Fintech Adoption Patterns Among Young Consumers and SME Growth Dynamics: An Analytical Study in Visakhapatnam

Mr.KALA MANI KANTA , Research Scholar, BBA Department, KLEF.

Mail id: manikantakala001@gmail.com ,

Dr. K KRISHNA RAO , Assistant Professor, BBA Department, KLEF.

Mail id: krishnaraokunapareddy@kluniversity.in ,

Abstract

FinTech has changed the way people in India pay for things, but most research stops at the individual: it asks why someone decides to use a payment app and rarely asks what happens next. This study examines how young consumers in three localities of Visakhapatnam (AU Campus Area, Siripuram and Dwaraka Nagar) are adopting FinTech and whether respondents see that adoption supporting the growth of small and medium enterprises (SMEs). Primary data were collected with a structured questionnaire of 27 items, and 90 responses from persons aged 18 to 35 were analysed. Descriptive statistics, Cronbach's alpha, Pearson correlation, chi-square tests, one-way ANOVA and linear regression were used. UPI was used by every respondent and 66.7% paid digitally every day. The chi-square tests showed that payment frequency and the share of transactions made digitally are significantly associated with age, occupation, SME linkage, internet reliability and gender (frequency only). The ANOVA showed that adoption intensity differs by age ($F(2, 87) = 6.22$, $p = .003$), occupation ($p = .002$) and network quality ($p = .001$) but not by income. In the multiple regression ($R^2 = .206$, $p = .001$) social influence was the only significant predictor of adoption ($\beta = .266$, $p = .010$); effort expectancy ($p = .063$) and trust ($p = .078$) were marginal. Personal adoption intensity did not predict perceived SME growth ($\beta = -.083$, $p = .436$), although respondents with an SME link rated FinTech's SME benefits higher. The data file contained only 30 distinct response patterns, each recorded three times, so the significance levels should be treated as provisional (Section 7.9).

Keywords: FinTech adoption, UPI, digital payments, young consumers, SME growth, Visakhapatnam, chi-square, ANOVA, linear regression.

Introduction

FinTech has changed how people manage money almost everywhere, and India is one of the clearest examples of that change. Cheap smartphones, affordable data and government-backed systems like UPI have made digital payments part of everyday life for millions of people. UPI in particular stands out globally: it lets users move money between any two banks instantly and for free, which is not something most other countries' payment systems can do.

Most research on why people adopt FinTech uses standard models like TAM (Technology Acceptance Model; Davis, 1989) and UTAUT (Unified Theory of Acceptance and Use of Technology; Venkatesh et al., 2003). These models are useful. They tell us that people adopt digital payments because the services are easy to use, useful, or because they trust the platform (Sivathanu, 2019; Hu et al., 2020). Other studies look at the bigger picture, connecting digital finance to financial inclusion and economic growth at a national or global level (Ozili, 2018). But almost all of this research is either about big-city consumers or broad, country-level trends. Very little of it asks a simpler, more practical question: once people start using FinTech, does it actually help the businesses around them?

This gap matters most in cities like Visakhapatnam, a growing port city in Andhra Pradesh with a large student population and a dense mix of small businesses. Areas like the AU Campus Area, Siripuram and Dwaraka Nagar are full of young people using digital payments every day, and full of small shops, vendors and SMEs trying to keep up. But little is known about whether this everyday youth adoption is translating into anything measurable for those businesses: more sales, better records, easier access to credit, or simply fewer customers asking for cash.

This study tries to answer that question directly. Instead of only asking why young people adopt FinTech, it looks at what happens after they do, and how that adoption relates to SME growth in Visakhapatnam's key commercial and university areas. The aim is to move the conversation from theory to ground reality and to give a clearer, more local picture of what FinTech adoption means for a Tier-2 city.

Research Gap

Existing FinTech adoption literature remains anchored in individual-level behavioural models (TAM, UTAUT) applied largely to metro consumers or macro cross-national contexts (Sivathanu, 2019; Ozili, 2018; Hu et al., 2020), overlooking downstream economic effects within India's emerging Tier-2/Tier-3 commercial clusters. Empirical evidence is scarce on how merchants, SMEs and youth in regional hubs (Visakhapatnam's AU Campus Area, Siripuram, Dwaraka Nagar, or the Vizag–Chennai corridor) translate adoption into measurable economic activity. Moreover, prevailing frameworks, calibrated to East Asian or Western markets, underexamine India's interoperable UPI ecosystem at the semi-urban level. This study addresses these gaps by empirically investigating the localised economic spillover of FinTech adoption in India's regional commercial corridors.

Conceptual Framework

The framework treats SME growth dynamics as the final outcome. Adoption drivers (performance expectancy, effort expectancy, trust, social influence and access) shape the intention to adopt FinTech, intention leads to actual FinTech usage, and usage is expected to feed through four channels into SME growth: transactions, formalization, credit access and revenue. In the survey, the drivers are measured through Likert statements on usefulness, ease of use, trust and security, social influence and rewards, and access through smartphone ownership, internet reliability and network quality. Actual usage is measured by payment frequency and the share of transactions made digitally, and SME growth dynamics through five statements on sales and reach, credit access, costs, record keeping and overall growth.

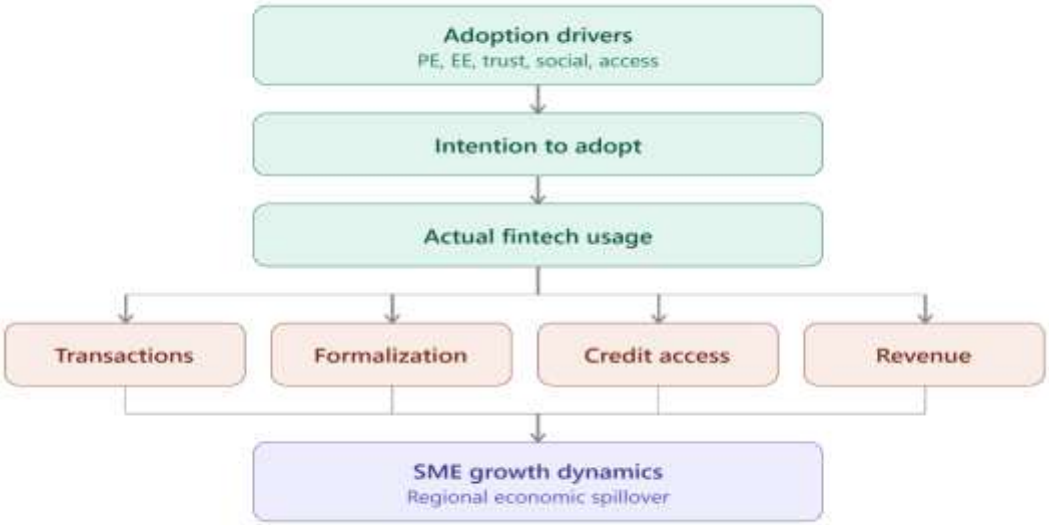


Figure 1. Conceptual framework of the study

Review of Literature

Hu et al. (2020) examined FinTech adoption from a consumer perspective with an integrated risk-benefit model using perceived benefit, brand image, perceived financial risk and legal risk as predictors of adoption intention. Perceived benefit and brand trust outweighed perceived risks, raising adoption likelihood among young, tech-literate consumers. The model is grounded in developed East Asian markets and does not account for India's interoperable UPI ecosystem in semi-urban and regional centres.

Amnas et al. (2023) integrated UTAUT2 with the Trust Theoretic Model, testing performance expectancy, effort expectancy, social influence, habit, price value, facilitating conditions and trust. All of these factors significantly influenced adoption intention, with trust playing a crucial role in shaping both intention and actual FinTech use. The dual-theory framework is rare in the literature, but the study has no region-specific retail or educational lens and does not localise trust dynamics to India's Tier-2 commercial zones.

Kurniasari et al. (2023) examined FinTech adoption within organisational settings using the UTAUT approach, testing performance expectancy, effort expectancy, social influence, trust and regulatory services. Performance and effort expectancy positively affected adoption intention among organisational users. The organisational lens is less explored than individual consumer studies, but it does not extend to consumer behaviour within India's regional retail or university corridors.

Alamoodi and Selamat (2021) applied an extended TAM to identify factors influencing FinTech product and service adoption among bank customers in Saudi Arabia, surveying demographic factors alongside adoption intentions. The study offers region-specific evidence from a Gulf banking context, but its scope is limited to Saudi bank customers and does not address Tier-2 urban FinTech penetration in India.

Fahad and Shahid (2022) examined UPI adoption in India using Diffusion of Innovation theory, testing relative advantage, complexity and observability. Relative advantage, low complexity and observability were significantly and positively associated with the intention to adopt UPI. The study shifts attention from UPI's operational aspects to user adoption determinants but does not map adoption onto localised university corridors or retail hubs.

Singh et al. (2020) proposed an integrated framework combining TAM, UTAUT, ServPerf and WebQual 4.0 to examine FinTech adoption across adoption, behavioural and technological dimensions. Using data from 439 active internet users, they found that perceived ease of use, usefulness, social influence, security and responsiveness significantly shaped FinTech adoption behaviour. The multi-theory integration is rarely attempted, but the findings are not localised to specific regional economic corridors in India.

Gulia and Singh (2023) applied the Meta-UTAUT model to examine UPI adoption among rural users in Haryana villages. In a survey of 195 rural UPI users, social influence, performance expectancy, effort expectancy and facilitating conditions directly and positively influenced attitude toward UPI adoption. The study is rare empirical evidence from India's rural population but does not capture adoption dynamics in urban university corridors or commercial retail hubs.

Chawla and Joshi (2019) proposed a multidisciplinary TAM-UTAUT model to examine Indian consumers' attitude and intention to adopt mobile wallets. In a national survey of 744 respondents, perceived ease of use, usefulness, trust, security, facilitating conditions and lifestyle compatibility significantly shaped adoption intention. The large-scale model is valuable, yet its findings are not localised to specific regional retail or educational corridors.

Singh, Sinha and Liébana-Cabanillas (2019) examined the effect of innovativeness, stress to use and social influence on users' recommendation of mobile wallet services in India. These factors meaningfully influenced willingness to recommend m-wallets to others, extending beyond simple adoption intention. The study does not connect this recommendation behaviour to actual economic activity in specific local commercial zones.

Bagale and Srivastava (2023) integrated TAM and Diffusion of Innovation theory to examine Indian consumers' intent to adopt e-wallets and validated a model linking established adoption theories to e-wallet-specific behaviour. The combination of two frameworks is a methodological contribution, but the study does not examine how e-wallet adoption translates into localised retail or university-linked spending patterns.

Prasad et al. (2025) examined cryptocurrency investment adoption intentions among Gen Z and millennial investors in Hyderabad, testing perceived risk, regulatory framework, social influence, effort expectancy and price value. Investment behaviour, regulatory framework and perceived risk significantly influenced adoption intentions, with fear of missing out (FOMO) mediating the relationship. Being specific to Hyderabad's metro investors, the study does not extend to the broader Tier-2 retail or university-linked FinTech ecosystem.

Nain and Shivanna (2024) applied an extended UTAUT2 model, adding personal innovativeness, perceived risk and technological anxiety, to examine robo-advisor adoption among Indian investors. Using PLS-SEM, they identified the antecedents and barriers shaping investment decision-making through robo-advisory platforms. The framework is specific to automated investment advice and does not examine the downstream effect of adoption on regional retail or educational commercial hubs.

Overall review

The studies above explain why individuals adopt mobile wallets, UPI, FinTech services and investment technologies, mostly through TAM, UTAUT and their extensions, and they point to performance expectancy, effort expectancy, social influence, trust and security as recurring drivers (Sivathanu, 2019; Chawla & Joshi, 2019; Amnas et al., 2023). A smaller group links digital payments to MSME efficiency and financial inclusion (Gupta & Xia, 2020; Ozili, 2018). Very few of them examine, within a single study, both the adoption behaviour of young consumers and the perceived effect of FinTech on SMEs, and almost none do so for a Tier-2 city such as Visakhapatnam. This study addresses that gap.

Objectives

1. To profile the FinTech usage of young consumers in Visakhapatnam.

2. To test whether digital payment behaviour is associated with demographic, occupational, SME-linkage and access characteristics.

3. To compare FinTech adoption intensity, perceived SME growth and satisfaction across respondent groups.

4. To assess the influence of performance expectancy, effort expectancy, trust and security, social influence and rewards on FinTech adoption.

5. To examine whether actual FinTech usage is related to perceived SME growth dynamics.

Hypotheses

H1: Performance expectancy does not significantly influence FinTech adoption intention among young consumers (Null); performance expectancy has a significant positive influence on FinTech adoption intention among young consumers (Alternative).

H2: Effort expectancy does not significantly influence FinTech adoption intention among young consumers (Null); effort expectancy has a significant positive influence on FinTech adoption intention among young consumers (Alternative).

H3: Trust/security does not significantly influence FinTech adoption intention among young consumers (Null); trust/security has a significant positive influence on FinTech adoption intention among young consumers (Alternative).

H4: Actual FinTech usage among youth does not significantly influence local SME growth dynamics, i.e., transaction volume, formalization, credit access, and revenue (Null); actual FinTech usage among youth has a significant positive influence on local SME growth dynamics, i.e., transaction volume, formalization, credit access, and revenue (Alternative).

Research design

The study is a quantitative, cross-sectional survey. Primary data were gathered from young consumers in three localities of Visakhapatnam (AU Campus Area, Siripuram and Dwaraka Nagar), areas that combine student, salaried and small-business populations, using a structured, self-administered questionnaire.

Data collection and sampling

The respondents were persons aged 18 to 35. The data file contains 90 responses with no missing values, and all 90 rows were analysed as recorded. A data-quality check (Section 7.9) found that the file consists of 30 distinct response patterns, each recorded three times; results for the 30 distinct responses are therefore reported alongside for comparison. [Author to confirm: sampling technique, number of questionnaires circulated, mode and period of data collection.] Because the sample is small and non-random, the findings cannot be generalised to all young consumers in Visakhapatnam.

Instrument and variables

The questionnaire has two parts. Part A (Q1–Q12) collects age, gender, occupation, education, monthly income, smartphone ownership, internet reliability, network quality, FinTech services used, payment frequency, share of transactions made digitally and SME linkage. Part B (Q13–Q27) consists of 15 statements rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Construct scores are averages of their items (range 1 to 5), and a score below 2.50 is classed as Low, 2.50 to 3.49 as Moderate and 3.50 or above as High.

Variable	Items and construction
Performance expectancy (PE)	Mean of Q13 (useful for managing money) and Q20 (helps save, budget, invest)
Effort expectancy (EE)	Mean of Q14 (easy to learn and use) and Q19 (enough digital knowledge)
Trust and security (TS)	Mean of Q15 (trust in security) and reverse-coded Q16 (worry about fraud)
Social influence (SI)	Q18 (friends and family influenced adoption)
Rewards (RW)	Q17 (cashback, rewards and offers influence use)
Adoption index	Mean of payment frequency (Rarely = 1, Few times a week = 3, Daily = 5) and share of digital transactions (Below 25% = 1, 25–50% = 2.33, 51–75% = 3.67, Above 75% = 5)
SME growth perception (SGP)	Mean of Q22 (sales and reach), Q23 (credit access), Q24 (transaction and cash-handling costs), Q25 (digital record keeping) and Q26 (overall growth)
Access variables	Smartphone ownership (Q6), reliable internet (Q7), network quality (Q8)

Q21 (willingness to use digital loan apps) and Q27 (overall satisfaction) are analysed as single items.

Statistical tools

Data preparation and analysis were carried out in Microsoft Excel (COUNTIFS, SUMPRODUCT, CHIDIST, FDIST and LINEST formulas) and the results were checked using Python (SciPy). Cronbach's alpha was used to assess reliability. Chi-square tests of independence (with Cramér's V and Monte Carlo permutation p-values as a check where expected counts were below 5), one-way ANOVA with Tukey post hoc comparisons, Welch's F and the Kruskal–Wallis test as robustness checks, Pearson correlation and ordinary least squares regression were used at the 5% significance level.

Respondent profile

Table 1. Profile of respondents (N = 90)

Variable	Category	Count	Percent
Age	18–22 years	24	26.7%
	23–27 years	39	43.3%
	28–35 years	27	30.0%
Gender	Female	45	50.0%
	Male	45	50.0%
Occupation	Student	36	40.0%
	Works in an SME	24	26.7%
	Salaried employee	18	20.0%
	Self-employed / SME owner	12	13.3%
Education	Higher secondary	12	13.3%
	Undergraduate	45	50.0%
	Postgraduate	33	36.7%
Monthly income	Below ₹10,000	18	20.0%
	₹10,000–₹25,000	21	23.3%
	₹25,001–₹50,000	39	43.3%
	Above ₹50,000	12	13.3%

Source: Survey data.

The sample is evenly split by gender (50% each) and is young: 43.3% are aged 23 to 27 and 30.0% are aged 28 to 35. Students form the largest occupational group (40.0%), followed by SME employees (26.7%), salaried employees (20.0%) and SME owners (13.3%). Half the respondents are undergraduates, and 43.3% earn ₹25,001 to ₹50,000 per month. Group sizes for SME owners, higher-secondary respondents and the highest income band are small (12 each), which limits the power of group comparisons.

Digital access and FinTech usage

Table 2. Digital access and FinTech usage (N = 90)

Variable	Category	Count	Percent
Owns a smartphone	Yes	87	96.7%
	No	3	3.3%
Reliable internet	Yes	75	83.3%
	No	15	16.7%
Network quality	Poor	9	10.0%
	Average	33	36.7%
	Good	36	40.0%
	Very good	12	13.3%
Digital payment frequency	Daily	60	66.7%
	Few times a week	21	23.3%
	Rarely	9	10.0%
Share of transactions made digitally	Above 75%	36	40.0%
	51–75%	27	30.0%
	25–50%	21	23.3%
	Below 25%	6	6.7%

Variable	Category	Count	Percent
SME linkage	No SME link	33	36.7%
	Works in an SME	24	26.7%
	Family business	21	23.3%
	Owns an SME	12	13.3%
FinTech services used (multiple response)	UPI apps	90	100.0%
	Mobile banking	30	33.3%
	Digital wallets	21	23.3%
	Digital loan / BNPL apps	21	23.3%
	Investment / trading apps	18	20.0%
	Insurance apps	6	6.7%

Source: Survey data. Percentages for services are of respondents (N = 90) and do not sum to 100.

Smartphone ownership is almost universal (96.7%) and 83.3% report reliable internet, although only 13.3% rate their network as very good. UPI is used by every respondent, mobile banking by one third, and wallets, digital loan/BNPL apps and investment apps by about one in five. The average respondent uses 2.07 services. Two thirds (66.7%) pay digitally every day, and 70.0% make more than half of their monthly transactions digitally. Almost two thirds (63.3%) have some link with an SME.

Table 3. Mean scores of individual statements (scale 1–5)

Statement	Mean
Q13 FinTech apps are useful for managing my money	3.90
Q14 FinTech apps are easy to learn and use	3.77
Q15 I trust the security of digital payment platforms	3.40
Q16 I worry about fraud or data theft	3.00
Q17 Cashback, rewards and offers influence my use	3.37
Q18 Friends and family influenced me to adopt	3.73
Q19 I have enough digital/financial knowledge	3.60
Q20 FinTech helps me save, budget or invest better	3.57
Q21 I would use digital loan/credit apps when needed	2.97
Q22 Digital payments increase SME sales and reach	3.83
Q23 FinTech lending improves SME access to credit	3.60
Q24 FinTech reduces SME transaction and cash-handling costs	3.67
Q25 Digital record keeping helps SME growth	3.77
Q26 SMEs in Visakhapatnam would grow faster with wider adoption	3.97
Q27 Overall, I am satisfied with FinTech services	3.63

Source: Survey data.

The highest-rated statements are that SMEs in Visakhapatnam would grow faster with wider adoption (Q26, 3.97), that FinTech apps are useful for managing money (Q13, 3.90) and that digital payments raise SME sales and reach (Q22, 3.83). The lowest are willingness to use digital loan apps (Q21, 2.97) and worry about fraud (Q16, 3.00), the latter at the neutral midpoint. Trust in platform security (Q15, 3.40) is only moderate. Respondents are therefore positive about FinTech's usefulness and especially about its value for SMEs, but cautious about digital credit.

Reliability and descriptive statistics

Table 4. Descriptive statistics and reliability of constructs

Construct	Items	Mean	SD	Cronbach's α	Reliability
Performance expectancy (PE)	2	3.73	0.74	.35	Low
Effort expectancy (EE)	2	3.68	0.66	.09	Low
Trust and security (TS)	2	3.20	0.60	.37	Low
Social influence (SI)	1	3.73	0.90	—	Single item
Rewards (RW)	1	3.37	0.84	—	Single item
Adoption index	2	3.92	0.93	.04	Low
SME growth perception (SGP)	5	3.77	0.41	.02	Low

Scale 1–5. Inter-item correlations: PE r = .21, EE r = .05, TS r = .23 (Q16 reversed).

Internal consistency is low for every multi-item construct, well below the usual .70 criterion (Nunnally, 1978). The pairs of items behind PE, EE and TS, and the five SME growth statements, therefore capture distinct facets rather than a single tight construct, and the SME growth items are essentially uncorrelated with one another (α = .02). Results based on these composites should be read as indicative rather than definitive.

Level of constructs

Table 5. Distribution of respondents by level of construct (N = 90)

Construct	Low	Moderate	High	% High
Performance expectancy (PE)	3	15	72	80.0%
Effort expectancy (EE)	0	27	63	70.0%
Trust and security (TS)	3	45	42	46.7%
Social influence (SI)	9	24	57	63.3%
Rewards (RW)	18	24	48	53.3%
Adoption index	6	24	60	66.7%
SME growth perception (SGP)	0	18	72	80.0%

Low < 2.50; Moderate 2.50–3.49; High ≥ 3.50.

Most respondents are in the High category on every construct except trust and security, where only 46.7% are High and half are Moderate. Performance expectancy and SME growth perception are the highest (80.0% High each), and none of the respondents rate SME growth perception as Low.

Correlation

Table 6. Pearson correlation matrix (N = 90)

	PE	EE	TS	SI	RW	Adoption	SGP
PE	1	.396**	.308**	−.108	−.166	.213*	.192
EE	.396**	1	.375**	−.203	−.246*	.280**	.174
TS	.308**	.375**	1	.006	−.279**	.317**	.218*
SI	−.108	−.203	.006	1	−.048	.216*	−.318**
RW	−.166	−.246*	−.279**	−.048	1	−.178	−.415**
Adoption	.213*	.280**	.317**	.216*	−.178	1	−.083
SGP	.192	.174	.218*	−.318**	−.415**	−.083	1

* p < .05; ** p < .01 (two-tailed).

Adoption intensity is positively and significantly correlated with trust and security (r = .317), effort expectancy (r = .280), social influence (r = .216) and performance expectancy (r = .213), but not with rewards. Perceived SME growth, in contrast, is unrelated to adoption intensity (r = −.083) and is negatively correlated with rewards (r = −.415) and social influence (r = −.318). Respondents who are more influenced by cashback and by peers are therefore less convinced that FinTech drives SME growth. The correlations among the predictors are modest (all below .40 in absolute value), so multicollinearity is not a concern.

Chi-square tests of independence

Table 7. Chi-square test results (N = 90)

Association tested	χ^2	df	p	Cramér's V	Permutation p	Cells with expected count < 5
Gender × Payment frequency	10.03	2	.007	.33	.006	2 of 6
Age × Payment frequency	11.58	4	.021	.25	.016	3 of 9
Occupation × Payment frequency	24.55	6	<.001	.37	<.001	6 of 12
SME link (yes/no) × Payment frequency	14.33	2	<.001	.40	<.001	1 of 6
Reliable internet × Digital share	39.34	3	<.001	.66	<.001	3 of 8
Age × Digital share	27.19	6	<.001	.39	<.001	3 of 12
Income × Digital share	24.41	9	.004	.30	.003	9 of 16
Gender × Digital share	0.76	3	.859	.09	.899	2 of 8

Permutation p-values are from 10,000 random permutations and are shown as a check where expected counts are small. Payment frequency: Rarely / Few times a week / Daily. Digital share: four bands from below 25% to above 75%.

Seven of the eight associations are significant at the 5% level, and the permutation p-values lead to the same conclusions. **Gender:** males pay digitally more often than females (73.3% daily against 60.0%) and none of the males pay rarely against 20.0% of females, yet gender is unrelated to the share of transactions made digitally (p = .859). **Age:** respondents aged 28 to 35 are the most digitised, with 77.8% making more than 75% of their transactions digitally, against 30.8% of those aged 23 to 27 and 12.5% of those aged 18 to 22. **Occupation and SME link:** 91.7% of students pay daily, compared with 50.0% of SME employees, SME owners and salaried employees. Everyone without an SME link pays at least a few times a week (90.9% daily), whereas 15.8% of those with an SME link pay rarely. **Internet access:** reliable internet is the strongest association (V = .66): 44.0% of those with reliable internet make more than 75% of transactions digitally and none fall below 25%, while 40.0% of those without reliable internet fall below 25%. **Income** is also associated with the digital share, although 9 of 16 cells have small expected counts. Hypothesis H5 is therefore largely supported.

One-way ANOVA

Table 8. One-way ANOVA results

Dependent variable by grouping factor	F	df	p	η^2	Welch p	Kruskal–Wallis p	Result
Adoption index by Age	6.22	2, 87	.003	.125	.009	.009	Sig.
Adoption index by Occupation	5.39	3, 86	.002	.158	<.001	.003	Sig.
Adoption index by Income	0.50	3, 86	.683	.017	.593	.572	Not sig.
Adoption index by Network quality	6.08	3, 86	.001	.175	<.001	.001	Sig.

Dependent variable by grouping factor	F	df	p	η²	Welch p	Kruskal–Wallis p	Result
SME growth perception by SME link	4.17	3, 86	.008	.127	.002	.009	Sig.
SME growth perception by Education	7.15	2, 87	.001	.141	.003	.006	Sig.
Satisfaction (Q27) by Income	4.56	3, 86	.005	.137	<.001	.004	Sig.

Levene's test indicated unequal variances for most comparisons (for example $p < .001$ for occupation), so Welch's F and the Kruskal–Wallis test are reported as checks. All conclusions are the same under the three tests.

Table 9. Group means (SD) for the significant comparisons and Tukey HSD results

Outcome / Group	n	Mean (SD)	Tukey HSD (p < .05)
Adoption index by age			
18–22 years	24	3.46 (1.14)	vs 28–35: diff 0.87, p = .002
23–27 years	39	3.92 (0.75)	—
28–35 years	27	4.33 (0.80)	—
Adoption index by occupation			
Student	36	4.31 (0.68)	vs SME owner: 0.97, p = .007; vs works in SME: 0.72, p = .012
Salaried employee	18	4.00 (0.84)	—
Works in an SME	24	3.58 (1.21)	—
Self-employed / SME owner	12	3.33 (0.55)	—
Adoption index by network quality			
Poor	9	3.44 (0.33)	Average vs Poor: 0.98, p = .017
Average	33	4.42 (0.74)	Average vs Good: 0.73, p = .004; vs Very good: 0.84, p = .025
Good	36	3.69 (0.94)	—
Very good	12	3.58 (1.16)	—
SME growth perception by SME link			
No SME link	33	3.58 (0.33)	vs works in SME: 0.34, p = .008
Works in an SME	24	3.92 (0.29)	—
Family business	21	3.83 (0.50)	—
Owns an SME	12	3.85 (0.50)	—
SME growth perception by education			
Higher secondary	12	4.15 (0.40)	vs postgraduate: 0.48, p = .001; vs undergraduate: 0.42, p = .004
Undergraduate	45	3.73 (0.45)	—
Postgraduate	33	3.67 (0.25)	—
Satisfaction by income			
Below ₹10,000	18	4.00 (0.84)	—
₹10,000–₹25,000	21	3.43 (0.93)	—
₹25,001–₹50,000	39	3.38 (0.94)	Above ₹50,000 vs ₹25,001–₹50,000: 0.87, p = .017

Outcome / Group	n	Mean (SD)	Tukey HSD (p < .05)
Above ₹50,000	12	4.25 (0.45)	—

Only Tukey pairs significant at the 5% level are listed.

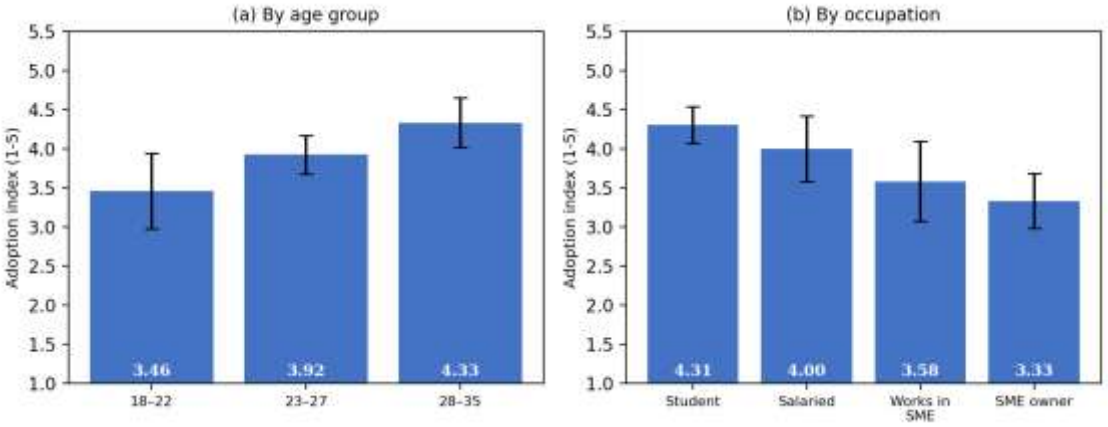


Figure 2. Mean adoption index (with 95% confidence intervals): (a) by age group, (b) by occupation

Adoption intensity rises with age: respondents aged 28 to 35 score 0.87 points higher than those aged 18 to 22. It is highest among students (4.31) and lowest among SME owners (3.33) and SME employees (3.58). Respondents who rate their network quality as Average have the highest adoption index (4.42), higher than the Good, Poor and Very good groups, so the pattern is not a straight line from poor to excellent networks and should not be read as better networks lowering adoption. Income has no significant effect on adoption intensity ($p = .683$). Perceived SME growth is higher among those who work in an SME than among those with no SME link, and higher among higher-secondary respondents than among graduates. Satisfaction is higher in the top income band than in the ₹25,001–₹50,000 band, but not in a consistent order across income groups. Hypothesis H6 is supported for six of the seven comparisons.

Linear regression

Model 1: multiple regression for H1–H3. The adoption index was regressed on performance expectancy, effort expectancy, trust and security, social influence and rewards.

Table 10. Multiple linear regression (dependent variable: adoption index)

Predictor	B	SE	β	t	p	VIF
Constant	0.533	1.024	—	0.52	.605	—
Performance expectancy (PE)	0.112	0.136	.089	0.82	.414	1.23
Effort expectancy (EE)	0.307	0.163	.215	1.89	.063	1.38
Trust and security (TS)	0.302	0.169	.195	1.78	.078	1.26
Social influence (SI)	0.277	0.104	.266	2.66	.010	1.06
Rewards (RW)	−0.048	0.115	−.043	−0.42	.677	1.12

$R^2 = .206$, adjusted $R^2 = .159$, $F(5, 84) = 4.36$, $p = .001$, SE of estimate = 0.857; Durbin–Watson = 2.08.

The model is significant and explains about 21% of the variation in adoption intensity. Social influence is the only predictor significant at 5% ($\beta = .266$). Effort expectancy ($\beta = .215$, $p = .063$) and trust and security ($\beta = .195$, $p = .078$) have positive coefficients that are significant only at the 10% level, while performance expectancy and rewards are not significant. H1 is not supported, and H2 and H3 are not supported at the 5% level. All VIF values are below 1.4 (Hair et al., 2019) and the Durbin–Watson value is close to 2, so multicollinearity and autocorrelation are not a concern. The residuals depart from normality (Shapiro–Wilk $W = .890$, $p < .001$), which is common with bounded Likert-based indices, so the coefficients should be treated as approximate.

Models 2 and 3: regression for H4. SME growth perception was regressed on the adoption index alone and then with SME linkage added as a dummy variable (1 = any SME link).

Table 11. Linear regression (dependent variable: SME growth perception)

Model	Predictor	B	SE	β	t	p
Model 2	Constant	3.910	0.187	—	20.86	<.001
	Adoption index	−0.036	0.046	−.083	−0.78	.436
Model 3	Constant	3.490	0.217	—	16.11	<.001
	Adoption index	0.021	0.047	.048	0.45	.658
	Any SME link (1 = yes)	0.306	0.091	.363	3.37	.001

Model 2: R^2 = .007, F(1, 88) = 0.61, p = .436; 95% CI for B (adoption index): −0.129 to 0.056. Model 3: R^2 = .121, adjusted R^2 = .101, F(2, 87) = 6.02, p = .004; Durbin–Watson = 1.96.

Adoption intensity does not predict perceived SME growth, either alone (β = −.083, p = .436) or after controlling for SME linkage (β = .048, p = .658), so H4 is not supported. Having a link with an SME is the significant predictor: respondents with such a link score 0.31 points higher on SME growth perception (p = .001). The perception is therefore driven by closeness to SMEs rather than by one's own payment behaviour.

Robustness and data-quality check

No respondent gave the same score to all 15 Likert statements, so straight-lining is not a concern. However, comparing the rows showed that the 90 rows consist of only 30 distinct response patterns, and each pattern appears exactly three times (rows i, i + 30 and i + 60 of the data file). Repeating every response three times multiplies each chi-square value by exactly three and shrinks standard errors by about √3, which makes p-values smaller than they would be for 90 independent respondents. The analyses were therefore repeated on the 30 distinct responses.

Table 12. Key results on all 90 rows compared with the 30 distinct responses

Test	All 90 rows	30 distinct responses
Chi-square: Gender × Frequency	χ^2 = 10.03, p = .007	χ^2 = 3.34, p = .188
Chi-square: Age × Frequency	χ^2 = 11.58, p = .021	χ^2 = 3.86, p = .425
Chi-square: Occupation × Frequency	χ^2 = 24.55, p < .001	χ^2 = 8.18, p = .225
Chi-square: SME link × Frequency	χ^2 = 14.33, p < .001	χ^2 = 4.78, p = .092
Chi-square: Internet × Digital share	χ^2 = 39.34, p < .001	χ^2 = 13.11, p = .004
Chi-square: Age × Digital share	χ^2 = 27.19, p < .001	χ^2 = 9.06, p = .170
Chi-square: Income × Digital share	χ^2 = 24.41, p = .004	χ^2 = 8.14, p = .521
ANOVA: Adoption by Age	F = 6.22, p = .003	F = 1.93, p = .165
ANOVA: Adoption by Occupation	F = 5.39, p = .002	F = 1.63, p = .207
ANOVA: Adoption by Network quality	F = 6.08, p = .001	F = 1.84, p = .165
ANOVA: SME growth by SME link	F = 4.17, p = .008	F = 1.26, p = .308
Regression Model 1 (H1–H3)	R^2 = .206, p = .001; SI p = .010	R^2 = .206, p = .319; no predictor significant
Regression Model 2 (H4)	β = −.083, p = .436	β = −.083, p = .662
Regression Model 3: SME link	β = .363, p = .001	β = .363, p = .071

Source: Survey data. The coefficients themselves are unchanged because the duplicated rows are identical; only the standard errors, test statistics and p-values change.

Only the association between reliable internet access and the digital share of transactions remains significant on the 30 distinct responses (p = .004); every other significant result in Sections 7.6 to 7.8 loses significance. The findings

based on the full file should therefore be treated as provisional until they are confirmed on the complete, independent set of responses.

Summary of Findings

• UPI is used by all respondents, 66.7% pay digitally every day and 70.0% make more than half their transactions digitally. Perceived usefulness (M = 3.90) and the belief that SMEs would grow faster with wider adoption (M = 3.97) are high, whereas willingness to use digital loan apps (M = 2.97) and trust in platform security (M = 3.40) are low to moderate.

• Payment frequency and the share of digital transactions are significantly associated with age, occupation, SME linkage and internet reliability, and payment frequency with gender (seven of eight chi-square tests significant). Reliable internet is the strongest association (V = .66). H5 is largely supported.

• Adoption intensity differs by age (28–35 highest), occupation (students highest, SME owners lowest) and network quality, but not by income. Perceived SME growth differs by SME linkage and education, and satisfaction by income. H6 is supported for six of seven comparisons.

• In the regression, social influence is the only significant predictor of adoption ($\beta = .266$, $p = .010$); effort expectancy ($p = .063$) and trust and security ($p = .078$) are marginal, and performance expectancy and rewards are not significant.

• Adoption intensity does not predict perceived SME growth ($\beta = -.083$, $p = .436$); SME linkage does ($\beta = .363$, $p = .001$).

• On the 30 distinct responses in the data file, only the internet-access association stays significant, so the remaining results are provisional (Section 7.9).

Table 13. Summary of hypothesis outcomes

Hypothesis	Test	Result	Evidence
H1: PE → adoption	Multiple regression	Not supported	$\beta = .089$, $p = .414$
H2: EE → adoption	Multiple regression	Not supported at 5% (marginal)	$\beta = .215$, $p = .063$
H3: Trust/security → adoption	Multiple regression	Not supported at 5% (marginal)	$\beta = .195$, $p = .078$
H4: Usage → SME growth	Simple and multiple regression	Not supported	$\beta = -.083$, $p = .436$
H5: Behaviour × characteristics	Chi-square	Supported for 7 of 8 associations	$p < .05$; Gender × Digital share $p = .859$
H6: Group differences	One-way ANOVA	Supported for 6 of 7 comparisons	$p < .05$; Adoption × Income $p = .683$

Source: Survey data.

Discussion

The finding that social influence is the strongest identifiable driver of adoption intensity agrees with studies that found peers and family to be significant in mobile wallet and UPI adoption (Madan & Yadav, 2018; Gulia & Singh, 2023; Singh et al., 2020) and with evidence that social influence shapes users' willingness to recommend m-wallets (Singh, Sinha & Liébana-Cabanillas, 2019). Among young people in the three localities, using FinTech appears to be a largely social norm, adopted through friends, family and campus peers.

Performance expectancy did not predict adoption here, although earlier work reports it as significant (Kurniasari et al., 2023; Gulia & Singh, 2023; Amnas et al., 2023). One plausible reason is that UPI has become the default payment method for these respondents (usage is universal and usefulness is rated high by most), so differences in perceived usefulness no longer separate heavier from lighter users. Effort expectancy and trust show positive but

only marginal effects. This is in line with studies that treat ease of use and trust as important (Chawla & Joshi, 2019; Amnas et al., 2023) and with the finding that security concerns remain a barrier (Sivathanu, 2019): trust in platform security is only moderate here (M = 3.40, with 46.7% High). With a larger independent sample these two factors may reach significance.

The most distinctive result concerns SMEs. Respondents with an SME link are the most convinced that FinTech helps SMEs grow, yet SME owners and employees use digital payments less intensively than students, and personal usage does not predict the belief. This suggests a belief–practice gap: small businesses recognise the benefits that studies such as Gupta and Xia (2020) report at the national level (lower cash-handling costs, faster transactions), but cash habits, customer preferences or limited digital skills may keep their own practice behind. The low appetite for digital loans (M = 2.97), set against a more positive view of FinTech lending for SME credit access (M = 3.60), similarly suggests that the credit channel highlighted by Ozili (2018) is still more an expectation than a practice among young consumers.

Differences by age, gender and internet reliability point to access and familiarity effects. Older respondents (28–35) and students are the heaviest users, men pay more often than women, and reliable connectivity is the strongest correlate of the digital share of transactions. The non-monotonic network-quality result should be read with caution because perceived quality may be tied up with other respondent characteristics. Finally, the weak internal consistency of the scales and the duplication found in the data file (Section 7.9) mean that these interpretations are provisional.

Suggestions and Implications

- SMEs and business associations in Visakhapatnam could run hands-on training in QR acceptance, digital invoicing and record-keeping apps, since SME-linked respondents believe in FinTech's value but use it less intensively.
- FinTech providers and banks could use peer and community channels (student ambassadors, merchant associations, family-oriented campaigns), because social influence is the strongest driver. Visible security features and easy fraud-grievance mechanisms would help build trust, which is only moderate.
- Local bodies and service providers should prioritise reliable connectivity in under-served pockets, as internet reliability is most strongly associated with the digital share of transactions, and promote digital literacy among women and first-time users.
- Digital credit needs responsible promotion: financial education on borrowing through FinTech apps would help translate the expected credit benefits for SMEs into practice.
- Universities in the study area could involve students, who are the most active users, in outreach programmes that help neighbouring small businesses adopt digital tools.

Limitations and Future Research

The study has several limitations. The sample is small (n = 90), drawn from three localities of one city, and cannot be taken as representative of all young consumers in Visakhapatnam or India. The data file contains only 30 distinct response patterns, each recorded three times, so significance levels are overstated until the findings are confirmed on independent responses (Section 7.9). The multi-item constructs have low internal consistency and several are built from only two items, and social influence and rewards are single items. The questionnaire measures actual usage intensity rather than stated intention, and SME growth is measured as perception rather than as firm-level sales, credit or cost data. Several cross-tabulations have sparse cells, Likert-based indices were treated as interval data, and residuals depart from normality. All variables come from the same respondents at one point in time, so the design cannot demonstrate cause and effect. Future studies should use larger, probability-based samples from several Tier-2 cities, validated multi-item scales tested with factor analysis and structural equation modelling, a direct measure of adoption intention, and firm-level data from SMEs to link consumer adoption directly to SME performance.

Conclusion

This study examined FinTech adoption among 90 young consumers in the AU Campus Area, Siripuram and Dwaraka Nagar of Visakhapatnam and its relation to perceived SME growth. Digital payment use is almost universal, but its intensity varies with age, occupation, SME linkage, gender and, above all, internet reliability. Social influence is the clearest driver of adoption, with effort expectancy and trust playing a smaller, marginal role. Respondents who are linked to SMEs hold the strongest belief that FinTech supports SME growth, yet they are not the heaviest users, and personal usage intensity does not predict this belief. Peer-led promotion, SME-focused digital training, stronger trust-building and better connectivity are therefore the practical routes for turning wide FinTech access into measurable gains for local SMEs. Given the small sample, the low scale reliability and the repeated responses in the data file, the results should be regarded as preliminary and validated on a larger, independent sample.

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