

SOCIO-ECONOMIC DIFFERENCES IN FINTECH ADOPTION AND FINANCIAL INCLUSION AMONG URBAN STREET VENDORS: EVIDENCE FROM KOTA, RAJASTHAN, INDIA

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ABSTRACT

Digital payments have spread rapidly among India's street vendors, but their use does not necessarily indicate broader fintech adoption or financial inclusion. This study examines differences in fintech adoption and financial inclusion by gender, age, monthly income and education among 440 street vendors in Kota, Rajasthan, who had prior exposure to UPI or other digital payment modes. Data were collected through a bilingual face-to-face questionnaire and analysed using t-tests, one-way ANOVA with Tukey post-hoc tests and multiple regression. Men reported higher fintech adoption (3.19 vs. 2.86; $d = 0.32$) and financial inclusion (3.08 vs. 2.70; $d = 0.39$) than women. Adoption declined with age and increased with income and education, with education showing the strongest association ($\eta^2 = 0.097$), while financial inclusion differed by gender, age and education but not income. Gender, age and education remained significant predictors of both outcomes in regression analysis. Fear of fraud (48.4%), limited digital knowledge (47.3%) and customers' preference for cash (45.2%) were the most frequently reported barriers. The findings highlight the need for targeted digital training and accessible grievance-redressal mechanisms, particularly for women, older and less-educated vendors.

Keywords: fintech adoption; financial inclusion; street vendors; informal economy; UPI; digital divide; India

1. INTRODUCTION

The Global Findex shows that owning an account does not guarantee active saving, digital payment use, formal borrowing or resilience (Demirgüç-Kunt et al., 2022), and India's National Strategy for Financial Inclusion now treats access, usage and quality as separate dimensions (Reserve Bank of India, 2020). This distinction is especially relevant for informal workers. Street vendors earn irregular incomes, keep few records and have long relied on informal credit, with limited access to formal institutions (Bhowmik & Saha, 2013).

Their status has since received legal recognition through the Street Vendors (Protection of Livelihood and Regulation of Street Vending) Act, 2014 (Government of India, 2014), and financial recognition through PM SVANidhi, which since June 2020 has combined collateral-free working-capital loans with cashback incentives of up to ₹1,600 for digital transactions (Press Information Bureau [PIB], 2025).

UPI and QR-code payments have altered the transactional routines of many vendors, as funds are credited within seconds and each sale generates a digital record. The presence of a QR code at a stall, however, reveals little about how it is used: some vendors operate and verify payments independently, whereas others depend on a relative or neighbouring trader at every

stage. In Jaipur, even adopting small merchants settled roughly four-fifths of their transactions in cash (Ligon et al., 2019), and in Srinagar vendors rely on intermediaries and literate family members (Mir & Wani, 2025). Where the depth of use varies in this manner, the benefits of digital finance are unlikely to be distributed evenly.

1.1 Study context: Kota

Kota is a municipal-corporation city in south-eastern Rajasthan with a population of 1,001,694 and a literacy rate of 82.8% according to the 2011 Census (Office of the Registrar General & Census Commissioner, India, 2011). As an educational hub, its markets, roadside clusters and stalls near coaching institutes, hostels and transport nodes serve a large, predominantly young and transient student population as well as long-settled residential neighbourhoods. The vendors themselves come from a considerably wider range of educational and economic backgrounds than the city-wide literacy rate suggests; 14.1% of the respondents in this study had no formal education. Kota thus combines a visible digital-payment environment with marked heterogeneity among vendors.

Published evidence from Kota is limited, and municipal records cover only registered or certified vendors. As no sampling frame of digitally active vendors exists, primary data were collected (Section 3.1).

1.2 Aim and contribution

This study draws on primary data collected from 440 street vendors in Kota who use digital payments to some extent. It investigates (i) whether fintech adoption, conceptualised as the level and depth of use, and financial inclusion differ by gender, age, monthly income and education, and (ii) which practical barriers vendors report. The sample was restricted to existing users so that the analysis focuses on the intensity of use among adopters rather than on the adoption decision itself.

The study contributes by (i) measuring adoption and inclusion as related but distinct constructs, (ii) reporting effect sizes and regression models in which gender, age, education and income are examined simultaneously, and (iii) adding vendor-level quantitative evidence from a city that has received little attention.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1 Fintech use and inclusion among street vendors

Early research documented the exclusion of street vendors from formal credit and their dependence on moneylenders (Bhowmik & Saha, 2013). Digital payments were subsequently promoted as a pathway out, but the evidence on uptake is mixed: small Indian retailers showed considerable awareness of cashless options but low participation relative to cash (Chattopadhyay et al., 2018). Vendor-specific extensions of the technology-acceptance framework identify performance and effort expectancy, facilitating conditions, trust and digital financial literacy as determinants of QR-code payment intention (Nandru et al., 2023; Nandru & Senthil Kumar, 2024), while barrier-focused studies rank perceived risk, lack of trust, lack of awareness, cash culture and low literacy among the principal obstacles (Bakhshi et al., 2024; Srivastava & Singh, 2023).

The literature on the inclusion side is less settled. Ozili (2018) argued that digital finance can widen access but that its benefits depend on how it is actually used, and Senyo and Osabutey (2020) examined the antecedents through which fintech usage translates into financial inclusion. Both perspectives support treating adoption and inclusion as distinct outcomes.

2.2 Socio-economic characteristics and hypotheses

The unified theory of acceptance and use of technology (UTAUT) specifies gender, age and experience as moderators of the relationship between perceptions and usage (Venkatesh et al., 2003), and its consumer extension adds individual differences more broadly (Venkatesh et al., 2012). Women may have limited control over a shared device or the business account, and women vendors have been treated as a group facing distinct adoption constraints (Nandru & Senthil Kumar, 2024). Male vendors are therefore expected to report deeper adoption and higher inclusion.

H_{1a}: Male vendors report higher fintech adoption than female vendors.

H_{1b}: Male vendors report higher financial inclusion than female vendors.

Older vendors have typically had less exposure to smartphones and may rely on cash-handling habits formed over long careers; both outcomes are therefore expected to decline with age.

H_{2a}: Fintech adoption is lower among older vendors.

H_{2b}: Financial inclusion is lower among older vendors.

Income may determine whether a vendor can afford a capable device and mobile data and can absorb the cost of a failed transaction; lower-income vendors may therefore use fintech less intensively. Whether this extends to inclusion is less certain, because the inclusion scale also covers savings, credit and insurance, which depend on institutional supply as well as on the vendor's means.

H_{3a}: Fintech adoption is higher among vendors with higher monthly income.

H_{3b}: Financial inclusion is higher among vendors with higher monthly income.

Education enables vendors to read transaction messages, follow on-screen instructions and recognise suspicious requests. Qualitative evidence from Srinagar links vendors' dependence on intermediaries to limited education (Mir & Wani, 2025), and the vendor-focused literature identifies digital financial literacy as a determinant of use (Nandru et al., 2023; Nandru & Senthil Kumar, 2024). Higher adoption and inclusion are therefore expected at higher levels of education.

H_{4a}: Fintech adoption is higher among vendors with higher levels of education.

H_{4b}: Financial inclusion is higher among vendors with higher levels of education.

2.3 Research gap

Three research gaps emerge from the studies reviewed above. First, most quantitative vendor studies model the intention to adopt (Nandru et al., 2023; Nandru & Senthil Kumar, 2024) or the barriers to adoption (Bakhshi et al., 2024); few examine the depth of use among existing users, and, to the authors' knowledge, none pairs depth of use with financial inclusion as a separate outcome. Second, demographic differences are usually treated as background characteristics or examined one at a time, so their independent contribution is seldom isolated, and the qualitative studies (Mir & Wani, 2025; Srivastava & Singh, 2023) offer no group comparisons or effect sizes. Third, the evidence is geographically uneven: Rajasthan-based research covers fixed-store merchants in Jaipur (Ligon et al., 2019), the Kota evidence rests on a very small user survey (Vergiya & Chaturvedi, 2025), and no vendor-level study of fintech adoption and inclusion in Kota was identified.

2.4 Research objectives and conceptual framework

RO1: To examine whether fintech adoption differs by gender, age, monthly income and education among street vendors in Kota (H1a–H4a).

RO2: To examine whether financial inclusion differs by gender, age, monthly income and education among street vendors in Kota (H1b–H4b).

RO3: To identify the practical barriers that vendors face while using digital payments.

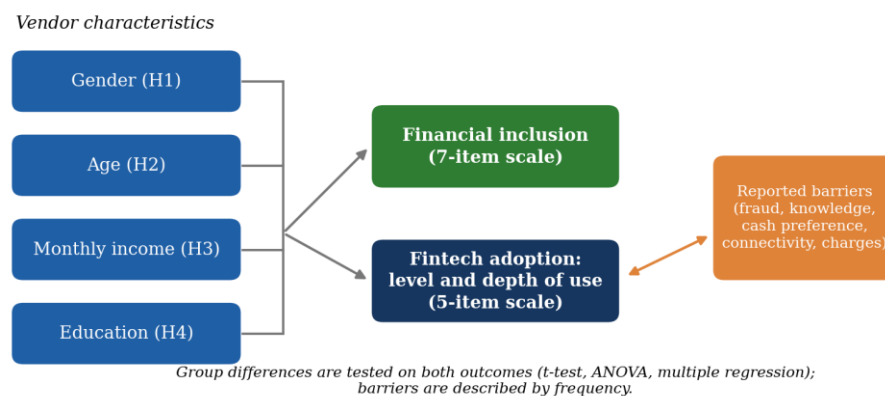


Figure 2.1 Proposed conceptual framework
Source: Authors' own.

3. METHODS

3.1 Setting, sampling and data collection

Data were collected using a structured bilingual questionnaire administered face to face in the city's principal vending zones, namely markets, roadside clusters, coaching areas, transport locations and residential neighbourhoods. Because no sampling frame of digitally active vendors exists (Section 1.1), purposive sampling with area-based coverage was adopted, and vendors with at least some exposure to UPI or other digital payment modes were approached.

In total, 600 questionnaires were distributed. Of these, 160 were excluded because they were duplicates, incomplete or exhibited careless response patterns such as straight-lining, resulting in 440 valid responses (73.33%). A minimum sample of 385 is required to estimate a proportion at the 95% confidence level with a 5% margin of error (Cochran, 1977); the final sample therefore exceeds this benchmark. Respondents were informed of the purpose of the study, participated voluntarily and responded anonymously.

3.2 Measures

The fintech adoption scale (five items) captured the extent, regularity and independence with which vendors use digital financial services. The financial inclusion scale (seven items) covered formal account use, savings, institutional credit, insurance, digital financial participation and reduced reliance on informal arrangements. Items were adapted from prior studies on fintech and mobile-payment adoption and financial inclusion (Nandru et al., 2021; Nandru & Senthil Kumar, 2024; Oliveira et al., 2016; Senyo & Osabutey, 2020) and rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The item wording was refined through a pilot with vendors, and a preliminary reliability assessment was conducted on a subsample of 50 respondents prior to the main survey. Each respondent's composite score was the mean of the scale items. Gender, age band, education, monthly income and

business type were recorded as categorical variables. Five practical barriers were recorded as separate dichotomous (yes/no) items, allowing respondents to report any number of barriers.

Both scales demonstrated satisfactory reliability and convergent validity in the full sample (adoption: Cronbach's $\alpha = 0.904$, composite reliability = 0.929, AVE = 0.724; inclusion: $\alpha = 0.924$, composite reliability = 0.939, AVE = 0.687). Since all measures were obtained from the same respondents at a single point in time, common method bias was assessed using Harman's single-factor test; the first factor accounted for 34.72% of the variance, well below the 50% threshold at which concern is generally raised (Podsakoff et al., 2003).

3.3 Analysis

Gender differences were tested with independent-samples t-tests, while differences across age, income and education were examined using one-way ANOVA followed by Tukey HSD post-hoc comparisons. Levene's test was non-significant in every comparison; hence, equal variances were assumed. Effect sizes were obtained from the SPSS output (Cohen's d for the t-tests and eta squared for the ANOVAs) and interpreted using Cohen's (1988) benchmarks (d = 0.2, 0.5 and 0.8 for small, medium and large effects; $\eta^2 = 0.01, 0.06$ and 0.14). As eight omnibus tests were conducted, the results were additionally evaluated against a Bonferroni-adjusted threshold of $0.05/8 = 0.00625$. Barriers were summarised using frequencies.

Because the hypotheses are directional whereas omnibus tests are not, decisions on H1–H4 were based jointly on the direction of the group means, the post-hoc contrasts and the sign of the regression coefficients. Since these tests compare group means one factor at a time, multiple regression models were subsequently estimated for each outcome, with gender, age, education and income entered simultaneously. Age and education were coded as ordinal scores from 1 to 5 and income as a score from 1 to 4, and the results were verified using HC3 robust standard errors and dummy-coded categories. Interactions between gender and each of age, education and income were examined as an exploratory step (Section 4.5). All analyses were performed in SPSS.

4. RESULTS

4.1 Sample characteristics

Table 4.1 Profile of respondents (N = 440)

Variable	Category	n	%
Gender	Male	337	76.59
	Female	103	23.41
Age (years)	25 and below	54	12.27
	26–35	127	28.86
	36–45	147	33.41
	46–55	82	18.64
	Above 55	30	6.82
Education	No formal education	62	14.09
	Primary	110	25.00
	Secondary	114	25.91
	Senior secondary	107	24.32
	Graduate and above	47	10.68
Monthly income	Below ₹10,000	86	19.55

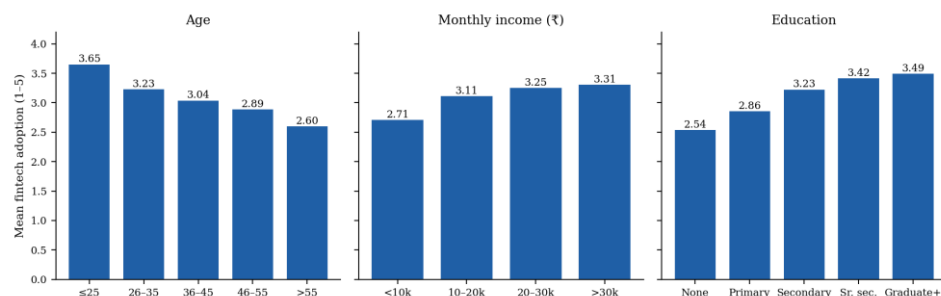
Variable	Category	n	%
	₹10,001–20,000	136	30.91
	₹20,001–30,000	142	32.27
	Above ₹30,000	76	17.27

Source: Survey data.

Men constituted 76.6% of the sample and women 23.4%; the gender comparison therefore involves unequal groups. Most respondents (62.3%) were aged 26 to 45 years, education was distributed fairly evenly from primary to senior secondary level, and about half of the respondents (50.5%) earned ₹20,000 or less per month. By business type, 31.8% sold food or snacks, 26.6% vegetables or fruits, 17.7% clothing or accessories, 12.7% household goods and 11.1% services or other items. Item-level means ranged from 3.07 to 3.15 for adoption and from 2.91 to 3.06 for inclusion, indicating that responses clustered near the scale midpoint, with inclusion lower than adoption.

4.2 Gender

Male vendors scored higher than female vendors on both adoption (3.189 vs 2.858; $t(438) = 2.856$, $p = 0.004$, $d = 0.32$) and inclusion (3.081 vs 2.696; $t(438) = 3.480$, $p < 0.001$, $d = 0.39$); group means and standard deviations are in Table 4.2. Both differences were statistically significant and of small-to-medium magnitude, so H1a and H1b are supported. The gap in inclusion was somewhat larger than that in adoption.



4.3 Age, income and education

Table 4.2 Mean fintech adoption and financial inclusion by gender, age, income and education

Factor	Group	n	Adoption mean (SD)	Inclusion mean (SD)
Gender	Male	337	3.189 (1.012)	3.081 (0.980)
	Female	103	2.858 (1.079)	2.696 (0.989)
Age	25 and below	54	3.652 (0.941)	3.275 (1.069)
	26–35	127	3.231 (1.006)	3.067 (1.014)
	36–45	147	3.038 (1.058)	2.987 (0.939)
	46–55	82	2.888 (0.926)	2.894 (0.942)
	Above 55	30	2.600 (1.078)	2.438 (0.984)
Income	Below ₹10,000	86	2.709 (1.037)	2.859 (0.971)
	₹10,001–20,000	136	3.110 (0.975)	3.074 (1.032)
	₹20,001–30,000	142	3.252 (1.023)	3.084 (0.999)
	Above ₹30,000	76	3.305 (1.062)	2.820 (0.920)

Factor	Group	n	Adoption mean (SD)	Inclusion mean (SD)
Education	No formal education	62	2.539 (0.941)	2.565 (0.910)
	Primary	110	2.856 (0.979)	2.805 (1.028)
	Secondary	114	3.225 (1.003)	3.075 (0.879)
	Senior secondary	107	3.417 (0.931)	3.208 (0.990)
	Graduate and above	47	3.494 (1.158)	3.289 (1.062)

Source: Authors' calculations from survey data. Values are means with standard deviations in parentheses.

Table 4.3 One-way ANOVA results and effect sizes

Factor	Outcome	F (df)	P	η^2
Age	Adoption	7.481 (4, 435)	< 0.001	0.064 (medium)
	Inclusion	3.908 (4, 435)	0.004	0.035 (small to medium)
Income	Adoption	6.296 (3, 436)	< 0.001	0.042 (small to medium)
	Inclusion	1.996 (3, 436)	0.114	0.014 (small)
Education	Adoption	11.702 (4, 435)	< 0.001	0.097 (medium)
	Inclusion	6.678 (4, 435)	< 0.001	0.058 (small to medium)

Source: Authors' calculations from SPSS output. η^2 = eta squared as reported by SPSS.

Age: Mean adoption declined from 3.652 among vendors aged 25 or below to 2.600 among those above 55 ($\eta^2 = 0.064$; Table 4.3). Tukey post-hoc comparisons indicated that the youngest group scored significantly higher than the 36–45, 46–55 and above-55 groups, and that the 26–35 group scored higher than the above-55 group. Inclusion followed the same direction (3.275 to 2.438; $\eta^2 = 0.035$), with the above-55 group scoring lower than the three youngest groups. H2a and H2b are supported.

Income: Adoption increased with income ($\eta^2 = 0.042$; Table 4.3), from 2.709 in the lowest band to 3.305 in the highest. The lowest-income group scored lower than each of the three higher-income groups, which did not differ appreciably from one another; the income effect on adoption is therefore concentrated at the lower end of the distribution. Inclusion did not differ significantly across income bands ($F(3, 436) = 1.996$, $p = 0.114$, $\eta^2 = 0.014$). H3a is supported and H3b is not.

Education: Adoption rose from 2.539 among vendors with no formal education to 3.494 among graduates ($\eta^2 = 0.097$; Table 4.3), the largest effect among the four characteristics. Vendors with no formal education or only primary education scored significantly lower than those with secondary, senior secondary and graduate-level education. Inclusion exhibited a similar pattern (2.565 to 3.289; $\eta^2 = 0.058$). H4a and H4b are supported. Every significant result also satisfies the Bonferroni-adjusted threshold of 0.00625.

4.4 Reported barriers

Table 4.4 Barriers reported by vendors (multiple responses possible)

Rank	Barrier	Yes (n)	No (n)	Yes (%)
1	Fear of fraud and security concerns	213	227	48.41
2	Lack of digital knowledge	208	232	47.27
3	Customer preference for cash	199	241	45.23

Rank	Barrier	Yes (n)	No (n)	Yes (%)
4	Internet connectivity issues	179	261	40.68
5	High transaction charges	157	283	35.68

Source: Survey data (N = 440).

Each of the five barriers was reported by between 36% and 48% of vendors, with fear of fraud and security concerns (48.4%) and lack of digital knowledge (47.3%) ranked highest. The percentages do not sum to 100 because respondents could report multiple barriers or none.

4.5 Multivariate regression

Age, education and income are correlated, so the one-way comparisons may partly reflect one another. Each outcome was therefore regressed simultaneously on gender, age, education and income (Table 4.5). Multicollinearity was not a concern (VIF = 1.00 to 1.07; the highest correlation among the predictors was between education and income, $r = 0.25$), and HC3 robust standard errors yielded the same conclusions.

Table 4.5 Multiple regression of fintech adoption and financial inclusion on vendor characteristics

Predictor	Adoption b	p	β	Inclusion b	p	β
Female (1 = yes)	-0.332	0.002	-0.14	-0.384	< 0.001	-0.16
Age (per band)	-0.226	< 0.001	-0.24	-0.157	< 0.001	-0.17
Education (per level)	+0.225	< 0.001	+0.26	+0.198	< 0.001	+0.24
Income (per band)	+0.114	0.015	+0.11	-0.072	0.124	-0.07
R ²	0.178			0.113		
Adjusted R ²	0.170			0.105		

Source: Authors' calculations (N = 440). b = unstandardised coefficient; β = standardised coefficient. Age, education and income entered as ordinal scores.

Gender, age and education remained significant predictors of both outcomes. Holding the other characteristics constant, women scored 0.33 points lower than men on adoption and 0.38 points lower on inclusion; each successive age band was associated with 0.23 lower adoption and 0.16 lower inclusion, and each higher level of education with 0.23 higher adoption and 0.20 higher inclusion. Education had the largest standardised coefficient for both outcomes ($\beta = 0.26$ and 0.24), so the decisions on H1, H2 and H4 remain unchanged.

Income showed a different pattern. Its association with adoption weakened to $b = 0.114$ ($p = 0.015$), and its partial η^2 declined from 0.042 in the one-way analysis to 0.021. When income was entered as four categories, a Type II test yielded $p = 0.0275$, which does not satisfy the Bonferroni threshold of 0.00625 applied above. In the dummy-coded model, only the lowest band (below ₹10,000) differed significantly, scoring 0.32 to 0.39 points lower than each of the other three bands ($p = 0.007$ to 0.015). For inclusion, income was not a significant predictor ($b = -0.072$, $p = 0.124$). Much of the bivariate income gap in adoption therefore appears attributable to education and the other characteristics, and support for H3a should be interpreted as weaker than Table 4.5 suggests.

The models account for a modest share of the variance ($R^2 = 0.178$ for adoption and 0.113 for inclusion). Dummy-coded versions gave the same picture ($R^2 = 0.193$ and 0.133), so treating age, education and income as ordinal scores does not materially affect the results.

Exploratory analyses. Interactions between gender and each of age, education and income were tested for both outcomes. Only the gender-by-income interaction for inclusion reached $p = 0.010$; as one of six tests (Bonferroni threshold $0.05/6 = 0.0083$), it is regarded as suggestive only. Adoption and inclusion were correlated at $r = 0.55$, and adoption continued to predict inclusion after controlling for the demographic variables ($b = 0.50$, $R^2 = 0.33$), indicating that the two outcomes are related but not interchangeable.

5. DISCUSSION

Among Kota vendors who already use digital payments, both the depth of use and the level of inclusion vary by gender, age and education. This is consistent with technology-acceptance research, in which individual characteristics are theorised to condition usage (Venkatesh et al., 2003, 2012), and with qualitative accounts of unequal digital capability among vendors (Mir & Wani, 2025). It also resonates with the Jaipur finding that adopting a digital option does not imply using it for most transactions (Ligon et al., 2019); here too, scores clustered near the scale midpoint and inclusion lagged behind adoption.

Education showed the strongest association with adoption ($\eta^2 = 0.097$), followed by age (0.064) and income (0.042), which is consistent with vendor studies that emphasise literacy and understanding as determinants of use (Mir & Wani, 2025; Nandru et al., 2023; Nandru & Senthil Kumar, 2024). Education is not synonymous with digital capability, and the present data cannot disentangle the two. Nevertheless, the gradient is steepest between vendors with no or only primary education and all others, which suggests that basic reading and numeracy skills may be important. In Kota, a city-wide literacy rate above 80% coexists with a sizeable minority of vendors with little or no formal education, and these vendors record the lowest scores.

The income result is less straightforward to interpret. Income distinguished the lowest-income vendors from the rest on adoption but not on inclusion. One possible explanation is that income affects the means to use digital services (device quality, mobile data and tolerance for a failed payment), whereas the inclusion items cover savings, credit and insurance, which depend on whether institutions serve vendors at all. Once education and the other characteristics are held constant, the association between income and adoption weakens considerably, which suggests that part of the one-way income gap reflects education. This is compatible with the argument that digital finance yields benefits only through active and appropriate use (Ozili, 2018), although this mechanism was not tested and a null result from a single sample provides weak grounds for firm conclusions.

Women scored lower on both outcomes, a gap of the kind that has led researchers to examine women vendors as a separate group (Nandru & Senthil Kumar, 2024). The gap is small to medium ($d = 0.32$ to 0.39), should not be interpreted as a difference in ability, and persisted after controlling for age, education and income. Plausible explanations such as device ownership, control over business finances, time constraints and mobility were not measured. A fieldwork observation that the questionnaire did not capture may help: many of the women and older vendors encountered accepted payments through a QR code but usually with the assistance of their children, whereas younger vendors, and those with children living with them, also used UPI for everyday transactions. If this impression holds, accepting QR payments and operating them independently are distinct behaviours, which would explain how women and older vendors can be well represented among QR users yet score lower on a scale capturing the regularity and independence of use, and it is in line with the reliance on literate family members described by Mir and Wani (2025). Future surveys should record who sets up and operates the vendor's payment account.

The barriers reported by vendors are consistent with this interpretation. Close to half of the respondents cited fear of fraud and limited digital knowledge, which agrees with studies identifying trust, awareness and literacy as interlinked obstacles (Bakhshi et al., 2024; Srivastava & Singh, 2023). Customers' preference for cash (45.2%) is a demand-side constraint that vendor training cannot remove, in line with evidence that cash retains practical value among small traders (Chattopadhyay et al., 2018; Ligon et al., 2019). As barriers were not disaggregated by vendor group, it cannot be established whether, for instance, fear of fraud is concentrated among older or less-educated vendors.

6. IMPLICATIONS, LIMITATIONS AND FUTURE RESEARCH

6.1 Implications

From a practical standpoint, the findings suggest that policy attention should shift from the acceptance of digital payments towards their effective use. Hands-on training in the local language, building on the peer-learning practices that vendors already follow, is likely to reach vendors with low levels of education more effectively than written guidance, and accessible mechanisms for reporting suspicious payments and disputing failed transactions would address the most commonly reported concern, fraud. Because PM SVANidhi already reaches vendors with credit and digital-transaction incentives (PIB, 2025), urban local bodies and banks in Kota could attach short digital-skills sessions to its existing touchpoints. Monitoring should capture the extent of digital finance use, not merely account ownership or the display of a QR code, and uniform programmes would probably under-serve women, older vendors and those with low levels of education, who record the lowest scores.

6.2 Limitations

The use of purposive sampling in a single city limits the ability to estimate population prevalence and restricts the generalizability of the findings to street vendors beyond the study area. The sample includes only vendors with some degree of digital exposure; this range restriction may therefore have reduced the observed differences and limits the ability to identify the factors that distinguish adopters from non-adopters in the first place. The design is cross-sectional and based on self-reported data, so the results indicate associations rather than causal effects. The regression in Section 4.5 addresses the one-way comparisons' tendency to reflect other characteristics, although it treats age, education and income as ordinal scores with equal intervals, and the four characteristics explain only 11 to 18% of the variance. Finally, composite scores treat five-point Likert items as interval data, the gender comparison involves unequal group sizes, and the interaction tests are exploratory, so the one nominally significant result is suggestive only.

6.3 Future research

Future research should test the suggestive gender-by-income interaction in a larger sample and measure the mechanisms not observed here, such as device ownership, control over business finances and digital skills. Longitudinal data, including data collected before and after a training intervention, would help establish causal relationships. Samples that include non-users would permit analysis of the adoption decision itself, and data from other cities, including those without a large student population, would show whether the Kota pattern holds elsewhere.

CONCLUSION

Among urban street vendors in Kota who already use digital payments, fintech adoption and financial inclusion differ significantly by gender, age and education, with education showing

the strongest association. Income is associated with adoption but not with inclusion, and even the adoption association weakens once the other characteristics are controlled. Fear of fraud and limited digital knowledge are the barriers reported most frequently. Wider acceptance has not equalised how vendors use digital finance; support targeted at women, older vendors and those with low levels of education is therefore likely to be more beneficial than further expansion of acceptance infrastructure. These findings are associations observed in a purposive sample of existing users and require longitudinal confirmation.

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