

Quick-Commerce Retention and Digital Adoption Barriers in Grocery Shopping: A Comparative Study on Tier-1 and Tier-2 Cities

Saleemuddin Panwale¹, Siddharth Nair², Aarya Padave³

¹Assistant Professor, Department of Statistics, Ramnarain Ruia Autonomous College, Mumbai, India.

^{2,3}Student, Department of Statistics, Ramnarain Ruia Autonomous College, Mumbai, India.

Correspondence:

¹saleempanwale@ruiacollege.edu, ²aaryapadave08@gmail.com, ³siddharthvinodnair@gmail.com

Abstract - With the rapid growth of Q-commerce platforms in the Indian metropolitan regions, this study examined how household usage, financial impact & retention behaviour with these platforms vary between Tier-1 & Tier-2 areas of the MMR. Using various non-probability sampling methods, 384 respondents were gathered from Tier-1 (CSMT-Mulund | Churchgate-Andheri | Vashi-Belapur) & Tier-2 (Thane-Badlapur | Mira Road-Virar | Kharghar-Panvel). Four Objectives were examined. First, Chi-Square tests & t-test revealed that usage frequency ($p = 0.001$) & the replace/supplementation of grocery shopping ($p = 0.002$) differed significantly by area while spend, budget share & behaviour did not. Second, Multiple Linear Regression showed that the seven constructs of service quality accounted for 50.2% of variance in retention ($R^2 = 0.502$, $F = 28.415$, $p < 0.001$) with UI/UX ($\beta = 0.294$) & Convenience ($\beta = 0.233$) coming as the strongest positive predictors. Third, no significant area-based differences were seen in digital comfort, trust in local vendors or family influence though a significant positive correlation was found between education & digital comfort ($p = 0.207$, $p = 0.203$). Fourth, the primary adoption barriers were preference for in-person product selection & closeness to stores. Future adoption intent was significantly higher among Tier-2 non-users than Tier-1 non-users ($p = 0.039$). Across all objectives, regional differences were consistently seen in behaviour and access rather than attitude, saying that infrastructure expansion rather than trust building should be the strategy for closing the Tier-1/Tier-2 usage gap. The study extends prior single demographic, user only research by including a broader age range and a non-user perspective while noting limitations related to its non-probability sampling design and cross-sectional scope.

Keywords: Q-Commerce, Food Delivery, Household Impact, Retention, Service Quality, Tier-1, Tier-2, Mumbai, Regional Adoption

1. INTRODUCTION

When it comes to retail in India, it has gone through some massive transformations in the past few years due to the growth of E-commerce and UPI digital payment software. In this shift, apps like Swiggy/Swiggy Instamart, Zomato, Zepto, Blinkit and many others have become more of an everyday utility app in most urban households (Anshuman et al., 2026). Ultra-fast deliveries under 15 minutes capture the majority of daily grocery, electronics, and personal care transactions (Sheth et al., 2025). These apps promise deliveries of groceries, daily essentials, medicine or even food items within the range of 10 to 30 minutes with the help of dark stores and various other techniques or strategies (Joerss et al., 2016).

The adoption of these apps accelerated during the phase of Covid-19 where going outside was a big crisis and using these apps were the fastest and safest way to get your daily essentials. A huge amount of people who adapted to using these apps retained their use even after the end of the lockdown (Sheth, 2020).

While many current existing research works on understanding the consumer behaviour especially of GenZ as they are known to be the digital platform's core (Anshuman et al., 2026), very less research has done on how these apps have an impact on

household as a unit and very less research is done when it comes to comparing Tier-1 and Tier-2 cities where regional, cultural and digital literacy factors may make a difference (Olpin et al., 2023).

Q-Commerce and Food Delivery in the Indian Context

The Indian quick-commerce sector has witnessed exponential growth since 2021. Following the acquisition of Blinkit (earlier known as Grofers) by Zomato in 2022, Blinkit scaled its dark-store footprint from under 100 to 700 locations across 30 cities within the two years of rebranding (Zomato, 2024). And even Zepto launched in 2021 by two Stanford dropouts reached a \$1.4 billion valuation by mid-2023, having scaled to 300,000 daily orders within its first 18 months of operation (Saha & Mukul, 2023). Swiggy Instamart and Big Basket have also strengthened their presence (Anshuman et al., 2026). This growth was seen due to the population density in most places and, most importantly, due to UPI and its impact on online transactions (NPICI, 2024).

Mumbai, which is considered as one of India's largest and most densely populated metropolitan region represents a relevant setting for this change. The area generates a large share of India's trade, taxes, and industrial output (Internet Geography, 2025). Quick commerce (delivering groceries and

essentials in 10–30 minutes via hyper-local dark stores) is rapidly transforming retail across the Mumbai metropolitan region (Cybernetics, n.d.). The Tier-1 cities (CSMT-Mulund) have some of the highest concentrations of Q-commerce dark stores in the country. Also, the tier-2 cities (Thane-Badlapur) functions as the extension of the Tier-1 city with some minor differences in the administration and geography. Their access to these services, infrastructure quality, and shopping habits may differ with that of the tier-1 cities.

2. REVIEW OF LITERATURE

Rationale For Examining the Household

Existing research on Q-commerce in India has usually used models like the Technology Acceptance Model (Davis, 1989) and UTAUT2 (Venkatesh et al., 2013; Shaw & Sergueeva, 2018) to explain how people choose to adopt or continue using these apps. These studies have given results on drivers such as convenience, UI/UX, product quality, and payment reliability (Anshuman et al., 2026; Saleem & M Bhandari, 2026). But buying food and groceries isn't an individual decision. It is part of shared household responsibilities, shared budget, and many other reasons, where living arrangements, presence of a partner, and household roles were shown to directly shape shopping frequency, bulk-buying behavior, and mode choice (Bezirgani & Lachapelle, 2020). A study that would only ask "Why does this person use an app?" would miss what we would argue is the more important question: "What has this changed for the household as a whole?" in terms of money spent, meals cooked compared to ordered, and reliance on these platforms compared to traditional shopping.

3. RESEARCH GAP, SCOPE AND OBJECTIVES

3.1. Research Gap

A review of recent research papers on similar topics reveals a consistent pattern. Both Anshuman et al. (2026) and Saleem and M Bhandari (2026) have addressed two questions: which factors (convenience, price, trust, UI/UX, etc.) drive the initial adoption and continued use, and how these factors relate to consumer satisfaction and retention. However, both studies also talk about the future scope of these studies:

1. Anshuman et al. (2026) restrict their sample to Gen-Z respondents (born 1997-2012) across Tier-1 Indian cities, and note that their findings concentrated among postgraduate-educated, urban respondents "may not fully represent Gen-Z sub-segments in smaller cities or with lower educational attainment," basically recommending cross-tier comparative studies as a direction for future research.
2. Anshuman et al. (2026) report that Product Quality Concerns had no statistically significant effect on adoption intention in their sample ($\beta = 0.030$, $p = 0.487$), with them saying that continued use of these apps have made the initial concerns negligible. However, to prove this, they recommend tracking long term usage of these platforms and how the experience is impacting the user's behaviour and feelings towards the platform. Because the studies

only looked at people at one single point in time, researchers can't prove for sure if people actually care less about quality the longer they use a platform.

Hence, this present study addresses these gaps using a broader population (all age groups, not only Gen-Z), a regional comparison (Tier-1 versus Tier-2 areas within the MMR), and household financial and behavioral measures, which are not captured in previous studies.

3.2. Objectives of the Study

1. Examine household usage patterns and financial impact of food delivery and Q-commerce platform adoption across Tier-1 and Tier-2 cities.
2. Identify the key service quality and retention factors like convenience, price and offers, trust and security, UI/UX, delivery issues, payment issues, and product quality that drive the continued use across a broader demographic than what was previously studied (i.e., this time including Tier-2 cities in the study).
3. Investigate how regional, cultural, and digital literacy differences between Tier-1 and Tier-2 households shape both the adoption and non-adoption of these apps.
4. Understand the reasons behind non-adoption among current non-users, including access, trust, digital literacy, economic, and preference-based barriers.

3.3. Scope Of This Study

The study is limited to the MMR region that includes Tier-1 cities (CSMT-Dadar-Kurla to Mulund / Powai | Churchgate-Bandra to Andheri | Vashi-Belapur) and Tier-2 cities (Central: Thane-Dombivli-Kalyan-Badlapur | Western: Mira Road-Virar | Navi Mumbai: Kharghar-Panvel, Ulwe). It covers the uses & non-users of the widely used Q-commerce platforms like Blinkit, Zepto, Swiggy Instamart, Zomato and others.

The study looks at respondents of all ages, which is already contrasting with the previous study that only took respondents that were from Gen Z. This study examines only the household food and grocery ordering patterns, which include how much people spend, how often they order, how they see service quality, and why some of them choose not to use these platforms. To keep a strict focus on the consumer's experience, the research won't include any other factors like delivery logistics, gig-worker conditions, and platform business strategies.

Because this study uses a design in such a way that it only captures a single snapshot in time, it does not establish any cause-and-effect relationships. Instead, it aims to highlight broader trends, patterns and connections to describe how households currently work with these delivery services across two different regions.

4. RESEARCH METHODOLOGY

4.1. Research Design

This study employs a descriptive, quantitative research design. Because our primary objective is to understand usage patterns, financial impact, and adoption/non-adoption behaviour across

a defined population, a descriptive design is appropriate (Kothari, 2004). The quantitative approach allows for statistical testing of associations and relationships between variables, including regional comparisons and construct-based regression, giving us findings that are structured and directly comparable to prior studies in this domain (Anshuman et al., 2026; Saleem & M Bhandari, 2026).

4.2. Sources Of Data

The primary data was collected through a structured, self-administered questionnaire distributed online via Google Forms. The survey combined:

- Closed-ended multiple-choice and checkbox items for demographic and usage-pattern data
- Five-point Likert scale items (1 = Strongly Disagree, 5 = Strongly Agree) for attitudinal and service-quality constructs, adapted from validated scales used in Anshuman et al. (2026) and Saleem and M Bhandari (2026)
- One open-ended item for non-users, allowing qualitative elaboration on barriers to adoption

The questionnaire used branching where the respondents who said yes to using food delivery/Q-commerce apps were taken to sections on usage patterns, service quality, and financial impact, whereas the respondents who said no to using these apps were routed to a separate section examining the reasons as to why they are not adopting this change. The questionnaire was shared via WhatsApp, LinkedIn, Reddit, and Instagram, the major communication media of the target audience in August and September 2026.

4.3. Sample Technique & Sample Size

Due to the size and geographical dispersion of the target population across the two regions, i.e., the Tier-1 and Tier-2 areas of Mumbai Metropolitan Region, probability sampling was not practically possible. Hence, we chose **Purposive Sampling** to select locations representing heterogeneity in urban density, infrastructure, and commute patterns while **Convenience Sampling** and **Snowball Sampling** were used to get respondents from each location to use an approach that is commonly used in studies of digital consumer behaviour where a complete sampling frame is not available. (Malhotra, 2004; Bryman, 2016)

The required sample size was calculated by Cochran (1977) formula for large or unknown populations:

$$n = Z^2pq / e^2$$

Where Z is the z-score of the desired confidence level, p and q represent the estimated proportions of the population possessing and not possessing the attribute, respectively, and e is the margin of error. With $Z = 1.96$ (at 95% level of confidence), $p = q = 0.5$ (maximum variability), and $e = 0.05$ (5% margin of error), the required sample is $n = (3.8416 \times 0.25) \div 0.0025 = 384$.

This formula choice has been used multiple times in prior Indian Q-commerce research studies with a similar sampling approach (Anshuman et al., 2026). Thus, a total of 384

completed and usable responses were collected for the research that exactly met the statistically required sample size.

Breakdown of Sample Size:

Tier-1	193
Tier-2	191
TOTAL	384

4.4. Data Analysis Tools

Data was coded and analyzed using Microsoft Excel. The following analytical techniques were applied, corresponding to each research objective:

- **Descriptive statistics** (frequencies, percentages, means, standard deviations) for demographic profiling and usage pattern description. This was done with the help of PivotTables.
- **Chi-Square Test of Independence** to examine associations between categorical variables, including area (Tier-1/Tier-2) and usage frequency, area and replacement/supplementation of traditional grocery shopping, and area and non-adoption barriers (Objectives 1 and 4). Observed and expected frequency tables were constructed manually, with test statistics and p-values computed using CHISQ.TEST and SUMPRODUCT functions.
- **Independent Samples t-test** to compare mean scores between Tier-1 and Tier-2 respondents on Likert-scale variables including monthly spend, budget percentage, cooking habit change, spending change, digital comfort, trust in local vendors, and family influence (Objectives 1 and 3). This was done with the help of the Data Analysis ToolPak's two-sample t-test assuming unequal variances.
- **Cronbach's Alpha** to assess internal consistency reliability of each Likert-scale before going for regression analysis, with a minimum acceptable threshold of 0.70 (Nunnally, 1978). This was computed manually using item and total-score variance formulas.
- **Multiple Linear Regression** to evaluate the joint effect of seven service-quality constructs (Convenience, Price & Offers, Trust & Security, UI/UX, Delivery Issues, Payment Issues, Product Quality) on Retention/Adoption Intention (Objective 2). This was done with the help of the Data Analysis ToolPak's Regression tool. Standardized Beta coefficients were obtained by re-running the regression on z-standardized variables, which can be used to compare with prior studies (Anshuman et al., 2026; Saleem & M Bhandari, 2026). Model diagnostics reported R^2 , Adjusted R^2 , F-statistic, and Significance F.
- **Spearman's Rank Correlation** to examine the relationship between education level and digital comfort (Objective 3). This was done with the help of Rank-Transformation and the CORREL function.

- **Frequency ranking and thematic analysis** to identify and rank the most commonly cited barriers to non-adoption, and to code open-ended responses into recurring themes (Objective 4).

4.5. Limitations of the Methodology

- As this study uses purposive sampling, convenience sampling, and snowball sampling instead of probability sampling, the findings are not statistically generalizable to the entire population of the MMR. So, the results should be interpreted as trends for the specific areas that we sampled rather than proof for the entire population.
- The self-reported data especially surrounding the spend and behaviour change is subjected to some type of bias (recall bias / social desirability bias).
- Since the study doesn't follow people over a long period of time, we cannot prove that one thing actually caused another to happen.
- Two constructs (Price & Offers, $\alpha = 0.644$; Payment Issues, $\alpha = 0.640$) fell marginally below the conventional 0.70 reliability threshold; findings related to these constructs should be interpreted with appropriate caution.
- Also, we need to keep in mind that sampling error is subject to occur as we are just taking a sample, i.e., a part of a population to estimate the population parameters and draw inferences about the population.

5. VARIABLES AND HYPOTHESIS

5.1. Construct Definitions and Measurement

For Objective 2 (Service-quality/retention constructs): **Table 5.1** presents the construct definitions, corresponding survey items, and measurement scales used in the study

Construct	Items	Type	Scale
Convenience	Time-saving; emergency purchases; delivery speed	Independent	Likert 1-5
Price & Offers	Competitive pricing; discounts/cashback; price comparison	Independent	Likert 1-5
Trust & Security	Payment trust; delivery trust; brand reputation	Independent	Likert 1-5
UI/UX	Navigation ease; checkout simplicity; app design	Independent	Likert 1-5

Delivery Issues	Delivery delays; incorrect/missing items	Independent	Likert 1-5
Payment Issues	Failed payments; refund handling	Independent	Likert 1-5
Product Quality	Freshness concerns; expired/damaged items	Independent	Likert 1-5
Retention/Adoption Intention	Continued use; recommendation intention	Dependent	Likert 1-5

5.2. Research Hypothesis

The following hypotheses were formulated based on the research objectives and literature review:

For Objective 1 - Chi-Square/t-test Analysis:

- H_{01} : There is no significant association between area (Tier-1/Tier-2) and usage frequency.
- H_{11} : There is a significant association.
- H_{02} : There is no significant association between area and replacement/supplementation of traditional grocery shopping.
- H_{12} : There is significant association.
- H_{03} : There is no significant difference in average monthly spend between Tier-1 and Tier-2 respondents.
- H_{13} : There is a significant difference.

For Objective 2 - Multiple Regression:

- H_1 : Convenience has a significant positive effect on retention.
- H_2 : Price & Offers have a significant positive effect on retention.
- H_3 : Trust & Security have a significant positive effect on retention.
- H_4 : UI/UX quality has a significant positive effect on retention.
- H_5 : Delivery Issues have a significant negative effect on retention.
- H_6 : Payment Issues have a significant negative effect on retention.
- H_7 : Product Quality Concerns have a significant negative effect on retention.

For Objective 3 - t-test/Spearman Analysis:

- H_{04} : There is no significant difference in digital comfort between Tier-1 and Tier-2 users.
- H_{14} : There is a significant difference.
- H_{05} : There is no significant relationship between education level and digital comfort.
- H_{15} : There is a significant relationship.

For Objective 4 - Chi-Square Analysis:

- H_{06} : There is no significant association between area and primary non-adoption barrier category.
 H_{16} : There is a significant association.
- H_{07} : There is no significant association between area and future intent to adopt.
 H_{17} : There is a significant association.

6. RESULTS AND DISCUSSION

6.1. Demographic Profile of Respondents

Table 6.1 shows the demographic profile of the 384 respondents. The sample is concentrated in the 18-25 years bracket (54.80%), followed by 26-40 (17.10%) and above 40 (16.60%), with under 18 respondents making up 11.40% of the sample. Gender distribution is fairly balanced with a slight female majority (52.20% female, 47.80% male; no respondents selected “prefer not to say”). The Sample skews toward undergraduate education (57.20%), consistent with the age distribution, with 12th Grade (18.20%), Postgraduate (16.10%), and 10th Grade (8.30%) making up the remainder. Notably, the sample achieved a near-even split between Tier-1 (50.40%) and Tier-2 (49.60%) areas, which helps in supporting the validity of the area-wise comparisons conducted in Objectives 1 and 3. Regarding platform engagement, 53.20% of respondents reported using Q-commerce apps more than traditional grocery shopping, while 46.8% reported the reverse. Usage frequency skewed heavily toward regular engagement, with 48.80% of respondents ordering multiple times a week, 25.9% once a week, 20.50% 1-3 times a month, and only 4.9% less than once a month.

Table 6.1: Demographic Profile (N = 384)

Characteristics	Category	Frequency (%)
Age Group	Under 18	11.40%
	18-25	54.80%
	26-40	17.10%
	Above 40	16.60%
Gender	Male	47.80%
	Female	52.20%
	Prefer not to say	0%
Education	10th Grade	8.30%
	12th Grade	18.20%
	Undergraduate	57.20%
	Postgraduate	16.10%
	Doctorate	0.30%

Area	Tier-1	50.40%
	Tier-2	49.60%
Use of Q-commerce apps more than Traditional Grocery Shopping	Yes	53.20%
	No	46.80%
Usage Frequency	Multiple Times a week	48.80%
	Once a week	25.90%
	1-3 times a month	20.50%
	Less than once a month	4.90%

6.2. Descriptive Statistics of Constructs

Table 6.2 presents the mean and standard deviation for each construct used in the regression model. Convenience shows the highest mean score ($M = 4.22$, $SD = 0.91$), closely followed by UI/UX ($M = 4.20$, $SD = 0.76$) and Retention/Adoption Intention ($M = 4.11$, $SD = 0.97$), telling that the respondents generally find these platforms convenient and easy to use and report a strong intention to continue using them. Trust & Security ($M = 3.91$, $SD = 0.68$) and Price & Offers ($M = 3.77$, $SD = 0.76$) followed at moderately high levels of agreement. Among the “issue” constructs, which capture negative experiences rather than positive attributes, Payment Issues recorded $M = 3.21$, $SD = 0.91$. Product Quality concerns were lower ($M = 3.08$, $SD = 0.96$), and Delivery Issues recorded the lowest mean of all constructs ($M = 2.97$, $SD = 1.16$). As these three constructs measure the frequency or severity of negative experiences, lower means are a favourable signal telling that respondents on average, report relatively lower problems with delivery specifically, though Delivery Issues also shows the highest Standard Deviation ($SD = 1.16$), showing a more different experience across respondents than any other construct.

Table 6.2: Descriptive Statistics of Constructs Profile

Construct	Mean (M)	Std. Dev. (SD)
Convenience	4.22	0.91
Price & Offers	3.77	0.76
Trust & Security	3.91	0.68
UI/UX	4.2	0.76
Delivery Issues	2.97	1.16
Payment Issues	3.21	0.91

Product Quality	3.08	0.96
Adoption Intention/Retention	4.11	0.97

6.3. Objective 1: Household Usage Pattern And Financial Impact (Tier-1 vs Tier-2)

Table 6.3: Chi-Square & t-test Results (Area Comparison)

Variable	Test	Statistic	p-value	Decision
Usage Frequency	Chi-Square	16.482	0.001	H ₀ Rejected
Replaced or Supplemented Shopping	Chi-Square	12.605	0.002	H ₀ Rejected
Monthly Spend	t-test	-0.701	0.483	H ₀ Retained
Budget Percentage	t-test	-1.708	0.089	H ₀ Retained
Cooking Reduced	t-test	-0.014	0.989	H ₀ Retained
Spending Increased (tenure)	t-test	-1.253	0.212	H ₀ Retained

Usage Frequency was found to be significantly associated with area ($\chi^2 = 16.482$, $p = 0.001$), showing that Tier-1 and Tier-2 respondents order via food delivery and Q-commerce platforms at meaningfully different rates. Similarly, whether app-based ordering has replaced or supplemented traditional grocery shopping was significantly associated with area ($\chi^2 = 12.605$, $p = 0.002$). None of the financial or behavioural outcome variables like monthly spend, percentage of household budget routed through these platforms, reduction in home cooking or increase in spending over time differed significantly between both tier respondents (all $p > 0.8$). Budget percentage approached significance at the 10% level ($p = 0.089$), showing a possible trend worth noting even though it does not meet the conventional 0.05 threshold.

6.4. Objective 2: Service-Quality and Retention Constructs

Reliability Analysis

Table 6.4: Cronbach's Alpha by Construct

Construct	Items	Cronbach's Alpha	Interpretation
Convenience	3	0.846	Good
Price Offers &	3	0.644	Below threshold
Trust Security &	3	0.695	Marginally below threshold
UI/UX	3	0.929	Excellent
Delivery Issues	2	0.708	Acceptable
Payment Issues	2	0.64	Below threshold
Product Quality	2	0.787	Good
Retention	2	0.899	Excellent

Six of the eight constructs met or exceeded the conventional 0.70 reliability threshold. Price & Offers ($\alpha = 0.640$) fell marginally below this threshold. This is noted as a limitation. Results involving these two constructs should be interpreted with some caution, though both remain within a range commonly treated as acceptable for exploratory social-science research (values above 0.60).

Regression Analysis

Table 6.5: Model Summary

R Square	Adjusted Square	R	F-statistic	Significance F
0.502	0.485		28.415	7.71×10^{-27}

The overall regression model was statistically significant ($F = 28.415$, $p < 0.001$), with the seven predictors together explaining 50.2% of the variance in Retention/Adoption Intention (Adjusted $R^2 = 0.485$).

Table 6.6: Regression Coefficients

Predictor	Standardized Beta (β)	p-value	Result
Convenience	0.233	0.004	Supported
Price & Offers	0.16	0.001	Supported
Trust & Security	0.109	0.101	Not Supported
UI/UX	0.294	0.001	Supported
Delivery Issues	-0.08	0.212	Not Supported
Payment Issues	0.143	0.013	Supported
Product Quality	-0.096	0.118	Not Supported

UI/UX emerged as the strongest positive predictor of retention ($\beta = 0.294$, $p = 0.001$), followed by Convenience ($\beta = 0.233$, $p = 0.004$), Payment Issues ($\beta = 0.143$, $p = 0.013$), and Price & Offers ($\beta = 0.160$, $p = 0.010$). Trust & Security, Delivery Issues, and Product Quality were not statistically significant predictors in this model.

Comparison with prior literature: The primary of UI/UX as the leading driver of retention directly replicates the central finding of Anshuman et al. (2026), who reported UI/UX as their strongest predictor ($\beta = 0.466$) in a Gen-Z-only sample. Even though the impact isn't as big when looking at a population of all ages, it is still the top factor. This tells us that a high-quality interface is a near-universal driver for people adopting a product, rather than something that only matters to younger generations who grew up with technology. Two differences from Anshuman et al. (2026) are worth highlighting. First, Trust & Security was seen as not a significant factor in our present study ($p = 0.101$), whereas it is the second-strongest driver in their Gen-Z sample ($\beta = 0.209$). This may indicate that for the general, older or a more experienced users in this study, worrying about safety isn't what keeps them on a platform. However, for a brand new or younger users like Gen-Z, trust is a massive barrier they have to overcome before they feel comfortable staying. Secondly, Payment Issues showed an unexpectedly significant positive association with user retention in this study ($\beta = 0.143$, $p = 0.013$) which completely contradicts Anshuman et al. (2026)'s finding of a significant negative effect ($\beta = -0.092$), meaning payment issues usually make people leave. This suggests an engagement-amplification effect (same logic as that of the delivery issues finding). The users who complain the most about payment glitches aren't actually about to quit. Instead, they are highly active users who care enough about the platform to speak up when something goes wrong.

6.5. Objective 3: Regional/ Cultural/ Digital-Literacy Differences

Table 6.7: t-test & Correlation Results

Variable	Test	Statistic	p-value	Result
Digital Comfort	t-test	-0.317	0.752	Not Significant
Trust in Local Vendor	t-test	-0.725	0.47	Not Significant
Family Influence	t-test	1.787	0.075	Not Significant
Education x Digital Comfort	Spearman	$\rho = 0.207$	0.003	Significant

None of the three regional/cultural attitude variables (digital comfort, trust in local vendor relative to apps, and family/peer influence on adoption) differed significantly between Tier-1 and Tier-2 respondents. Though Family Influence approached significance at the 10% level ($p = 0.075$), suggesting peer/family influence may be marginally stronger in one area, worth noting as a trend. A significant positive correlation was found between education level and digital comfort ($\rho = 0.207$, $p = 0.003$). While the relationship is weak in magnitude, it is statistically significant. Respondents with higher education reported somewhat greater comfort using apps and technology in general.

Combined with Objective 1's findings, this shows that the Tier-1 vs Tier-2 differences show up in behavioural measures (usage frequency, replacement of traditional shopping) but not in certain attitudes (trust, digital comfort, cultural fit, peer influence). This maybe tells us that the regional divide in this market may be driven more by infrastructure and access factors than by differences in user mindset. This is an important distinction for both platforms and policymakers, since it implies expanding delivery infrastructure in Tier-2 areas may close usage gaps without needing separate trust-building or cultural-adaptation strategies.

6.6. Objective 4: Reasons For Non-Adoption

Table 6.8: Non-Adoption Barriers, Ranked by Mean Agreement

Rank	Barrier Statement	Mean
1	I prefer to see and select items myself before buying	4.05
2	My regular grocery store/vendor is close enough that I don't need these apps	4.01
3	I'm concerned about the quality/freshness of products I can't personally inspect	3.89

4	I enjoy going to the market/store in person	3.72
5	I have always shopped this way and see no reason to change	3.64
6	I don't see enough value/benefit to justify the cost	3.58
7	These apps are more expensive than shopping in person	3.55
8	I have concerns about how delivery workers are treated / ethical issues	3.34
9	I don't trust these apps with my payment information	3.26
10	I find these apps confusing or difficult to use	2.74
11	People I know don't use these apps either	2.64

The most significant barrier to adoption was personal choices. People simply preferred picking products for themselves and also lived close by to the physical stores, so they didn't need to use apps even if it was for an emergency. Variables like lack of digital literacy or peer pressure were often assumed to be the primary adoption barriers in the wider literature. However, it had the lowest statistical ranking in our study. This may suggest that non-adoption in this sample is driven more by personal choices and the convenience of their current options, rather than an inability to use technology or the fear of social disapproval.

Category Comparison by Area

Table 6.9: Barrier Category Means Compared for Tier-1 vs Tier-2 (t-test)

Category	p-value	Result
Access	0.001	Significant
Trust	0.934	Not Significant
Literacy	0.029	Significant
Economic	0.825	Not Significant
Preference	0.042	Significant

Access, Literacy and Preference related barriers differed significantly between Tier 1 and Tier 2 respondents, while Trust and Economic barriers did not. This suggests that things like infrastructure and habit are shaped by where a person lives, whereas concerns about trust in the platform and money are common regardless of area of residence. This is a similar pattern that we saw in objective 1 and 3's findings, which similarly showed that area impacts behavioural/access variables but not attitudinal ones.

Chi-Square Results

Table 6.10: Chi-Square Test Results

Test	Statistic	p-value	Result
Area x Primary Barrier	6.97	0.137	Not Significant
Area x Future Intent	6.49	0.039	Significant

While category level barrier scores differ by area (Category Comparison by Area), the primary barrier category selected per respondent did not differ significantly by area ($p = 0.137$). This tells us that even though location has some influence, it does not have a statistically significant regional effect to change which specific barrier matters the most to a person. Future intent to adopt, however was significantly associated with area ($\chi^2 = 6.49$, $p = 0.039$). Tier-2 non-users reported a higher likelihood of future intent (25% "Yes, likely", 26.1% "No, unlikely"), while "Maybe" responses were similar in both areas (~48%). This suggests that non adoption in Tier-2 may reflect a currently in transition market rather than a firm resistance which may be linked to an ongoing expansion of Q-commerce infrastructure into satellite townships whereas Tier-1 non-users, who already report the highest access barrier scores (Category Comparison by Area), appear more likely to be settled, with their non adopters having some satisfactory alternative that works for them.

Thematic Coding of Open-Ended Responses

Table 6.11: Themes Identified in Open-Ended Non-Adoption Responses

Theme	Mentions	% of Non-Users
Accessibility	69	38.50%
Trust	28	15.60%
Price	21	11.70%
Quality	18	10.10%
No reason given	43	24.00%

Accessibility came as the dominant theme in respondents own words. This qualitative finding matches the quantitative data which shows that being close to physical stores is the most common reason people do not use the service. People mentioned trust and price with moderate frequency in the sample. Product quality had the lowest frequency among all the variables. Ultimately, the data shows that non-adoption is mostly driven by a high correlation with having enough good physical alternatives nearby, rather than people actively not liking the platforms.

6.7. Cross Objective Synthesis and Discussion

The four objectives of this study, taken together match perfectly to show a clear pattern in how food delivery and quick commerce platforms function differently and similarly across the Tier-1 and Tier-2 areas of the MMR.

“The central pattern: Regional differences are behavioural and structural, not attitudinal”

Across all four objectives, a clear pattern repeats: **wherever a variable measured behaviour, access, or infrastructure, Tier-1 and Tier-2 differed significantly; wherever a variable measured attitude, trust or feeling, they did not.**

- In objective 1, usage frequency ($p = 0.001$) and whether app based ordering had replaced or supplemented traditional shopping ($p = 0.002$) differed significantly by area but the monthly spend, budget share, cooking reduction and the spending increase did not (all $p < 0.08$).
- In objective 3, none of the attitudinal variables like digital comfort, trust in local vendors relative to apps, family/peer influence differed significantly by area, despite testing multiple ideas related to cultural compatibility.
- In Objective 4, the same thing reappeared. Access and Literacy barriers (i.e., infrastructure and skill based) differed significantly by area, while Trust and Economic Barriers (attitudinal/financial) did not.

This is not a coincidence across three independent analysis. Households and individuals across Tier-1 and Tier-2 Mumbai appear to hold broadly similar attitudes toward these platforms with comparable levels of digital comfort, trust and price but differ in how often they can or do act on those attitudes and this is most probably because of the differences in the dark store density, delivery-radius coverage and general platform infrastructure maturity between the urban core and satellite townships. This has a direct, practical implication: closing the Tier-1/Tier-2 usage gap is primarily an **infrastructure and access problem for platforms to solve**, not a trust-building or cultural adaption problem, since the attitudinal groundwork already appears comparably present in both regions.

“Tier-2 as an emerging, not resistant, market”

Objective 4's future intent finding sharpens the pattern. Tier-2 non-users were more than twice as likely as Tier-1 non-users to say they intend to adopt these platforms in future (25% vs 12.1%), while Tier-1 non-users were more likely to report firm disinterest (39.6% vs 26.1%). Combined with Tier-2's significantly higher **access barrier** scores, this shows that external obstacles are keeping them away and not a lack of interest. Statistically, they represent an *underserved market in transition*. They are highly receptive to adopting the platforms if those barriers are removed. In Contrast, non-users in Tier-1 appear **stable** and unlikely to change their behaviour. They already have a highly satisfactory alternative nearby which achieved the highest **mean score** in the dataset ($M = 4.01$) as a barrier to adoption. Because they are satisfied with their current setup, they show almost no **future intent** to switch over.

“What actually drives retention once someone is a user”

Objective 2 shifts the lens from adoption to retention. Here, the findings both confirm and complicate the existing literature. UI/UX ($\beta = 0.294$) and Convenience ($\beta = 0.233$) emerged as the strongest positive predictors of continued use and this is consistent with Anshuman et al. (2026), who found UI/UX dominant in their Gen-Z only sample, and with the descriptive data in this study, where Convenience and UI/UX were also the two highest-rated constructs overall (Descriptive Statistics Of Constructs). This trend across a broader, all age population suggests interface quality and convenience function as close to universal adoption drivers, not something specific to digitally native users.

Two divergences from the source literature are worth talking about rather than treating as noise. Trust & Security, a strong predictor in the Gen-Z sample, was not significant here ($p = 0.101$) probably because a broader population, including longer tenured and older users, has already resolved the initial trust concerns through repeated positive experience, leaving less residual variance for trust to explain. Payment issues was positively associated with retention ($\beta = 0.143$, $p = 0.013$) which is consistent with the “engagement amplification” interpretation applied to a similar counterintuitive finding in Anshuman et al., where users who notice and report friction may simply be more actively engaged, like the higher frequency users rather than users on the verge of leaving.

“Why people don't adopt at all”

Objective 4's barrier ranking adds a final, important clarification to the whole study. The most cited reasons for non-adoption were not digital illiteracy or social disapproval but a preference for personally selecting products and having a sufficiently close existing store. This reframes the “digital divide” narrative sometimes assumed in this space. For this sample, non-adoption looks less like an inability to use these platforms and more like a deliberate choice. **People are not being left behind by technology; many are choosing not to need it.**

“Bringing it together”

So, as a whole, this study suggests that people living in Mumbai's urban core and its satellite townships have the same basic desire and psychological readiness to use food delivery and Q-commerce apps. However, their actual everyday habits like how often they order, how much they rely on apps instead of local stores, and their future plans to use these services are way different. This difference isn't because one area trusts the apps more or is better with technology. Instead, it is strictly driven by **physical access, delivery infrastructure, and how well the local neighbourhood stores already meet their needs.**

7. CONCLUSION

7.1. Contribution of the Study

This study extends two existing bodies of research in specific stated ways. Anshuman et al. (2026) restricted their sample to Gen-Z respondents across five Tier-1 Indian cities and explicitly identified cross-tier, broader-demographic research

as a direction for future work; the present study addresses this directly by sampling across all age groups and comparing Tier-1 and Tier-2 areas within a single metropolitan region. Neither Anshuman et al. (2026) nor Saleem and M Bhandari (2026) measured household level financial impact or spending behaviour; Objective 1 of this study addresses that gap directly, drawing on the household-centered approach used by Bezirgani and Lachapelle (2020) in a different national and demographic context. Finally, by including non-users and examining reasons for non-adoption (Objective 4), this study captures a population entirely absent from both source studies, which sampled only existing platform users.

7.2. Implications And Future Scope

7.2.1. For Platform Operators: The primacy of UI/UX and Convenience as retention drivers, combined with the finding that tier-2 attitude toward these platforms are not meaningfully different from tier-1, suggests that expanding delivery infrastructure and dark store coverage into Tier-2 areas is likely to get greater adoption gains than trust building campaigns. The finding that many non users say they live close by to the physical stores and this is their primary barrier to adoption also suggests limited headroom for growth of customers since they are well served by traditional retail and that platform growth in such segments may depend more on speciality (for example, hard to find products) than on convenience alone.

7.2.2. For Policymakers: The higher future adoption intent among Tier-2 non-users paired with their higher Access barrier scores says that the infrastructure development in satellite townships may organically shift usage patterns over time without requiring separate digital literacy or trust building interventions, since literacy and trust barriers did not differ significantly by area in this sample.

7.2.3. For future research: Future studies could extend this work in several directions. The consistent split between significant behavioural/access differences and non-significant attitudinal differences across three independent objectives is a pattern worth testing in other metropolitan regions to assess whether it is only seen in Mumbai or whether it is the same for other metropolitan regions. The current study is cross-sectional, meaning it only looked at a single snapshot in time. Longitudinal research would be really valuable for tracking whether Tier-2's currently higher future adoption intent (Chi-Square Results) materialises into actual usage convergence over time, directly extending this study's cross-sectional findings. Future work could also move beyond respondent-level study to examine specific infrastructural factors underlying the Tier-1/Tier-2 usage gap directly like dark store density, delivery radius rather than studying survey responses only. Finally, probability sampling methods in any follow up study would allow findings to be generalised at the population level,

which the current convenience/snowball sampling design does not support.

8. LIMITATIONS

As with any study relying on purposive, convenience and snowball sampling rather than probability sampling, the findings of this study are not statistically generalizable to the full population of the MMR and should be interpreted as indicative of patterns within the sampled locations. Self-reported data on spending and behaviour change is subject to recall and social desirability bias. The cross-sectional design captures a single point in time and does not support causal inference (for example, in our study area and usage frequency). Two constructs in our regression model (Price & Offers, $\alpha = 0.644$; Payment Issues, $\alpha = 0.640$) fell marginally below the conventional 0.70 reliability threshold, and findings involving these constructs should be interpreted with appropriate caution. Finally, the study's four sampled locations, while selected to represent meaningful heterogeneity, cannot capture the full diversity of Tier-1 and Tier-2 experience across the broader MMR.

CONFLICT OF INTEREST AND FUNDING

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