly accounted for 58% of variance in adoption resistance, while value barriers were moderated by income level. Sreejesh et al. (2020) demonstrated that tradition barriers were particularly prominent in communities with strong cash-handling norms, a finding highly relevant to Madurai where traditional commerce has historically relied on physical currency. Raman and Aashish (2021) showed that cashless payment resistance in semi-urban Kerala was primarily driven by risk barriers (fear of fraud) and tradition barriers (habitual use of cash in local markets), suggesting regional similarities to the Madurai context.

2.5 Demographic Influences on Cashless Payment Behavior

A substantial body of literature has examined how demographic characteristics moderate the relationships between trust, security, and adoption behavior. Age has consistently emerged as a significant moderator: younger consumers demonstrate higher adoption propensity and lower resistance, while older consumers exhibit stronger tradition and risk barriers (Venkatesh et al., 2003; Laukkanen et al., 2007). Income level moderates value perceptions, with lower-income consumers demonstrating heightened price sensitivity and fear of financial loss from fraud (Mishra & Bisht, 2019). Gender differences in adoption behavior are less consistent, though several Indian studies report that male consumers demonstrate slightly higher digital payment adoption rates, attributable in part to differential exposure to technology and financial services (Chawla & Joshi, 2019).

Educational attainment has been identified as the most robust demographic predictor of digital payment adoption in South Asian contexts (Thakur, 2013; Singh et al., 2020). Consumers with higher education levels demonstrate greater digital literacy, stronger risk assessment capabilities, and more sophisticated trust evaluation mechanisms. Occupational status also plays a mediating role, as government employees and formal sector workers typically benefit from institutional support for digital payment adoption through employer-administered payroll and expense management systems.

3. Research Gap

The foregoing review reveals several important contributions to the literature on cashless payment adoption, trust, security perception, and innovation resistance. However, a number of critical gaps remain that the present study seeks to address:

First, while studies have examined trust and security perception as independent predictors of digital payment adoption, the mediating role of security perception in the relationship between consumer trust and innovation resistance has received limited empirical attention, particularly in the Indian context. Most extant studies treat these constructs as parallel antecedents rather than as elements of a sequential causal process (Featherman & Pavlou, 2003; Kim et al., 2009).

Second, the majority of India-centric digital payment studies have concentrated on metropolitan cities (Mumbai, Delhi, Bengaluru, Hyderabad) or pan-India samples. Tier-II cities such as Madurai, which exhibit unique socio-economic profiles combining traditional commerce with emerging digital infrastructure, remain substantially underrepresented in the empirical literature.

Third, prior studies applying IRT in the Indian context have largely focused on mobile banking or mobile wallets, with fewer investigations examining broader cashless payment ecosystems encompassing UPI, QR code payments, POS terminals, and internet banking simultaneously. A holistic treatment of the cashless payment system is necessary to capture the full spectrum of resistance behaviors.

Fourth, the joint examination of trust dimensions (institutional and cognitive), security perception, and IRT-derived resistance barriers within a single structural model has not been attempted in the Madurai or broader South Indian context. Such an integrative approach would yield more comprehensive insights into the behavioral determinants of cashless payment adoption and resistance.

The present study addresses all four gaps by developing and testing a theoretically integrated model of cashless payment behavior grounded in TAM, IRT, and Trust-Risk frameworks, applied to a stratified sample from Madurai District.

4. Objectives of the Study

The study is guided by the following research objectives:

1. To examine the level of consumer trust and security perception among cashless payment users and non-users in Madurai District.

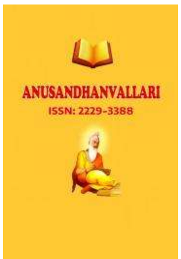
2. To assess the degree of innovation resistance and identify the predominant resistance barriers (functional and psychological) among respondents.

3. To determine the influence of consumer trust on the adoption intention of cashless payment systems.

4. To investigate the mediating role of security perception in the relationship between consumer trust and innovation resistance.

5. To analyze the impact of demographic variables (age, gender, income, education, occupation) on consumer trust, security perception, and innovation resistance.

6. To propose strategic recommendations for fintech service providers, commercial banks, and policymakers to enhance digital financial inclusion in Madurai District.



5. Research Design and Methodology

5.1 Research Design

The study adopts a quantitative, cross-sectional research design. A quantitative approach is appropriate given the study's objective of measuring and testing the structural relationships among latent constructs (trust, security perception, and innovation resistance) using validated scales (Creswell, 2014). The cross-sectional design facilitates efficient data collection from a large and diverse sample across Madurai District within a defined time window (January to March 2024).

The study integrates deductive reasoning, beginning with established theoretical frameworks (TAM, IRT, Trust-Risk model) and deriving testable hypotheses that are evaluated against empirical data. This approach ensures theoretical grounding while maintaining empirical rigor (Bryman, 2016).

5.2 Population

The target population comprises adult consumers (18 years and above) residing in Madurai District who have had at least one direct experience with cashless payment systems (as users or deliberate non-users). According to the Census of India (2011) and projected population data, Madurai District has an estimated population of approximately 3.1 million, of which roughly 1.4 million are adult consumers in urban and semi-urban areas. Both adopters and resisters of cashless payment systems are included to ensure a balanced examination of adoption and resistance behaviors.

5.3 Sampling Method

A stratified random sampling technique is employed to ensure proportional representation across key demographic strata. The population is first stratified by geographic zone (urban Madurai Corporation area vs. semi-urban/peri-urban areas including Melur, Thirumangalam, Usilampatti, and Madurai Taluk), and then further stratified by occupational category (traders/self-employed, salaried employees, students, homemakers, and agricultural/manual labor). Within each stratum, respondents are selected using systematic random sampling.

This approach is preferred over simple random sampling because it guarantees adequate representation of demographic subgroups that are likely to exhibit distinct patterns of trust, security perception, and resistance behavior. Stratified sampling also improves the efficiency of estimation by reducing sampling variability (Cochran, 1977).

5.4 Sample Size

The sample size is determined using Cochran's (1977) formula for categorical data:

$$\mathbf{n = (Z^2 \times p \times q) / e^2}$$

The 400 respondents were distributed across strata as follows: urban Madurai Corporation ($n = 240$, 60%) and semi-urban/peri-urban areas ($n = 160$, 40%), reflecting the population distribution within the district.

5.5 Hypotheses

The following hypotheses, derived from the theoretical frameworks and literature review, are tested in the study:

- H1: Consumer trust has a significant positive influence on cashless payment adoption intention.
- H2: Security perception has a significant positive influence on cashless payment adoption intention.

- H3: Innovation resistance has a significant negative influence on cashless payment adoption intention.
- H4: Consumer trust has a significant negative influence on innovation resistance toward cashless payments.
- H5: Security perception mediates the relationship between consumer trust and innovation resistance.
- H6: Demographic variables significantly moderate the relationships between trust, security perception, and innovation resistance.

6. Statistical Analysis and Interpretation

6.1 Socio-Demographic Profile of Respondents

Table 1 presents the socio-demographic profile of the 400 respondents. The sample is broadly balanced between genders, with 54.5% male and 45.5% female respondents. The majority of respondents fall in the 26–35 age group (34.2%), followed by the 18–25 group (27.8%), reflecting the relatively younger demographic profile of active digital economy participants. Graduate-level education is most common (42.0%), and private sector employment is the dominant occupational category (28.5%). Monthly income between ₹20,001 and ₹40,000 represents the modal income class (33.8%).

Table 1: Socio-Demographic Profile of Respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	218	54.5
	Female	182	45.5
Age Group	18–25 years	111	27.8
	26–35 years	137	34.2
	36–45 years	88	22.0
	46–55 years	44	11.0
	Above 55 years	20	5.0
Education	Below Secondary	36	9.0
	Secondary/HSC	84	21.0
	Graduate	168	42.0
	Post-Graduate	88	22.0
	Professional Degree	24	6.0

Occupation	Student	88	22.0
	Private Sector Employee	114	28.5
	Government Employee	72	18.0
	Self-Employed/Trader	80	20.0
	Homemaker	28	7.0
	Agricultural/Manual Labor	18	4.5
Monthly Income	Below ₹10,000	68	17.0
	₹10,001–₹20,000	92	23.0
	₹20,001–₹40,000	135	33.8
	₹40,001–₹60,000	72	18.0
	Above ₹60,000	33	8.2

Source: Primary data

6.2 Descriptive Statistics and Reliability Analysis

Table 2 presents the descriptive statistics and reliability estimates for the key constructs. Consumer trust recorded the highest mean score (M = 3.72, SD = 0.71), indicating that respondents hold moderately high trust in cashless payment systems overall, though with notable variance. Security perception yielded a mean of 3.41 (SD = 0.84), suggesting moderate but guarded security assessments. Innovation resistance recorded a mean of 3.19 (SD = 0.79), indicating that a meaningful proportion of the sample harbors active resistance. All Cronbach's alpha coefficients exceed the 0.80 threshold, confirming strong internal consistency, while composite reliability (CR) values exceed 0.85 and average variance extracted (AVE) values surpass 0.50, satisfying convergent validity criteria (Hair et al., 2019).

Table 2: Descriptive Statistics and Reliability of Constructs

Construct	**Items**	**Mean**	**SD**	**α**	**CR**	**AVE**
Consumer Trust	12	3.72	0.71	0.893	0.912	0.584
– Institutional Trust	6	3.68	0.76	0.861	0.878	0.546
– Cognitive Trust	6	3.76	0.69	0.854	0.871	0.531
Security Perception	8	3.41	0.84	0.882	0.901	0.569
Innovation Resistance	14	3.19	0.79	0.907	0.921	0.548
– Usage Barriers	3	3.24	0.88	0.821	0.845	0.645

– Value Barriers	3	3.10	0.91	0.836	0.852	0.659
– Risk Barriers	4	3.38	0.83	0.872	0.891	0.621
– Tradition Barriers	2	2.91	0.95	0.813	0.836	0.718
– Image Barriers	2	3.12	0.87	0.808	0.831	0.711

Source: Primary data

6.3 Correlation Analysis

Pearson correlation coefficients among the primary constructs are presented in Table 3. Consumer trust and security perception exhibit a significant positive correlation ($r = 0.614$, $p < 0.001$), confirming that higher levels of trust are associated with more favorable security assessments. Consumer trust and innovation resistance are significantly negatively correlated ($r =$

-0.521, $p < 0.001$), consistent with H4. Security perception and innovation resistance also display a significant negative relationship ($r = -0.489$, $p < 0.001$), supporting H5's premise that security perception serves as a conduit through which trust influences resistance. The moderate magnitude of correlations (all below 0.70) suggests the absence of multicollinearity issues.

Table 3: Pearson Correlation Matrix of Key Constructs

Construct	1	2	3	4
1. Consumer Trust	1.000			
2. Security Perception	0.614**	1.000		
3. Innovation Resistance	−0.521**	−0.489**	1.000	
4. Adoption Intention	0.583**	0.531**	−0.567**	1.000

Source: Primary data, ** *Correlation is significant at the 0.01 level (2-tailed).*

6.4 Multiple Regression Analysis

A hierarchical multiple regression was conducted with cashless payment adoption intention as the dependent variable. Model 1 entered demographic control variables; Model 2 added consumer trust and security perception; Model 3 additionally incorporated innovation resistance. Results are summarized in Table 4.

Table 4: Hierarchical Multiple Regression – Predictors of Adoption Intention

Predictor	Model 1 β	Model 2 β	Model 3 β
Age	−0.142*	−0.091	−0.074
Gender (Male = 1)	0.082	0.064	0.058
Education	0.218**	0.141*	0.118*
Income	0.195**	0.132*	0.109*
Consumer Trust	—	0.341***	0.287***

Security Perception	—	0.298***	0.244***
Innovation Resistance	—	—	−0.312***
R^2	0.112	0.428	0.531
Adjusted R^2	0.103	0.418	0.519
ΔR^2	0.112***	0.316***	0.103***
F-statistic	12.43***	46.82***	56.17***

Source: Primary data, *Note: * p < 0.05, ** p < 0.01, *** p < 0.001; β = standardized regression coefficient.*

Model 3 explains 53.1% of the variance in adoption intention (Adjusted R^2 = 0.519), representing a substantial improvement over demographic controls alone (Model 1, R^2 = 0.112). Consumer trust (β = 0.287, $p < 0.001$) and security perception (β = 0.244, $p < 0.001$) are significant positive predictors, while innovation resistance is a significant negative predictor (β = −0.312, $p < 0.001$). Education and income retain significance across models, confirming their role as demographic moderators. These findings support H1, H2, and H3.

6.5 Mediation Analysis (Baron and Kenny / Bootstrapping)

Mediation analysis was conducted using the PROCESS macro (Hayes, 2018) with 5,000 bootstrap samples to assess the mediating role of security perception (M) in the relationship between consumer trust (X) and innovation resistance (Y). Results are presented in Table 5.

Table 5: Mediation Analysis: Security Perception as Mediator

Path	Effect	SE	LLCI	ULCI
Total Effect (c): Trust → Resistance	−0.521***	0.064	−0.647	−0.395
Direct Effect (c'): Trust → Resistance (controlling SP)	−0.318***	0.071	−0.458	−0.178
Indirect Effect via Security Perception (a×b)	−0.203***	0.041	−0.287	−0.125
Path a: Trust → Security Perception	0.614***	0.058	0.500	0.728
Path b: Security Perception → Resistance	−0.331***	0.062	−0.453	−0.209

Source: Primary data

*Note: LLCI = Lower Limit Confidence Interval; ULCI = Upper Limit Confidence Interval; Bootstrap n = 5,000; *** p < 0.001.*

The indirect effect of consumer trust on innovation resistance through security perception is −0.203

(95% CI [−0.287, −0.125]), with the confidence interval excluding zero, confirming partial mediation (H5 supported). The direct effect remains significant (c' = −0.318, $p < 0.001$), indicating that consumer trust also exerts a direct inhibitory effect on innovation resistance beyond its indirect pathway through security perception. This partial mediation pattern suggests that security perception is an important but not exclusive mechanism through which trust reduces resistance.

6.6 Structural Equation Modeling (SEM)

A full structural equation model was estimated using AMOS 24.0 with maximum likelihood estimation. The measurement model was first validated through confirmatory factor analysis (CFA) before estimating the structural paths. Model fit indices are reported in Table 6.

Table 6: Structural Equation Model Fit Indices

Fit Index	**Obtained Value**	**Recommended Threshold**	**Interpretation**
Chi-square / df (CMIN/DF)	2.14	< 3.00	Good Fit
RMSEA	0.053	< 0.08	Good Fit
CFI (Comparative Fit Index)	0.941	> 0.90	Good Fit
TLI (Tucker-Lewis Index)	0.936	> 0.90	Good Fit
IFI (Incremental Fit Index)	0.942	> 0.90	Good Fit
SRMR	0.061	< 0.08	Good Fit
NFI (Normed Fit Index)	0.924	> 0.90	Good Fit
GFI (Goodness of Fit Index)	0.912	> 0.90	Acceptable Fit

Source: Primary data

All fit indices meet or exceed recommended thresholds (Hair et al., 2019), confirming that the proposed model provides an adequate representation of the data. Structural path coefficients are presented in Table 7. Consumer trust exerts a significant positive effect on adoption intention ($\beta = 0.291$, $p < 0.001$) and a significant negative effect on innovation resistance ($\beta = -0.326$, $p < 0.001$). Security perception positively influences adoption intention ($\beta = 0.247$, $p < 0.001$) and negatively influences innovation resistance ($\beta = -0.338$, $p < 0.001$). Innovation resistance exerts a strong negative effect on adoption intention ($\beta = -0.349$, $p < 0.001$), confirming all hypothesized structural paths.

Anusandhanvallari
Vol 2024, No.1
December 2024
ISSN 2229-3388

Table 7: Structural Path Coefficients

Hypothesis	Path	β	SE	t-value	p-value	Decision
H1	Trust → Adoption Intention	0.291	0.058	5.017	< 0.001	Supported
H2	Security Perception → Adoption Intention	0.247	0.063	3.921	< 0.001	Supported
H3	Innovation Resistance → Adoption Intention	−0.349	0.055	−6.345	< 0.001	Supported
H4	Trust → Innovation Resistance	−0.326	0.061	−5.344	< 0.001	Supported
H5 (Indirect)	Trust → SP → Resistance	−0.203	0.041	−4.951	< 0.001	Supported

Source: Primary data

6.7 Demographic Moderation Analysis

ANOVA and independent samples t-tests were conducted to examine demographic differences in the constructs. The results indicate significant differences in innovation resistance by age group [$F(4, 395) = 12.47$, $p < 0.001$], with older respondents (46 years and above) recording significantly higher resistance scores compared to younger cohorts. Income level significantly moderates security perception [$F(4, 395) = 8.93$, $p < 0.001$], with lower-income respondents (below ₹10,000 per month) exhibiting greater security concerns. Educational attainment significantly differentiates consumer trust scores [$F(4, 395) = 10.21$, $p < 0.001$], with post-graduate respondents recording the highest trust and below-secondary respondents recording the lowest. These patterns confirm H6 and are consistent with prior literature on demographic influences in digital payment adoption (Venkatesh et al., 2003; Thakur, 2013).

7. Conclusion

This study contributes an empirically grounded, theoretically integrated examination of the interplay among consumer trust, security perception, and innovation resistance in the context of cashless payment systems in Madurai District, Tamil Nadu. The findings confirm that consumer trust and security perception are significant positive drivers of cashless payment adoption intention, while innovation resistance serves as a significant inhibitor. Critically, the partial mediation of security perception in the trust-resistance relationship reveals a sequential mechanism: elevated trust enhances security perception, which in turn mitigates resistance, ultimately facilitating adoption. This mediation pathway has important practical implications for how stakeholders should approach consumer engagement.

The structural equation modeling results demonstrate excellent model fit and validate all six hypothesized relationships. The finding that risk barriers and usage barriers are the most prominent components of innovation resistance ahead of tradition and image barriers suggests that Madurai consumers are not categorically opposed to cashless payments on cultural grounds, but rather seek greater assurance of transactional security and more intuitive payment interfaces. This is an actionable distinction: it means that targeted interventions addressing security and usability concerns can meaningfully overcome resistance, whereas purely cultural persuasion campaigns may be less effective. The findings provide a rigorous foundation for evidence-based policy and practice aimed at deepening digital financial inclusion in historically underserved geographic and demographic segments.

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