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Demographic and Economic Impact of FinTech Services on Street Vendors: A Case Study of Rajouri District of Jammu and Kashmir

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Abstract
India's digital payment ecosystem has expanded at an unprecedented pace, with the Unified Payments Interface (UPI) processing nearly 70 billion transactions in 2022 and the RBI Digital Payments Index reaching 418.77 in March 2024. Yet the diffusion of Financial Technology (FinTech) within the informal economy — which contributes 45–50% of national GDP and employs over 90% of the workforce — remains uneven, particularly in semi-urban and geographically peripheral districts. This paper examines the demographic and economic impact of FinTech services on street vendors of Rajouri District in the Union Territory of Jammu and Kashmir. Using primary data collected through a structured personal-interview questionnaire from 384 street vendors across four tehsils — Rajouri, Thanna-Mandi, Nowshera and Sunderbani — selected using Cochran's formula and convenience sampling, the study applies frequency analysis, descriptive statistics, paired-samples t-test, and One-Sample t-tests (test value = 3) in IBM SPSS Statistics v26. Findings show that 75.0% of vendors use UPI, 94.3% transact digitally at least sometimes, and 72.1% transact daily. After FinTech adoption, the share of vendors earning below ₹10,000 per month fell from 57.0% to 7.3%, while those earning above ₹20,000 rose from 7.9% to 38.3%; the paired-samples t-test confirms this shift as highly significant ($t(383) = -32.538$, $p < 0.001$). All eight null hypotheses formulated for the study are rejected at the 5% level of significance, providing statistical evidence that vendor perception is significantly positive, that FinTech adoption significantly improves the economic position of vendors, and that demographic characteristics — age, gender, education and area of residence — significantly differentiate adoption behaviour. Fear of fraud ($M = 3.48$), technical glitches ($M = 3.37$), and limited knowledge ($M = 3.26$) emerge as the most binding residual barriers, while hardware and cost barriers have been largely overcome. The study contributes original district-level evidence from a semi-urban Himalayan context that is largely absent from existing FinTech adoption literature and offers evidence-based policy recommendations for deepening digital financial inclusion among informal-sector micro-entrepreneurs.

Keywords: Fintech Adoption, UPI, Street Vendors, Financial Inclusion, Demographic Determinants, Economic Impact, Informal Sector, Rajouri District, Jammu And Kashmir, PM-Svanidhi.

1. Introduction

The twenty-first century has witnessed an unprecedented convergence of finance and technology that has fundamentally reshaped how financial services are delivered, accessed and experienced. The Financial Stability Board (2017) defines Financial Technology (FinTech) as "technologically enabled financial innovation that could result in new business models, applications, processes or products with an associated material effect on financial markets and institutions and the provision of financial services." Within this global transformation, India has emerged as a world-leading laboratory for FinTech innovation at scale. The country recorded approximately 70 billion digital payment transactions in 2022 — a striking increase from 44 billion in 2021 — driven in large measure by the Unified Payments Interface (UPI), a real-time interoperable payment architecture launched by the National Payments Corporation of India (NPCI) in April 2016 (NPCI, 2024).

Despite the impressive macro-level growth of digital payments, India's informal economy — which contributes approximately 45–50% of the country's GDP and employs more than 90% of the national workforce — has not been uniformly integrated into the digital financial ecosystem (ILO, 2020; World Bank, 2020). Within this informal sector, street vendors constitute one of the most economically important and socially visible sub-groups. India is home to an estimated 10 million street vendors, who serve as the last-mile retail link between wholesale markets and urban consumers (Bhowmik, 2003; WIEGO, 2020). Their daily financial lives are typically characterised by cash dependence, transactional informality, and structural exclusion from formal banking — a configuration that simultaneously creates vulnerability to theft and irregular cash flow and excludes vendors from digital footprints that formal lenders use for credit assessment.

For street vendors, FinTech services — and especially UPI — offer a potentially transformative pathway. By accepting cashless transactions, vendors can automatically generate digital records, reduce cash-handling risk, broaden their customer base and begin building a digital financial footprint that may enable access to formal micro-credit over time (Sivasubramanian & Jaheer, 2021; Panda, 2022). The Government of India has actively incentivised this transition through landmark initiatives including Digital India (2015), the Pradhan Mantri Jan Dhan Yojana, demonetisation (November 2016) and, most directly relevant, the Pradhan Mantri Street Vendors AtmaNirbhar Nidhi (PM-SVANidhi) scheme of 2020, which combines micro-credit with cashback incentives for digital transactions. By 2024, more than 5.5 million street vendors had received loans under PM-SVANidhi (Government of India, 2020).

However, FinTech adoption among street vendors is neither simple nor automatic. The transition from cash-based to digital financial behaviour involves a complex interplay of technological readiness, financial literacy, social trust, customer behaviour and infrastructural enablement (Mathews, 2021; Chopra, 2019). The Technology Acceptance Model (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT and UTAUT2; Venkatesh et al., 2003, 2012) suggest that perceived ease of use, perceived usefulness, social influence and facilitating conditions collectively shape adoption — and that demographic moderators such as age, gender, education and area of residence shape these perceptions differentially.

The present paper situates this theoretical and empirical context in Rajouri District of the Union Territory of Jammu and Kashmir — a semi-urban, hilly, geographically dispersed district where FinTech adoption is ongoing but incompletely understood. The study generates original, district-level empirical evidence on (i) the demographic profile of FinTech-adopting street vendors, (ii) the measurable economic impact of FinTech adoption on income, sales, customer footfall and cash management, (iii) the influence of demographic characteristics on adoption behaviour and (iv) the remaining barriers and trust-related challenges that constrain deeper adoption.

1.1 Research Objectives

The specific objectives of this study are:

- To examine the demographic profile of street vendors using FinTech services in Rajouri District.
- To evaluate the economic impact of FinTech adoption on street vendors' income, sales, customer footfall and cash management.
- To assess the influence of demographic characteristics — age, gender, education and area of residence — on FinTech usage behaviour.
- To analyse the barriers and challenges faced by street vendors in adopting FinTech services.

1.2 Hypotheses

Eight null hypotheses were formulated for empirical testing:

- $H_0 1$: There is no positive perception of street vendors towards FinTech services.
- $H_0 2$: The economic position of street vendors does not significantly increase with the use of FinTech services.
- $H_0 3$(A): There is no significance of gender and use of FinTech services.
- $H_0 3$(B): There is no significance of education and use of FinTech services.
- $H_0 3$(C): There is no significance of age and use of FinTech services.
- $H_0 3$(D): There is no significance of location of street vendors and use of FinTech services.
- $H_0 4$(A): There is no significance of security, fraud and privacy and the use of FinTech services.
- $H_0 4$(B): Low awareness towards FinTech services does not influence the use of FinTech by street vendors.

2. Review of Literature

The literature on FinTech adoption in India has expanded rapidly since the launch of UPI in 2016 and the post-demonetisation surge in digital payments. The review below is organised thematically around (i) FinTech adoption among street vendors and small traders, (ii) the economic impact of digital payments, (iii) demographic influences on adoption, (iv) barriers and trust concerns and (v) theoretical frameworks of technology adoption.

2.1 FinTech Adoption Among Street Vendors and Small Traders

Chopra (2019) investigated mobile-wallet adoption among Indian street vendors and identified fear of fraud, data-privacy concerns and lack of confidence as the three most binding barriers. Swathi (2019) studied e-wallet usage among street food vendors in Bengaluru and found that customer demand was the principal motivator for adoption, though network unreliability and difficulty in withdrawing deposited funds were persistent challenges. Mathews (2021) reported that, while attitudes were generally positive, low digital literacy, weak connectivity and fraud fear remained the dominant constraints. Sivasubramanian and Jaheer (2021) showed that vendors in Chennai who adopted digital payments experienced measurable gains in revenue, sales volume and business productivity. Verma et al. (2022) studied Paytm usage among Lucknow vendors and concluded that, despite security concerns, customer pressure pushed adoption forward. Botta (2022) and Salim (2022) emphasised the role of customer preferences, ease of use and product diversification in adoption, while Panda (2022) documented improvements in transaction efficiency and record-keeping among Odisha vendors. Sushma et al. (2023), Prabhakar (2023) and Shivani (2023) extended the analysis to Sircilla, marginalised QR-code traders and UTAUT2-based vendor samples respectively, all highlighting the persistence of trust and infrastructure barriers. Suhail et al. (2024) found that female vendors in Phagwara reported higher satisfaction with UPI than male vendors, and that secondary-educated 20–50-year-olds were the most satisfied users. Mir (2025) conducted a qualitative study in Kashmir and reported gradual acceptance of digital payments alongside persistent network and security concerns.

2.2 Consumer Perception and Theoretical Frameworks

Joyjeet (2018), Singh and Rana (2020), Prakash (2022) and Kanchu and Suresh (2022) collectively demonstrate that consumer perception of digital payments has improved sharply on convenience and speed dimensions but remains constrained by perceived security risks. Fahad et al. (2022) applied Rogers' (1962) diffusion of innovations framework to UPI and identified perceived convenience, security and compatibility as the most important determinants of adoption. Dey (2023) projected continued strong growth in digital payment volumes across all economic segments.

The theoretical foundation of the present study draws on the Technology Acceptance Model (Davis, 1989), which posits perceived usefulness and perceived ease of use as the proximate determinants of technology adoption, and on UTAUT and UTAUT2 (Venkatesh et al., 2003, 2012), which incorporate performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit. Arner et al. (2016), Gomber et al. (2018), Nicoletti (2017), Thakor (2020) and Ozili (2018) provide complementary macro-level perspectives on how FinTech reshapes financial service delivery and extends inclusion to previously excluded populations.

2.3 Research Gap

A careful review of the literature reveals five interconnected gaps that the present study addresses. First, existing studies are overwhelmingly concentrated in metropolitan cities — Bengaluru, Chennai, Lucknow, Visakhapatnam — with very limited coverage of semi-urban district-level markets in the Union Territory of Jammu and Kashmir. Second, while many studies document perception and satisfaction, few rigorously quantify the economic outcomes of FinTech adoption using structured hypothesis testing on income, sales and cash management. Third, demographic moderators of FinTech adoption are widely acknowledged in TAM and UTAUT-based research but rarely subjected to formal statistical testing among street vendor populations. Fourth, structural barrier analysis — distinguishing hardware and cost barriers from trust, awareness and connectivity barriers — has not been systematically applied to the street vendor segment. Fifth, no existing study integrates perception, economic impact, demographic differentiation and barrier analysis within a single analytical framework applied to a semi-urban Himalayan district. The present study addresses all five gaps simultaneously.

3. Research Methodology

3.1 Research Design

The study employs a descriptive and analytical research design. The descriptive component systematically profiles vendor demographics, FinTech awareness, usage patterns and perceived barriers through frequency distributions and descriptive statistics. The analytical component is operationalised through paired-samples and One-Sample t-tests applied to Likert-scale and ordinal income variables, enabling formal hypothesis testing. This dual-design approach is consistent with the methodology recommended by Kothari (2004) and Sekaran and Bougie (2016) for social-science research involving perception measurement and hypothesis testing.

3.2 Sampling Frame, Method and Sample Size

The sampling frame comprises all active street vendors operating in the urban and semi-urban vending locations of Rajouri District. Out of twelve administrative tehsils, four were purposively selected on the basis of vendor population density, urban–semi-urban representation and logistical accessibility: Rajouri (district headquarters), Thanna-Mandi (weekly market hub), Nowshera (semi-urban commercial area) and Sunderbani (peri-urban trade corridor). Because no official registry of street vendors exists for the district, sample size was determined using Cochran's (1977) formula for unknown populations:

$n_0 = (Z^2 \times p \times q) / e^2 = (1.96^2 \times 0.50 \times 0.50) / 0.05^2 = 384.16 \approx 384$

where Z = 1.96 for the 95% confidence level, p = 0.50, q = 1 − p = 0.50, and e = 0.05 represents the acceptable margin of error. A final sample of 384 respondents was collected, with an equal allocation of 96 respondents from each of the four selected tehsils, ensuring balanced geographical representation. Convenience sampling was adopted as the primary technique because of the absence of a formal sampling frame and the time-sensitive availability of vendors at vending locations during non-peak hours.

Table 3.1: Sample Distribution Across Selected Tehsils

Tehsil	Type	Sample Allocated
Rajouri	Urban / District HQ	96
Thanna-Mandi	Semi-Urban	96
Nowshera	Semi-Urban	96
Sunderbani	Semi-Urban / Peri-Urban	96
Total	—	384

3.3 Data Collection and Period of Study

The study relies exclusively on primary data collected through a structured questionnaire administered by personal interview between January 2026 and April 2026. The questionnaire is organised into six sections covering (A) demographic profile, (B) FinTech usage patterns, (C) perception of FinTech services (17 five-point Likert items), (D) economic impact, (E) demographic influence on usage and (F) barriers and trust. The instrument design is informed by the UTAUT framework: Section C operationalises performance expectancy (time saving, income management, transaction efficiency) and effort expectancy (ease of use, ease of downloading, clarity); Section F operationalises facilitating conditions (smartphone access, connectivity, technical literacy); and Section B captures the social-influence dimension through awareness sources (Q12), revealing that 84.1% of awareness is peer-mediated. Secondary data from peer-reviewed journals, RBI and NPCI reports informed the literature review but were not used in primary hypothesis testing.

3.4 Statistical Tools

All valid completed questionnaires (N = 384) were coded and entered into IBM SPSS Statistics Version 26 (IBM Corp., 2019). Frequency and percentage analysis were applied to all nominal and ordinal categorical variables; means and standard deviations were computed for all Likert items; a paired-samples t-test was used to compare monthly income before and after FinTech adoption; and One-Sample t-tests (Test Value = 3, the neutral midpoint of the five-point Likert scale) were applied to test all eight null hypotheses. The level of significance for all hypothesis tests was set at $\alpha = 0.05$ (two-tailed). A p-value below 0.05 was taken as the criterion for rejecting the null hypothesis.

4. Data Analysis and Interpretation

4.1 Demographic Profile of Respondents

Table 4.1 presents the demographic profile of the 384 street vendors who participated in the study. Food vendors form the largest occupational group (37.8%), followed by vegetable sellers (21.6%), clothes vendors (15.1%), accessories vendors (14.6%) and others (10.9%). Stationary vendors dominate the sample (63.0%), with mobile-on-wheels (30.5%) and mobile head-load (6.5%) vendors making up the rest — a distribution structurally favourable for QR-code-based digital payments because fixed locations allow permanent display of UPI QR codes. The 21–40 years age group accounts for 57.6% of the sample, with 33.9% in the 41–60 group and only 1.3% above 60 years, providing a digitally receptive demographic environment. The sample is heavily male (77.9% vs. 22.1% female), reflecting socio-cultural norms of public outdoor vending in the region. Secondary education is the modal category (47.7%), with 19.3% graduates and 9.6% with no formal schooling — implying that approximately 67% of vendors possess at least the secondary-level literacy required to operate digital payment applications. A majority (58.9%) are local J&K residents, while 41.1% are inter-state migrants from Uttar Pradesh (17.4%), Bihar (16.9%) and Delhi (6.8%) — states with high UPI penetration that may have shaped prior digital exposure. Finally, 61.2% of respondents reside in urban areas, 22.7% in semi-urban areas and 16.1% in rural areas.

Table 4.1: Demographic Profile of Respondents (N = 384)

Variable	Category	Frequency	Percent (%)
Type of vending	Food	145	37.8
	Vegetables	83	21.6
	Clothes	58	15.1
	Accessories	56	14.6
	Others	42	10.9
Type of vendor	Stationary	242	63.0
	Mobile on wheels	117	30.5
	Mobile head-load	25	6.5
Age group	Below 20	28	7.3
	21–40	221	57.6
	41–60	130	33.9
	Above 60	5	1.3
Gender	Male	299	77.9
	Female	85	22.1
Education	No formal education	37	9.6
	Primary	90	23.4

Variable	Category	Frequency	Percent (%)
	Secondary	183	47.7
	Graduate	74	19.3
State of origin	J&K	226	58.9
	Uttar Pradesh	67	17.4
	Bihar	65	16.9
	Delhi	26	6.8
Area of residence	Urban	235	61.2
	Semi-urban	87	22.7
	Rural	62	16.1

4.2 FinTech Usage Patterns

UPI is the dominant FinTech service used by Rajouri's street vendors (75.0%, n = 288), followed equally by mobile wallets and banking apps (12.2% each, n = 47), with digital loan apps showing negligible penetration (0.5%, n = 2). The near-total dominance of UPI is attributable to its zero-cost transaction model, NPCI-backed interoperability and active promotion through PM-SVANidhi. For vendors with narrow profit margins, the zero-fee structure is decisive. A substantial 72.1% of vendors use digital payments daily and 22.1% sometimes, producing a combined active-use rate of 94.3% — confirming that FinTech has crossed from occasional experimental use into habitual commercial practice. FinTech awareness is overwhelmingly peer-driven: 69.3% learnt about digital payments from friends and 14.8% from relatives, meaning 84.1% of awareness has diffused through informal social networks. Television (11.2%) and print advertising (4.7%) contributed minimally — a pattern that implies peer-ambassador programmes would be substantially more effective than mass-media campaigns.

Table 4.2: FinTech Usage Patterns

Indicator	Category	Frequency	Percent (%)
FinTech service used	UPI	288	75.0
	Mobile wallets	47	12.2
	Banking apps	47	12.2
	Digital loan apps	2	0.5
Frequency of use	Daily	277	72.1
	Sometimes	85	22.1
	Rarely	22	5.7
Source of awareness	Friends	266	69.3

Indicator	Category	Frequency	Percent (%)
	Relatives	57	14.8
	Television	43	11.2
	Print advertising	18	4.7

4.3 Perception of FinTech Services

All 17 perception items in Section C recorded mean scores above the neutral midpoint of 3.0, with 16 items exceeding 3.70 — placing them firmly in the "Agree" zone of the five-point Likert scale. The highest-rated items were "reduces the chance of cash theft" (M = 4.24, SD = 0.763), "reduces the need to carry cash" (M = 4.11, SD = 0.749), "saves time compared to cash" (M = 4.07, SD = 0.722) and "checking balance online" (M = 4.03, SD = 0.709). These results confirm that vendors value FinTech most strongly for risk-reduction and operational-efficiency benefits. The only item near the neutral midpoint was "suitable for people of all age groups" (M = 3.24, SD = 0.861), reflecting vendors' awareness of the age-based digital divide even as they themselves use FinTech confidently.

4.4 Economic Impact of FinTech Adoption

Section D evaluates the economic impact of FinTech adoption on income, sales, customer footfall, payment speed, cash-handling risk and savings. The findings are striking. A combined 88.3% of vendors reported an increase in sales after adopting digital payments — 35.4% significantly and 52.9% slightly — while only 1.6% reported any decline. 84.6% reported an increase in customer footfall, 92.2% confirmed faster payment receipt, 97.1% reported reduced cash-handling risk and 73.2% indicated that FinTech helped them save money.

The most analytically important finding concerns monthly income. The income variable was coded on a four-point ordinal scale (1 = below ₹10,000; 2 = ₹10,001–₹20,000; 3 = ₹20,001–₹30,000; 4 = above ₹30,000). A paired-samples t-test comparing income before and after FinTech adoption ($N = 384$) yielded a mean of 1.54 ($SD = 0.649$) before and 2.45 ($SD = 0.770$) after adoption — an upward shift of +0.91 on the four-point scale. The paired t-test result, $t(383) = -32.538$, $p < 0.001$, with a mean difference of −0.904 ($SD = 0.544$) and a 95% confidence interval of [−0.958, −0.849] that lies entirely below zero, confirms a statistically and substantively significant improvement. In distributional terms, the share of vendors earning below ₹10,000 per month fell from 57.0% to 7.3% post-adoption, while the share earning above ₹20,000 grew from 7.9% to 38.3% — a dramatic upward migration across the income distribution. The Pearson correlation between pre- and post-adoption income was $r = 0.718$ ($p < 0.001$), suggesting that gains were broadly distributed across the income spectrum rather than confined to a single segment.

Table 4.3: Economic Impact Indicators of FinTech Adoption

Indicator	Affirmative %	Negative / Neutral %	Source
Sales increased after FinTech adoption	88.3	11.7	Section D, Q22
Customer footfall increased	84.6	15.4	Section D, Q24

Indicator	Affirmative %	Negative / Neutral %	Source
Faster payment receipt	92.2	7.8	Section D, Q25
Cash-handling risks reduced	97.1	2.9	Section D, Q26
FinTech helped save money	73.2	26.8	Section D, Q27
Income shifted ≥ 1 bracket upward	Mean Δ = +0.91*	—	Paired t-test

**Paired-samples t-test: $t(383) = -32.538$, $p < 0.001$; 95% CI [−0.958, −0.849].*

Table 4.4: Monthly Income Distribution Before vs. After FinTech Adoption (% of vendors)

Monthly Income Bracket	Before Adoption (%)	After Adoption (%)
Below ₹10,000	57.0	7.3
₹10,001 – ₹20,000	35.1	54.4
₹20,001 – ₹30,000	6.3	28.4
Above ₹30,000	1.6	9.9

4.5 Demographic Influence on FinTech Adoption

Section E captures vendor perceptions of how demographic characteristics shape FinTech usage. The two most strongly endorsed demographic enablers are age and education. Vendors agreed strongly that "younger vendors adopt FinTech more easily" (M = 3.95, SD = 0.790) and that "education plays an important role in using FinTech" (M = 3.93, SD = 0.773). Income level was a moderate enabler (M = 3.56, SD = 0.762), while the gender-equality statement — "male and female vendors use FinTech equally" — scored near the neutral midpoint (M = 3.18, SD = 0.880) with the highest standard deviation in the section, indicating genuine respondent disagreement and reflecting the structural 77.9% male composition of the sample.

Table 4.5: Descriptive Statistics — Demographic Influence on FinTech Adoption

Statement	N	Mean	Std. Dev.
Younger vendors adopt FinTech more easily	384	3.95	0.790
Education plays an important role in using FinTech	384	3.93	0.773
Higher-income vendors more likely to adopt FinTech	384	3.56	0.762
Male and female vendors use FinTech equally	384	3.18	0.880

4.6 Barriers and Trust

The seven barrier items in Section F, ranked by mean score, divide cleanly into two groups. Four barriers were endorsed (mean above 3.0): fear of fraud (M = 3.48), technical glitches (M = 3.37), lack of knowledge

(M = 3.26) and poor internet connectivity (M = 3.24). Three barriers were rejected (mean below 3.0): transaction charges (M = 2.90), customer preference for cash (M = 2.71) and lack of smartphone (M = 2.67). This pattern is structurally optimistic: the remaining obstacles are trust, knowledge and connectivity issues rather than hardware or cost barriers — meaning they are directly addressable through targeted policy interventions. Trust data reinforce this picture: 72.9% of vendors trust digital payment platforms and 17.2% are unsure; 27.6% had personally experienced fraud or payment failure, providing concrete empirical grounding for the fear-of-fraud barrier.

Table 4.6: Barriers to FinTech Adoption (Ranked by Mean)

Rank	Statement	Mean	Std. Dev.	Interpretation
1	Fear of fraud / scam	3.48	0.833	Above neutral — strongest barrier
2	Technical issues / glitches	3.37	0.858	Above neutral — acknowledged
3	Lack of knowledge	3.26	0.857	Above neutral — acknowledged
4	Poor internet connectivity	3.24	0.771	Above neutral — acknowledged
5	Transaction charges	2.90	0.618	Below neutral — rejected
6	Customer preference for cash	2.71	0.924	Below neutral — rejected
7	Lack of smartphone	2.67	0.721	Below neutral — rejected

4.7 Hypothesis Testing (One-Sample t-Test, Test Value = 3)

All eight null hypotheses were tested using the One-Sample t-test against Test Value = 3 — the neutral midpoint of the five-point Likert scale — at $\alpha = 0.05$. The use of the One-Sample t-test against the neutral midpoint is theoretically consistent with the UTAUT framework: a mean score significantly above 3 indicates that vendors perceive FinTech services as offering a meaningful improvement over their existing cash-based practices, which UTAUT identifies as a prerequisite for sustained adoption. Conversely, a mean score significantly below 3 on a barrier item that is reverse-coded (1 = Yes) confirms a strong affirmative pattern in the underlying behaviour.

Table 4.7: Summary of Hypothesis Testing Results (One-Sample t-Test, N = 384, Test Value = 3)

Hypothesis	Mean (range)	t-value (range)	p-value	Decision
$H_0 1$: No positive perception of FinTech	3.24 – 4.24	5.45 – 31.97	< 0.001	Rejected
$H_0 2$: No significant economic impact	1.03 – 2.41	−231.28 – −15.12	< 0.001	Rejected
$H_0 3$(A): No gender significance	1.22 / 3.18	−83.85 / 4.05	< 0.001	Rejected
$H_0 3$(B): No education significance	2.77 / 3.93	−5.27 / 23.56	< 0.001	Rejected
$H_0 3$(C): No age significance	2.29 / 3.95	−22.53 / 23.64	< 0.001	Rejected

Hypothesis	Mean (range)	t-value (range)	p-value	Decision
$H_0$3(D): No location significance	1.55 / 1.34	−37.58 / −56.04	< 0.001	Rejected
$H_0$4(A): No security/fraud significance	3.48 / 1.72 / 1.44	11.39 / −55.86 / −39.66	< 0.001	Rejected
$H_0$4(B): No awareness significance	3.26 / 2.88	5.89 / −3.02	< 0.05	Rejected

All eight null hypotheses are rejected at the 5% significance level. The uniform rejection of null hypotheses is the central statistical finding of this study and confirms that the positive perception, economic improvement and demographic differentiation observed in the descriptive statistics are not artefacts of sampling chance but reflect statistically significant patterns in the vendor population of Rajouri District.

5. Discussion

5.1 Demographic Profile of FinTech-Adopting Vendors

The demographic profile that emerges from this study is that of a digitally receptive but socially uneven population. The concentration of respondents in the 21–40 age group (57.6%) and the secondary-or-above education category (67.0%) explains a substantial part of the high adoption rates observed. These are precisely the demographic strata that TAM and UTAUT research consistently identify as most likely to adopt new technologies because of higher baseline digital literacy and lower perceived effort costs. The dominance of stationary vendors (63.0%) is structurally important because fixed locations enable permanent QR-code display — the lowest-effort form of FinTech adoption available to micro-enterprises. The 41.1% inter-state migrant share (largely from UP and Bihar) likely contributes prior digital exposure from origin states with high UPI penetration, an underexplored channel for adoption diffusion in J&K.

Two demographic features signal genuine inequity. First, the 77.9% male composition of the sample reflects an entrenched gender gap in public outdoor vending that simultaneously restricts women's access to the economic benefits of FinTech adoption. Second, the concentration in urban areas (61.2%) shows that adoption diffusion has been uneven across the district's urban–semi-urban–rural gradient, with semi-urban and rural vendors trailing their urban counterparts in usage intensity.

5.2 Economic Impact of FinTech Adoption

The economic impact findings are the empirical centrepiece of this study. The contraction of the below-₹10,000 income bracket from 57.0% to 7.3% post-adoption, the expansion of the above-₹20,000 bracket from 7.9% to 38.3%, the 88.3% sales-improvement rate, the 84.6% increase in customer footfall, the 92.2% faster-payment confirmation and the 97.1% reduction in cash-handling risk together constitute one of the most consistent affirmative patterns reported in the Indian FinTech-adoption literature on street vendors. The paired-samples t-test ($t(383) = -32.538$, $p < 0.001$) places this pattern on rigorous statistical footing.

It is important to interpret these findings with appropriate caution. The income data are based on vendor self-recall of pre-adoption income levels and may be subject to recall bias and social-desirability bias. The cross-sectional design cannot fully isolate FinTech adoption from confounding macroeconomic and policy effects — including PM-SVANidhi loan disbursement, post-COVID demand recovery and broader district-level digital infrastructure improvements. Nevertheless, the consistency of the findings across multiple independent indicators (sales, income, footfall, payment speed, cash risk and savings) and across multiple statistical tests (frequency analysis, paired-samples t-test, One-Sample t-test) strengthens confidence that FinTech adoption has produced a substantively meaningful improvement in the economic position of Rajouri's street vendors.

The findings are consistent with Sivasubramanian and Jaheer (2021) for Chennai, Panda (2022) for Odisha and Suhail et al. (2024) for Phagwara, and they extend the empirical base for the economic-empowerment thesis to a semi-urban J&K context that has been largely absent from existing literature. At the macro level, they corroborate Thakor (2020), Gomber et al. (2018) and Nicoletti (2017) on the structural transformation of financial service delivery, and Ozili (2018) and the World Bank (2020) on the financial-inclusion dividend of low-cost digital infrastructure.

5.3 Demographic Differentiation of Adoption

The One-Sample t-tests confirm that age, education, gender and area of residence are all significant differentiators of FinTech usage among Rajouri's street vendors. Age (Q37: $M = 3.95$, $t = 23.636$, $p < 0.001$) and education (Q38: $M = 3.93$, $t = 23.555$, $p < 0.001$) are the two strongest perceived enablers — consistent with TAM's prediction that perceived ease of use improves with digital literacy and with broader generational patterns of digital familiarity. Gender ($t = -83.845$, $p < 0.001$) and area of residence ($t = -37.584$, $p < 0.001$) emerge as significant structural differentiators, with male and urban vendors substantially outpacing female and semi-urban/rural vendors in adoption intensity. The gender gap is not merely a question of post-adoption satisfaction — Suhail et al. (2024) found that female vendors who do adopt UPI report higher satisfaction than male vendors — but of access and exposure prior to adoption, rooted in socio-cultural norms governing women's participation in public outdoor commerce.

5.4 Barriers and the Transition from Hardware to Trust Constraints

The barrier analysis identifies the defining feature of the current phase of FinTech adoption in Rajouri District: the transition from hardware and cost barriers to trust, knowledge and connectivity barriers. The clear rejection by vendors of lack of smartphone ($M = 2.67$), customer preference for cash ($M = 2.71$) and transaction charges ($M = 2.90$) as significant barriers indicates that the access-and-affordability dimensions of digital financial inclusion have been substantially addressed in this district through the combination of falling smartphone prices, UPI's zero-fee architecture and the rapid normalisation of digital payments among customers. What remain are the trust and capability dimensions: fear of fraud ($M = 3.48$), technical glitches ($M = 3.37$), lack of knowledge ($M = 3.26$) and poor internet connectivity ($M = 3.24$). Crucially, the fear of fraud is empirically grounded rather than speculative — 27.6% of vendors have personally experienced fraud or payment failure — and the lack of knowledge is reinforced by the awareness pattern in Section B, in which 84.1% of vendors learnt about FinTech from informal peer networks rather than formal institutional channels.

6. Conclusion and Policy Implications

6.1 Conclusion

This study set out to examine the demographic and economic impact of FinTech services on street vendors in Rajouri District of Jammu and Kashmir. Based on primary data collected from 384 vendors across four tehsils and analysed using frequency analysis, descriptive statistics, paired-samples t-test and One-Sample t-tests in IBM SPSS Statistics v26, four central conclusions emerge.

First, FinTech adoption among Rajouri's street vendors is already deep and habitual: 94.3% transact digittally at least sometimes and 72.1% do so daily, with UPI accounting for 75.0% of services used. Second, vendor perception of FinTech is significantly positive across all 17 measured dimensions — most strongly on cash-risk reduction, time saving and cashless convenience — with H_01 rejected. Third, FinTech adoption is associated with a statistically and substantively significant improvement in the economic position of vendors: the below-₹10,000 income bracket contracted from 57.0% to 7.3% post-adoption, sales improved for 88.3%, customer footfall rose for 84.6%, payment receipt accelerated for 92.2% and cash-handling risk declined for 97.1% of vendors, with H_02 rejected. Fourth, age, education, gender and area of residence all emerge as statistically significant differentiators of adoption (H_03A–D rejected), and security/fraud concerns (H_04A rejected) and low awareness (H_04B rejected) constitute the most binding residual barriers.

The uniform rejection of all eight null hypotheses at the 5% level of significance places these conclusions on rigorous statistical footing. The defining characteristic of the current phase of FinTech adoption in Rajouri is the transition from hardware and cost barriers — largely overcome — to trust, knowledge and connectivity barriers, which are directly addressable through targeted policy interventions.

6.2 Policy Implications and Recommendations

Interpreted through the UTAUT framework, the findings imply that effort-related barriers — not performance perceptions — should be the primary intervention priority in Rajouri District and comparable semi-urban contexts. Six evidence-based recommendations follow.

- Strengthen fraud grievance and redressal mechanisms tailored to street vendors, including a dedicated UPI-fraud helpline, simplified complaint registration through Common Service Centres, and mandatory transaction-failure reversal timelines.
- Launch peer-ambassador digital-literacy programmes that leverage the existing 84.1% peer-learning channel, training digitally proficient vendors to mentor others on safe UPI use, QR-code display and basic fraud avoidance.
- Design gender-targeted FinTech onboarding in collaboration with local Self-Help Groups (SHGs), Town Vending Committees and women's cooperatives to close the 77.9% / 22.1% gender gap in vendor participation and adoption.
- Invest in 4G and Wi-Fi connectivity in semi-urban and rural tehsils — particularly Thanna-Mandi and Sunderbani — under PM-WANI and BharatNet to address the connectivity barrier (M = 3.24).
- Deepen PM-SVANidhi outreach with explicit linkage between UPI transaction history and graduated credit eligibility, converting the 99.5% gap in digital-loan-app penetration into a pathway for formal micro-credit access.
- Pilot a UPI-history-based credit-scoring product through district lead banks and FinTech NBFCs, using vendors' accumulated digital footprints to underwrite working-capital loans of ₹25,000–₹100,000.

6.3 Limitations and Scope for Future Research

Six limitations should be considered when interpreting the findings. First, the cross-sectional design precludes strong causal inference; a longitudinal panel tracking the same vendors over three to five years would provide stronger causal evidence. Second, convenience sampling — although appropriate given the absence of a vendor registry — limits statistical generalisability. Third, income data are self-reported and subject to recall and social-desirability bias. Fourth, the 77.9% male sample restricts gender-specific inference; a gender-stratified study with adequate female representation is needed. Fifth, the single-district scope limits generalisation to other J&K districts or other Indian states. Sixth, common method variance arising from single-source self-report should be addressed in future research by triangulating with objective NPCI transaction data and PM-SVANidhi beneficiary records. Promising avenues for future research include a comparative multi-district J&K study, a Structural Equation Modelling application of UTAUT2, a credit-access deep-dive focused on the digital-loan-app gap, and a quasi-experimental PM-SVANidhi impact evaluation.

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