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Advanced Microeconomics II

A Non-Parametric Study of Income, Household Structure, and Behavioural Consistency in Quick Commerce Usage in Urban India

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A Non-Parametric Study of Income, Household Structure, and Behavioural Consistency in Quick Commerce Usage in Urban India

ABSTRACT

The study provides real-world evidence relevant to several areas of Advanced Microeconomics II. It relates to alternative theories of the firm, such as Baumol's model of sales revenue maximization and Williamson's model of managerial discretion, by examining how Q-Commerce platforms use discount strategies and non-price incentives to drive sales volume rather than purely maximizing profits. It also reflects behavioural theories of consumer and firm decision-making, as the research focuses on impulsive purchasing and discount sensitivity—behaviours that deviate from the standard rational consumer model. Furthermore, the study connects to the application of game-theoretic strategies in oligopolistic markets, where Q-Commerce firms compete through dynamic pricing, time-sensitive offers, and user-interface design rather than traditional quantity or price strategies. These strategic decisions align with models of Bertrand and Stackelberg competition, where firms anticipate and respond to consumer behaviour and competitor actions in real time. While the study does not model these interactions formally, it offers empirical support and interpretation of theoretical concepts discussed in microeconomic analysis.

INTRODUCTION:

The digital transformation of retail has catalysed the rise of Quick Commerce (Q-Commerce). This hyper-fast delivery model promises groceries and daily essentials within 10 to 30 minutes through mobile apps and location-optimized logistics. In India's urban centres, Q-Commerce has swiftly evolved from novelty to necessity, particularly in the domain of household provisioning. Unlike traditional e-commerce, which emphasizes variety and convenience, Q-Commerce thrives on immediacy, appealing to time-pressed consumers who increasingly Favor spontaneity over pre-planned grocery shopping.

This rapid shift is not merely technological—it reflects evolving household behaviours and decision-making structures. With the ability to place orders on a whim, consumers are increasingly bypassing traditional grocery planning, raising questions about budgeting discipline, impulse purchases, and the role of household dynamics in shaping Q-Commerce usage. Yet, the behavioural impact of this transition remains underexplored in the academic literature, especially in the context of India's diverse socio-demographic landscape.

While prior research has acknowledged a rise in impulse buying driven by real-time app interfaces (Verhoef et al., 2015; Sharma & Singh, 2021), it often generalizes findings across all forms of e-commerce. Few studies have specifically addressed how Q-Commerce influences household grocery habits—particularly the ways in which family structures (e.g., nuclear vs. joint) and income levels affect frequency of usage and impulsive spending behaviour.

A recent study by Nagarathinam, Elangovan, and Chella Samy (2025) highlights the significant role of intra-household dynamics in Q-Commerce adoption, suggesting that household type may influence not only access to resources but also purchasing tendencies.

Using a quantitative, survey-based approach, the study applies non-parametric statistical methods to examine the relationships between key socio-demographic factors and behavioural outcomes in the Q-Commerce space. The goal is to unpack how household characteristics—often overlooked in broader e-commerce literature—mediate emerging consumption patterns in India's ultra-fast delivery ecosystem. Insights from this research not only contribute to digital consumer behaviour theory but also offer valuable guidance for Q-Commerce platforms and policymakers seeking to enhance user experience while promoting responsible consumption.

LITERATURE REVIEW:

Tanskanen, Yrjölä, and Holmström (2002), in their study "The Way to Profitable Internet Grocery Retailing – Six Lessons Learned," identify key success factors and operational strategies crucial for profitable e-grocery delivery, particularly addressing the persistent "last mile" problem. The research was conducted as part of the ECOMLOG project—a substantial three-year academic-industry collaboration with a research budget of €1.5 million. Their methodology involved using real purchasing data from Finnish e-grocery operations and deploying cost and route simulation models to compare delivery strategies such as attended versus unattended deliveries. Additionally, they analysed international case studies including Tesco, Webvan, Streamline, and Peapod to develop a six-step strategic roadmap for profitable operations. While the study is comprehensive in analyzing supply chain design and financial viability, it lacks consideration of consumer psychology and adoption behaviour, particularly in emerging markets, representing a notable gap in the research.

Kämäräinen, Saranen, and Holmström (2001) build upon operational logistics in their paper "The Reception Box Impact on Home Delivery Efficiency in the E-Grocery Business." They examine how the use of reception boxes—both personal and shared—can affect the cost-efficiency and convenience of last-mile delivery. The research utilized advanced simulation modelling and routing software to evaluate different delivery scenarios. They compared the performance of traditionally attended deliveries with reception box alternatives by analyzing metrics such as delivery cost per drop and route optimization. Additionally, they conducted sensitivity analyses to observe the impact of delivery time windows on cost efficiency. Despite its valuable operational insights, this study overlooks the consumer dimension—particularly the acceptability and cultural fit of reception boxes in regions with varied housing infrastructures or privacy norms—revealing a gap in understanding user acceptance.

Teller, Kotzab, and Grant (2006), in their paper "The Consumer Direct Services Revolution in Grocery Retailing – An Exploratory Investigation," focus on how logistical infrastructure and consumer awareness shape the uptake of Consumer Direct Services (CDS). They conducted a web-based survey targeting consumers in developed countries who are technologically savvy and time-constrained. The study employed structural equation modelling (SEM) to assess relationships between lifestyle variables (e.g., ICT knowledge, time pressure) and channel choice decisions. The findings highlight that consumer perceptions of convenience and digital fluency strongly influence CDS adoption. However, the study primarily reflects the behaviour of digitally literate, urban consumers, and offers limited insight into the digitally excluded or low-income populations. This limits its applicability to more diverse socioeconomic and geographic settings, suggesting an area for further research.

In their timely study "The Impact of Online Grocery Shopping on Stockpile Behaviour in COVID-19," Hao, Wang, and Zhou (2020) investigate how different online platforms influenced stockpiling behaviour during the pandemic. Drawing on a survey of 540 urban residents in China, the authors used a bivariate probit model to estimate the likelihood of stockpiling as influenced by platform type, demographics, income, and risk perception. The econometric approach allowed them to analyse food and essential item stockpiling tendencies across consumer types. While their insights are critical in understanding pandemic-driven behaviour shifts, the study is geographically confined to urban China and lacks comparative insights from rural or global contexts. This restricts the generalizability of the findings and points to a need for broader comparative research across different cultural and geographic segments.

Unnikrishnan and Figliozzi (2021) contribute to understanding the broader behavioural shifts in their study “A Study of the Impact of COVID-19 on Home Delivery Purchases and Expenditures.” Based on an online survey in the Portland-Vancouver-Hillsboro region, the study employed ordered choice models to understand how consumer delivery frequency and spending changed during the pandemic. Key predictors included health concerns, income, education, and prior experience with home delivery services. While the study reveals how different demographic groups responded to the pandemic, it falls short in recommending policy measures or platform interventions to support equitable access. Further research could explore how platform-level designs or public programs could reduce digital exclusion and delivery deserts.

Spurlock et al. (2019), in their paper “Children, Income, and the Impact of Home Delivery on Household Shopping Trips,” analyse how income levels and family structure affect grocery delivery usage and its substitution effect on physical store trips. They conducted a household-level survey in the San Francisco Bay Area, applying a multinomial logit model to measure behavioural substitution. Independent variables included household income, presence of children, digital proficiency, and time constraints. Their findings show that low-income families with children are more likely to replace in-store trips with deliveries. However, the study does not evaluate the environmental or infrastructural consequences of increasing delivery dependence, nor does it explore how these behaviours evolve post-crisis—a gap that future research could address.

Verdugo et al. (2021) investigate future e-grocery logistics in “The Future of E-Grocery – A Study of the Micro-Fulfilment Model in the Spanish Market.” This qualitative study assessed the feasibility of implementing micro-fulfilment centres (MFCs) in Spain, drawing from interviews with logistics professionals and data from industry webinars and market reports. Their comparative analysis benchmarked Spain’s retail market against the more advanced U.S. context. While theoretically promising, the study lacks real-world consumer feedback and field data from Spanish shoppers. Without empirical testing, the model’s scalability and cultural adaptability remain speculative, highlighting the need for further pilot studies and consumer surveys in Southern European contexts.

Wiig and Smith (2008), in “The Art of Grocery Shopping on a Food Stamp Budget,” provide a mixed-methods investigation into how low-income mothers navigate grocery shopping under the SNAP (Supplemental Nutrition Assistance Program). Their methodology included focus group discussions and a structured shopping simulation, where participants were tasked with budgeting for a week’s groceries. Thematic analysis revealed that participants prioritize price over nutrition, often sacrificing quality for quantity. The study’s strength lies in its deep qualitative insight into financial stress and coping strategies. However, it does not explore the role of digital or online platforms in facilitating or hindering budget-friendly shopping. This presents a vital gap, especially given the increasing digitization of food assistance programs.

Lastly, Jensen et al. (2021) explore behavioural trends in “US Consumers’ Online Shopping Behaviours and Intentions During and After COVID-19.” Conducted through a national survey of 1,558 participants across all U.S. states, the study used a Cragg model to analyse the probability and intensity of online grocery adoption. A multinomial probit model was also employed to predict future channel preferences. Key explanatory variables included age, digital fluency, household structure, and perceived convenience. While the study successfully captures a large-scale behavioural shift, it does not extend into policy frameworks or platform incentives to support continued use, especially among digitally marginalised communities. This limits its contribution to sustained behavioural modelling in a post-pandemic world.

Chatterjee and Kumar (2019), in their paper “Digital Readiness for e-commerce in India: Challenges and Opportunities,” explore the state of digital infrastructure and preparedness for the adoption of e-commerce in India. The paper discusses key enablers such as mobile penetration, internet access, and government initiatives like Digital India, while also highlighting barriers including low digital literacy, fragmented logistics, and weak cyber security frameworks. The authors adopt a descriptive research methodology grounded in secondary data analysis, drawing from reports by TRAI, the Ministry of Electronics and IT, and industry whitepapers. The study is qualitative and synthesizes insights from various sources to assess the overall e-commerce readiness of the Indian market. Key findings suggest that despite growing smartphone usage and internet access, digital adoption is skewed toward urban centres, and there is a significant digital divide that restricts the inclusive growth of e-commerce. However, the paper does not delve into consumer behaviour or specific e-commerce models such as quick commerce. This creates a gap in understanding how emerging platforms are influencing purchasing behaviour in real-time, particularly in a post-pandemic digital economy.

Kadam (n.d.), in the paper "Electronic commerce: A study on benefits and challenges in an emerging economy," offers a broad overview of the potential advantages and barriers to e-commerce in developing economies, with contextual relevance to India. The study outlines benefits like improved operational efficiency, expanded market access for small businesses, and better customer engagement through digital platforms. Challenges discussed include infrastructural gaps, lack of trust in online transactions, poor delivery mechanisms in rural areas, and cybersecurity threats. The research methodology employed is qualitative and conceptual, primarily based on an extensive literature review and analysis of secondary sources such as policy documents, previous research papers, and government statistics. The approach is exploratory and aims to provide a foundational understanding of the ecosystem without engaging in empirical validation or statistical modelling. The paper effectively captures the macro-level benefits and concerns around e-commerce but fails to analyse consumer behaviour patterns or the distinct features of niche segments like online grocery shopping or quick commerce. Moreover, the absence of primary data limits its applicability in understanding real-time shifts in consumer preferences or business models in the current digital landscape.

Kshetri (2007), in his widely cited study titled "Barriers to e-commerce and competitive business models in developing countries: A case study," undertakes a detailed examination of structural, institutional, and economic impediments that restrict e-commerce growth in less developed countries. The paper presents a multi-country analysis with a comparative case study design, focusing on the commonalities and variances in barriers across different nations. The research methodology is based on a comparative case study approach, using a mix of secondary data from institutional databases, country reports, and qualitative policy reviews, combined with theoretical models of e-commerce development. The analysis includes cross-country benchmarking and draws on the Resource-Based View (RBV) and Institutional Theory to understand how internal capabilities and external structures interact to shape business models. Findings indicate that underdeveloped ICT infrastructure, institutional weaknesses, poor legal enforcement of e-commerce laws, and lack of consumer trust are major roadblocks. It also emphasizes that successful business models are those that localize their strategies, build consumer trust, and offer flexible payment options like cash on delivery. While the paper offers robust insights into systemic barriers and business strategy alignment, it is somewhat dated and does not consider the more recent developments in mobile commerce, app-based delivery platforms, or innovations such as ultra-fast deliveries (q-commerce). The absence of contemporary consumer behaviour analysis and country-specific post-pandemic data constitutes a significant research gap.

Finally, Luna Sanchez (2024), in the master's thesis titled "An analysis of the drivers of consumers' purchasing behaviour in quick commerce platforms," specifically investigates consumer preferences and psychological drivers in the context of quick commerce (q-commerce). The thesis focuses on how speed, convenience, pricing, and user experience shape purchasing decisions in ultra-fast delivery platforms. The methodology is quantitative, involving the use of structured surveys distributed to a sample population of q-commerce users, followed by statistical analysis using techniques such as regression analysis, correlation matrices, and factor analysis. The study also integrates behavioural frameworks such as the Theory of Planned Behaviour to interpret the findings. Results indicate that the primary drivers of purchasing decisions are speed of delivery, ease of app navigation, and availability of products. Emotional satisfaction and impulse buying behaviour also play a crucial role. However, the thesis is geographically limited in scope (focused on Finland), and though it offers rich insights into consumer psychology, its applicability to a developing country context like India remains limited. Furthermore, it does not examine the operational or sustainability challenges faced by q-commerce companies, nor does it explore long-term shifts in consumption patterns beyond immediate convenience.

RESEARCH METHODOLOGY:

This study adopts a quantitative, cross-sectional survey design to examine how behavioral tendencies, price sensitivities, and household dynamics shape the usage of Quick Commerce (Q-Commerce) platforms in urban India. The research framework is grounded in the need to understand behavioural differences across income groups and household structures, particularly in relation to impulse buying and discount responsiveness. Given the ordinal nature of the survey data and the possibility of non-normal distributions, non-parametric statistical methods were employed for analysis.

Primary data was collected through a structured questionnaire administered via Google Forms. The survey targeted urban Indian consumers and included sections on demographic information, household structure, income group, frequency of Q-Commerce usage, and attitudinal measures related to impulsivity and discount sensitivity. The questionnaire consisted of both frequency-based items (e.g., "How often do you use Q-Commerce services?") and agreement-based statements (e.g., "I often buy things I did not plan to buy"). To enable robust quantitative analysis, all responses were transformed into numerically coded values using Likert-type scales.

Specifically, responses to frequency-related questions were coded as follows: "Never" was assigned a value of 1, "Rarely" as 2, "Sometimes" as 3, "Often" as 4, and "Always" as 5. Similarly, for agreement-based statements, "Strongly Disagree" was coded as 1, "Disagree" as 2, "Neutral" as 3, "Agree" as 4, and "Strongly Agree" as 5. This transformation allowed for ordinal-level data to be ranked and analysed using non-parametric statistical techniques, which are suitable for survey data that do not meet the assumptions of normality or interval scaling.

The decision to employ non-parametric tests was guided by several methodological considerations. First, the data collected through Likert scales is ordinal in nature, making it inappropriate for parametric methods that rely on the assumption of interval-level measurement. Second, the distribution of responses across demographic groups was not guaranteed to be normal, and preliminary analysis suggested variability in group sizes. Third, the presence of potential outliers or skewed data further justified the use of distribution-free tests. Non-parametric methods are particularly effective in such contexts, as they compare ranked values and median distributions rather than means, thereby providing more reliable insights into group-level differences and associations.

In line with the objectives of the study, the following research questions were formulated:

1. Is there a significant difference in discount sensitivity across income groups in Q-Commerce usage?
2. Is there an association between household type (nuclear versus joint) and the frequency of Q-Commerce usage?
3. Does impulse buying behaviour significantly vary across income groups among Q-Commerce users?

These questions seek to unpack the interplay between economic segmentation, behavioural traits, and household composition in shaping consumer engagement with ultra-fast delivery services. The subsequent stages of the analysis apply appropriate non-parametric techniques to assess these relationships.

HYPOTHESES AND STATISTICAL TECHNIQUES:

Based on the research objectives and questions outlined, the study tests the following null and alternative hypotheses:

Hypothesis 1

- **H_{01}**: There is no significant difference in discount sensitivity across income groups in Q-Commerce usage.
- **H_{11}**: There is a significant difference in discount sensitivity across income groups in Q-Commerce usage.

Hypothesis 2

- **H_{02}**: There is no association between household type (nuclear vs. joint) and the frequency of Q-Commerce usage.
- **H_{12}**: There is a statistically significant association between household type and frequency of Q-Commerce usage.

Hypothesis 3

- **H_{03}**: Impulse buying behaviour does not significantly vary across income groups among Q-Commerce users.
- **H_{13}**: Impulse buying behaviour significantly varies across income groups among Q-Commerce users.

To test these hypotheses, the study employs non-parametric statistical methods, which are appropriate given the ordinal nature of the survey data, the potential for non-normal distributions, and the presence of unequal sample sizes across demographic groups. These techniques provide robust results without requiring assumptions about the underlying distribution of the data.

To test Hypotheses 1 and 3, the Kruskal–Wallis H test is employed. This test is a non-parametric alternative to the one-way analysis of variance (ANOVA) and is suitable for comparing three or more independent groups when the dependent variable is ordinal or not normally distributed. The Kruskal–Wallis test ranks all observations and compares the average ranks across the groups.

To test Hypothesis 2, the Chi-Square Test of Independence is used. This test examines the relationship between two categorical variables—in this case, household type and Q-Commerce usage frequency. It evaluates whether the distribution of one variable is independent of the other. A significant chi-square statistic implies that household structure and frequency of Q-Commerce usage are not independent, suggesting a meaningful association between the two.

All statistical tests are conducted at a 5% significance level ($\alpha = 0.05$). Results are interpreted in terms of both statistical significance and practical implications for understanding consumer behaviour in Q-Commerce.

DATA ANALYSIS

Given the ordinal nature of the survey data—most of which was collected using 5-point Likert scales—and the likelihood of non-normal distributions across groups, this study employs non-parametric statistical techniques for hypothesis testing. These methods are appropriate for data that do not meet the assumptions required for parametric tests such as the t-test or ANOVA, particularly when the variables are ranked, the sample sizes are unequal, or the variances are not homogeneous.

To examine differences in behavioural responses across income groups, the Kruskal–Wallis H test was employed. This test is the non-parametric counterpart to one-way ANOVA and is suitable for comparing the distribution of ordinal responses across three or more independent groups. It does not assume normally distributed data and operates on ranked values, making it ideal for Likert-scale dependent variables such as discount sensitivity and impulse buying behaviour.

To evaluate the association between two categorical variables—namely, household size and frequency of Q-Commerce usage—a Chi-Square Test of Independence was used. This test assesses whether the distribution of one categorical variable differs significantly across the levels of another, and is appropriate when both the independent and dependent variables are nominal or ordinal.

These statistical choices ensure the integrity and robustness of the analysis, given the structure and measurement scale of the collected data.

The dataset comprises responses from 254 participants who use instant grocery (Q-Commerce) services. The survey collected demographic variables including age group, household size, and monthly household income, alongside behavioural and attitudinal items related to Q-Commerce usage. The responses were recorded on a 5-point Likert scale for all subjective items, with the exception of average spending per order, which is measured as a continuous numerical variable.

The age distribution of respondents is spread across five categories: 18–20 years (n = 18), 21–30 years (n = 73), 31–40 years (n = 41), 41–50 years (n = 85), and 50–70 years (n = 37). In terms of household income, the sample includes four groups: ₹10,000–₹30,000 (n = 44), ₹30,000–₹50,000 (n = 43), ₹50,000–₹1,00,000 (n = 51), and ₹1,00,000–₹3,00,000 (n = 116). Household size is categorized into Small (n = 80), Large (n = 146), Solo (n = 9), and Extra Large (n = 19).

The average spending per order among respondents ranged from ₹100 to ₹2,500, with a mean of ₹683.70 and a median of ₹300.00. This indicates a right-skewed distribution, likely driven by a subset of high-expenditure users.

All behavioural responses were captured using 5-point Likert items and converted into numerical codes ranging from 1 to 5, with higher values indicating stronger agreement or higher frequency. These include items such as:

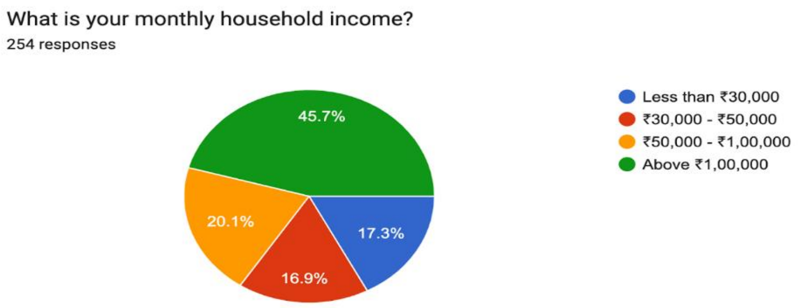
- Frequency of Q-Commerce usage
- Impulse buying tendencies
- Response to discounts and promotions
- Reactions to minimum order thresholds
- Perceived pressure due to time-sensitive deals
- Changes in grocery budgeting and tracking

Given the ordinal nature of this data and its non-normal distribution, non-parametric statistical tests were applied to examine differences and associations among groups.

DESCRIPTIVE STATISTICS:

This section presents the descriptive analysis of the survey responses collected to understand the impact of instant grocery delivery services on household grocery planning. A total of 254 responses were gathered through an online questionnaire. The descriptive statistics summarize key variables such as household income, household size, and the frequency of usage of instant grocery delivery platforms. This overview provides insights into the demographic and behavioural patterns of respondents, laying the foundation for further analysis and interpretation.

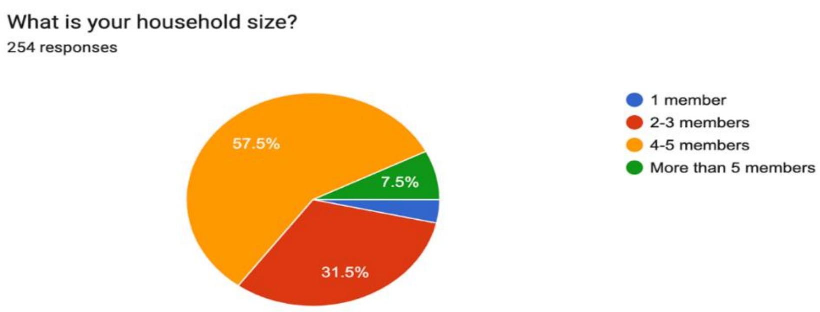
FIGURE 1:



The pie chart shows the distribution of monthly household income among 254 respondents. The largest segment (45.7%) reported a household income of above ₹1,00,000, followed by 20.1% in the ₹50,000–₹1,00,000 range. Meanwhile, 17.3% reported earning less than ₹30,000, and 16.9% fall within the ₹30,000–₹50,000 bracket.

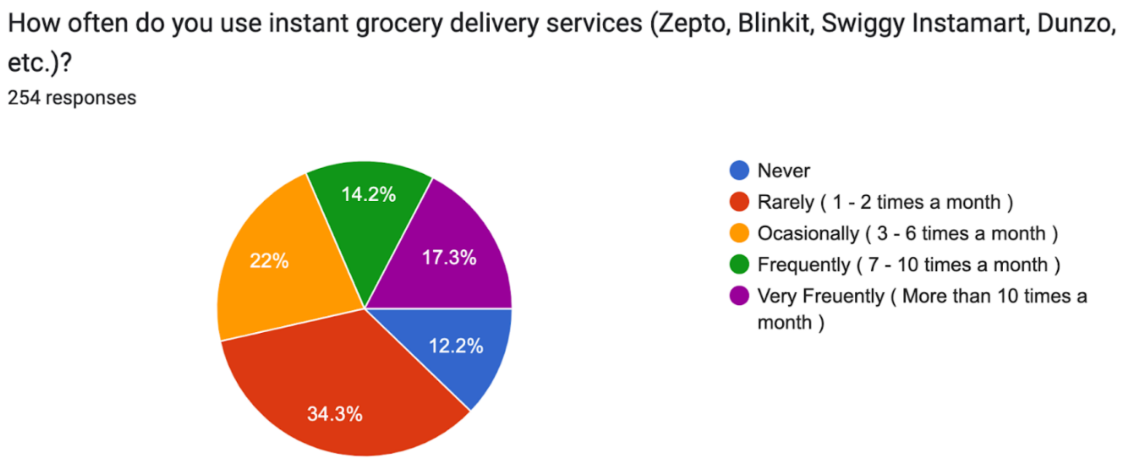
This indicates that the sample includes a diverse range of income groups, with a notable concentration of respondents from higher-income households. However, without cross-referencing with usage behaviour or preferences, no direct conclusions can be drawn about how income impacts the use of instant grocery delivery services.

FIGURE 2:



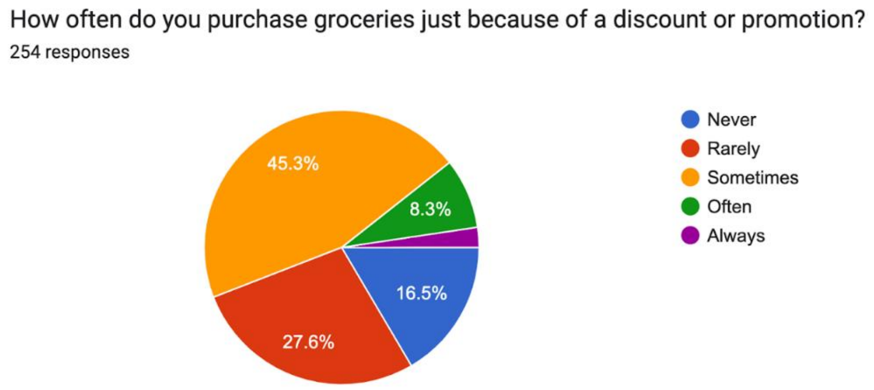
The household size distribution from the survey reveals that a majority of respondents (57.5%) belong to households with 4–5 members, followed by 31.5% who live in 2–3 member households. A smaller share, 7.5%, comes from households with more than 5 members, while only 3.5% live alone. This suggests that most users of instant grocery delivery services come from nuclear to mid-sized families, which typically have moderate to high grocery needs. The prevalence of 4–5 member households may indicate a demand for convenience in managing frequent or bulk grocery purchases, potentially making instant delivery platforms more attractive to such households.

FIGURE 3:



Out of 254 respondents, 34.3% reported using instant grocery delivery services rarely (1–2 times a month), while 22% use them occasionally (3–6 times a month). Additionally, 17.3% use them frequently (7–10 times a month), and 14.2% very frequently (more than 10 times a month). Only 12.2% of respondents stated that they never used such services. Overall, 87.8% of respondents use instant grocery delivery services to some extent, indicating broad adoption. Notably, 36.2% use these services more than three times a month, reflecting a considerable level of engagement. While most users fall into the lower usage categories, the presence of frequent and very frequent users highlights the growing role of instant delivery in everyday grocery shopping habits.

FIGURE 4:

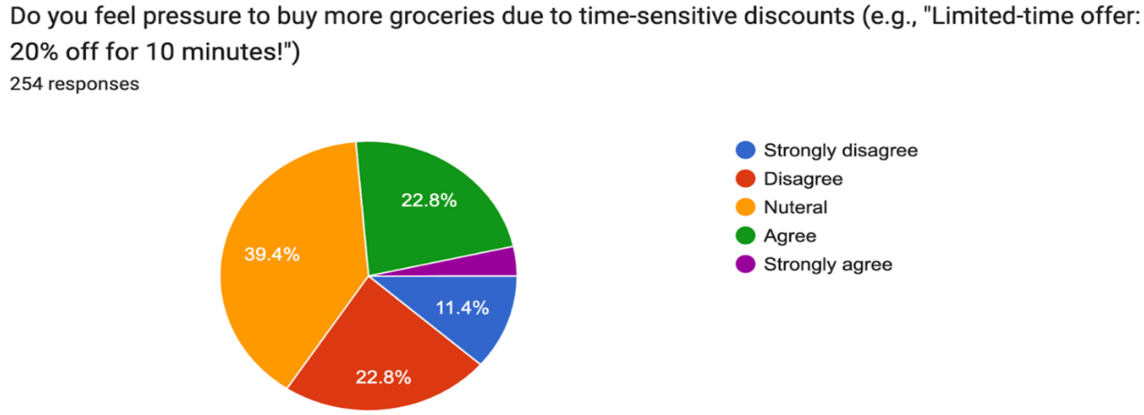


The pie chart shows that a significant portion of respondents (45.3%) sometimes purchase groceries just because of discounts or promotions, suggesting that promotional offers do have a moderate influence on consumer decisions.

Meanwhile, 27.6% rarely and 16.5% never do so, indicating that around 44.1% of consumers are less driven by such offers. On the other hand, a smaller group—8.3% often and 2.4% always—appears to be more susceptible to promotional triggers, pointing to a segment prone to impulse buying behaviour.

Overall, while not dominant, discount-driven purchasing is common, showing how Q-Commerce platforms can leverage offers to influence buying behaviour among certain consumer segments.

FIGURE 5:

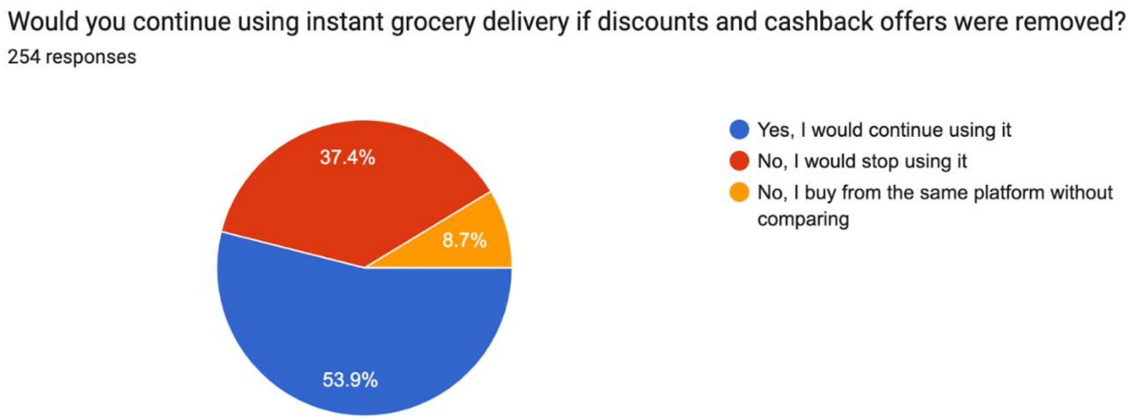


The pie chart reveals that a majority of respondents (50.8%) do not feel pressured to buy more groceries due to time-sensitive discounts, with 39.4% disagreeing and 11.4% strongly disagreeing. This suggests that most users maintain control over their purchases, even when faced with urgency-based offers.

However, 26.3% of participants (22.8% agreeing, 3.5% strongly agreeing) admit feeling influenced by such promotions, indicating that a notable segment is susceptible to impulse buying triggered by limited-time deals. Additionally, 22.8% remain neutral, possibly reflecting uncertainty or occasional influence.

Overall, while Q-Commerce consumers show a general resistance to marketing-induced urgency, the presence of a vulnerable group points to diverse behavioural responses, shaped perhaps by individual, psychological, or contextual factors

FIGURE 6:

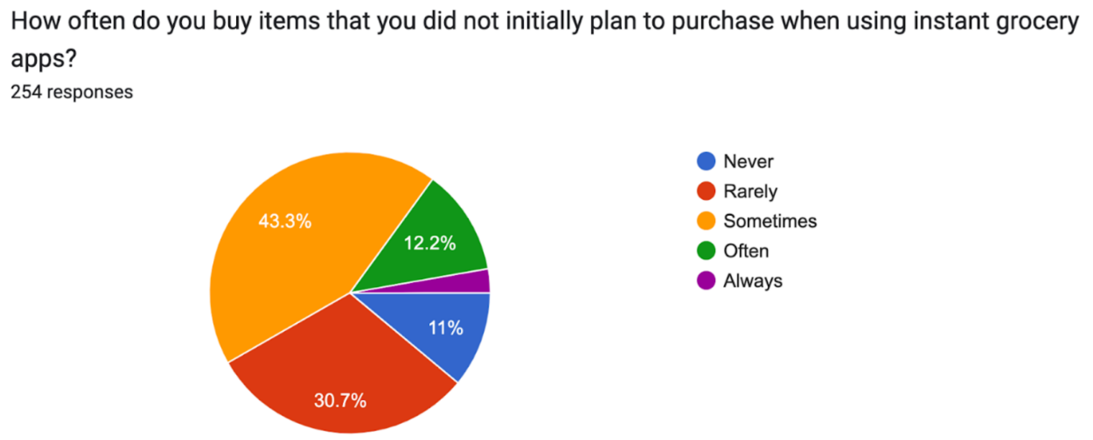


The pie chart reveals that 53.9% of respondents would continue using instant grocery delivery services even if discounts and cashback offers were removed. This suggests that convenience is a strong motivating factor for over half the users.

However, 37.4% say they would stop using these services, indicating that a sizable portion is primarily driven by promotional benefits. Additionally, 8.7% admit to buying from the same platform without comparing prices, highlighting a segment with brand loyalty or habitual use.

In summary, while convenience keeps many users engaged, removal of discounts could lead to a significant drop in platform usage for price-sensitive customers.

FIGURE 7:



A survey on the impact of instant grocery delivery on household planning reveals that while the largest group of users (30.7%) rarely make unplanned purchases, a significant portion either never (11%) or sometimes (43.3%) do. Notably, a combined 25.9% of respondents often (12.2%) or always (13.78%) buy items they didn't initially intend to. This suggests that while many users maintain shopping discipline, a considerable minority experiences impulse buying facilitated by the convenience and accessibility of these apps, potentially impacting their grocery planning and spending habits

NON-PARAMETRIC ANALYSIS

Hypothesis 1: Discount Sensitivity Across Income Groups

The first hypothesis aimed to assess whether discount sensitivity significantly varies across income groups. For this purpose, a Kruskal–Wallis H test was conducted, using income group as the independent variable and the Likert-scale responses to the question "How often do you purchase groceries just because of a discount or promotion?" as the dependent variable.

The test revealed no statistically significant difference in discount sensitivity across income levels, H(3)=3.27,p=0.352H(3) = 3.27, p = 0.352H(3)=3.27,p=0.352. This indicates that participants across all income brackets tend to exhibit similar levels of responsiveness to discounts and promotional offers on Q-Commerce platforms.

Since the test result is not significant, there is no statistical basis for rejecting the null hypothesis. As a result, no further pairwise (post hoc) comparisons were conducted. These findings suggest that discount-driven purchasing behaviour is relatively consistent across income segments in the sampled urban population. This may reflect a broader cultural or market-wide trend in which discount incentives are universally appealing, regardless of income status.

Hypothesis 2: Association Between Household Size and Frequency of Q-Commerce Usage

The second hypothesis examined whether the frequency of instant grocery delivery usage differs significantly across different household sizes. Specifically, the goal was to determine whether household structure—categorized as Solo, Small, Large, or Extra Large—is associated with how often individuals use Q-Commerce services.

To test this, a Chi-Square Test of Independence was conducted using the variable "What is your household size?" and the Likert-scale responses to the question "How often do you use instant grocery delivery services?" which ranged from 1 (Never) to 5 (Always). Both variables were treated as categorical, as appropriate for chi-square analysis.

The results of the test indicated no statistically significant association between household size and Q-Commerce usage frequency, χ2(12,N=254)=16.10,p=0.1866\chi^2 (12, N = 254) = 16.10, p = 0.1866χ2(12,N=254)=16.10,p=0.1866. Although differences in usage patterns were observed across household types—for example, a higher concentration of frequent users among larger households—the overall variation was not statistically significant at the 5% significance level.

A warning was generated indicating that the chi-squared approximation may be inaccurate due to low expected counts in some cells. This is particularly relevant for the Solo and Extra Large household categories, which had smaller sample sizes. Despite this limitation, the observed p-value remains well above the standard threshold for significance, and the null hypothesis cannot be rejected.

These findings suggest that, within the current sample, household size does not have a statistically significant influence on how frequently individuals use Q-Commerce platforms. Behavioural differences in usage frequency may thus be more strongly shaped by other variables such as income, individual lifestyle, or digital familiarity rather than household composition alone.

Hypothesis 3: Impulse Buying Behaviour Across Income Groups

The third hypothesis sought to determine whether impulse buying behaviour varies significantly across income groups among Q-Commerce users. The dependent variable was based on participants' responses to the statement "How often do you buy items that you did not initially plan to purchase when using instant grocery apps?", captured using a 5-point Likert scale. The independent variable was household income, categorized into four groups.

A Kruskal–Wallis H test was conducted to assess differences in impulse buying behaviour across the income groups. This non-parametric test is suitable for comparing ordinal data across three or more independent groups without assuming normal distribution or homogeneity of variances.

The test results indicated no statistically significant difference in impulse buying across income categories, H(3)=2.27,p=0.519H(3) = 2.27, p = 0.519H(3)=2.27,p=0.519. The null hypothesis could not be rejected, suggesting that impulse buying behaviour is relatively consistent across income levels in the sample.

This finding implies that impulsive purchasing tendencies on Q-Commerce platforms are not significantly shaped by income. It is possible that factors such as platform design, psychological triggers (e.g., urgency, app notifications), and consumer habits play a more universal role in driving unplanned purchases, regardless of an individual's income bracket.

DISSCUSSION

This study set out to investigate how behavioural factors such as discount sensitivity and impulse buying vary across income groups, and whether household structure influences the frequency of Q-Commerce usage in urban India. Contrary to expectations grounded in classical economic and behavioural theory, none of the three tested hypotheses produced statistically significant results. However, these findings yield valuable insights into the evolving nature of digital grocery consumption and open new avenues for future research.

KEY FINDINGS

1. Discount sensitivity does not significantly vary across income groups. The Kruskal–Wallis test revealed no significant difference in how frequently users across income segments reported being influenced by discounts and promotions on Q-Commerce platforms.

2. Household size is not significantly associated with Q-Commerce usage frequency. The Chi-square test showed no statistically significant relationship between household type (Solo, Small, Large, Extra Large) and how often individuals use instant grocery delivery services.
3. Impulse buying behaviour is consistent across income groups. The Kruskal–Wallis test for impulse purchases found no significant differences across income levels, suggesting that impulsive digital grocery behaviour is not tied to economic status.

These findings challenge conventional assumptions about the behavioural segmentation of consumers based on income and household structure. While demographic distinctions remain important for market classification, they appear to play a limited role in shaping key behavioural outcomes in the Q-Commerce space—at least within the scope of the current sample.

The first hypothesis tested whether discount sensitivity varied across income groups. Although previous research has often posited that lower-income consumers exhibit higher price sensitivity (Spurlock et al., 2019; Wiig & Smith, 2008), the current study found no significant difference across income segments. This suggests that discount-driven behavior may be a universal feature of Q-Commerce usage, possibly influenced more by platform design and promotional strategies than by economic need. With Q-Commerce platforms regularly using app-based notifications and real-time offers, consumers across income levels may be equally conditioned to respond to discounts, irrespective of their financial standing.

The second hypothesis explored whether household size is associated with the frequency of Q-Commerce usage. While descriptive statistics showed some variation—for example, large households appeared more frequently in higher usage categories—the Chi-Square Test of Independence did not yield a statistically significant association. This result complicates earlier assumptions that joint or larger households are inherently more structured and less spontaneous in consumption. It may reflect a growing trend of individualized decision-making within shared households, or the increasing autonomy of younger household members to place digital orders irrespective of family size or collective budgeting norms.

The third hypothesis examined whether impulse buying behavior varies across income levels. Again, no significant difference was found. While behavioral economics literature often links financial constraint with self-control or impulsivity (Hao et al., 2020; Sharma & Singh, 2021), the findings here suggest that impulse buying in Q-Commerce may be more psychologically than economically driven. Platform affordances such as frictionless checkout, time-limited deals, and algorithmic recommendations may stimulate impulse purchases uniformly across income brackets.

Taken together, these findings point toward the possibility that Q-Commerce behaviour is flattening traditional socio-demographic distinctions, at least in the urban Indian context. Behavioural responses such as discount-seeking and impulsive purchases may be more influenced by the technological and user-experience design of the platforms than by conventional variables like income or household structure. This underscores the need to supplement demographic analysis with psychological and behavioural variables such as digital literacy, app usage patterns, and cognitive load.

Furthermore, the lack of statistical significance across all three hypotheses calls attention to the need for larger and more diversified samples, especially for subgroups like Solo and Extra-Large households, which were underrepresented in this study. It also suggests potential benefits in adopting mixed-methods designs that integrate qualitative insights to unpack the "why" behind the observed patterns.

In summary, while the results do not support the initial hypotheses, they contribute meaningfully to the literature by highlighting the behavioural convergence among users across income and household categories in the context of Q-Commerce. The findings challenge assumptions about economic segmentation in digital consumer behaviour and suggest a potential democratization—or homogenization—of online grocery shopping patterns driven by platform architecture and user interface design

LIMITATIONS

- The study relies on self-reported survey data, which may be affected by social desirability bias, recall errors, or misinterpretation of Likert-scale items.
- The sample is not nationally representative and is skewed toward urban, digitally literate respondents, limiting the generalizability of findings to rural or less connected populations.

- Some demographic subgroups, such as Solo and Extra-Large households, had small sample sizes, potentially compromising the validity of the Chi-Square test results due to low expected cell counts.
- The study focuses primarily on socio-demographic and behavioural variables, without incorporating psychological constructs such as digital literacy, self-control, or urgency, which may influence Q-Commerce usage.
- The use of non-parametric statistical tests, while appropriate for ordinal data, limits the ability to model complex interactions or control for confounding variables.
- All data were cross-sectional, capturing behaviour at a single point in time, which restricts the ability to draw causal inferences or observe temporal changes in consumer behaviour.

CONCLUSION

This study explored how income levels and household structures relate to key behavioral patterns in the context of Quick Commerce (Q-Commerce) usage in urban India. Using a quantitative, survey-based approach and non-parametric statistical methods, the research tested whether discount sensitivity and impulse buying vary across income groups, and whether household size influences the frequency of Q-Commerce usage.

Across all three hypotheses, the study found no statistically significant differences or associations. Discount sensitivity and impulse buying behaviour appeared consistent across income categories, while household size showed no significant relationship with usage frequency. These findings challenge commonly held assumptions about consumer segmentation and suggest a possible behavioural convergence driven by digital platform design, marketing practices, and widespread app-based engagement.

Although the results did not support the original hypotheses, they contribute to the emerging literature on digital consumer behaviour by highlighting that demographic factors such as income and household structure may be less predictive of behavioural outcomes in Q-Commerce than previously assumed. The findings also emphasize the importance of considering psychological, contextual, and technological variables when studying emerging consumption models.

Given the study's limitations—particularly its urban sampling frame, reliance on self-reported data, and limited subgroup sizes—further research is needed using larger and more diverse samples. Future studies could also incorporate experimental or longitudinal designs, or explore cognitive and affective drivers of consumer behaviour, to better understand the mechanisms underlying decision-making in ultra-fast delivery environments.

In sum, while the hypotheses were not confirmed, the study offers valuable insight into the democratization of digital grocery shopping behaviour in India and calls for a broader, more nuanced understanding of the forces shaping Q-Commerce adoption and usage.

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APPENDICES

Appendix A: Survey Questionnaire Link

To collect data for this research, a structured online survey was created using Google Forms. The survey includes questions on demographic details, grocery planning behaviour, budgeting impact, and impulse buying tendencies related to instant grocery delivery services.

The full survey questionnaire can be accessed at the following link:

Survey Link: https://forms.gle/rLLTgkbRwhYjtQjFA

Appendix B: Justification for Questions

Section 1: Demographic & Control Variables

Question	*Justification*	*Scale Used*	*Bias Consideration*
Age Group	Determines if younger consumers are more likely to use instant grocery services.	Categorical	None
Household Size	Larger families may still prefer bulk shopping.	Categorical	Some respondents may approximate family size.
Income Level	Examines how disposable income affects grocery budgeting.	Categorical	Self-reported income may be under/overstated.

Location (Metro/Tier-2/Tier-3)	Urban vs. rural differences in adoption of quick commerce.	Categorical	Some small-town respondents may not fit neatly into provided categories.

Section 2: Usage of Instant Grocery Delivery (

Question	*Justification*	*Scale Used*	*Bias Consideration*
Frequency of use	Key independent variable measuring reliance on quick commerce.	Ordinal	Frequent users may understate their use.
Primary reason for usage	Helps segment users by motivation (convenience vs. discounts vs. urgency).		Self-reported motivations may not match actual behaviour.
Average spending per order	Determines if frequent users spend significantly more per order.	Numerical	Recall bias may affect accuracy.
Would you continue using instant grocery delivery if discounts were removed?	Tests price elasticity of demand.	Ordinal	Some users may answer aspirationally rather than truthfully.
Do you compare prices on multiple platforms before ordering?	Measures consumer price sensitivity.	Ordinal	Consumers may overstate rational behaviour.

Section 3: Changes in Grocery Planning

Question	*Justification*	*Scale Used*	*Bias Consideration*

Change in grocery shopping habits	Tests if quick commerce is replacing traditional bulk shopping.	Ordinal	Respondents may not consciously track changes.
Current grocery planning strategy	Differentiates between structured planners and impulse buyers.	Ordinal	May not capture hybrid planning behaviours.
Has instant grocery availability changed how you stock perishable vs. non-perishable goods?	Captures long-term storage habits.	Ordinal	Respondents may not be aware of subtle changes in their habits.

Section 4: Budgeting & Financial Impact

Question	*Justification*	*Scale Used*	*Bias Consideration*
Tracking grocery expenses	Tests whether quick commerce disrupts budgeting discipline.	Ordinal	Self-reported tracking may be overestimated.
Total grocery expenditure change	Measures financial impact of quick commerce adoption.	Ordinal	Difficult to measure exact increase in spending.
Perceived impact on spending behaviour	Examines psychological spending perception.	Ordinal	Subjective responses may differ from actual behaviour.

Section 5: Discounts, Impulse Buying & Consumer Psychology

Question	*Justification*	*Scale Used*	*Bias Consideration*

Purchases based on discounts/promotions	Evaluates role of pricing incentives in driving spending.	Ordinal	May not reflect real spending drivers.
Adding extra items to qualify for free delivery	Tests consumer reaction to platform pricing strategies.	Ordinal	Respondents may rationalize impulse purchases.
Unplanned purchases	Measures impulse buying behaviour influenced by quick commerce.	Ordinal	Social desirability bias may underreport impulse buying.

Appendix C: R Codes for Analysis

```
```{r}
# Install only if not already installed
# install.packages("tidyverse")
# install.packages("ggpubr")
# install.packages("rstatix")

library(tidyverse)  # Core packages: dplyr, ggplot2, readr, etc.
library(ggpubr)     # For easy boxplots and stats
library(rstatix)    # For non-parametric tests like Kruskal-Wallis
```
```

```
```{r}
library(readxl)
Micro_Data <- read_excel("C:/Users/madhu/OneDrive/Desktop/Madhumitha/SSE. Msc Economics/Semester 2/Micro II/Micro Data.xlsx")
View(Micro_Data)
```
```

```
```{r}
# Convert relevant columns to factors
Micro_Data <- Micro_Data %>%
  mutate(
    income_group = factor(Micro_Data$`What is your monthly household income?`),
    household_type = factor(Micro_Data$`What is your household size?`),
    age_group = factor(Micro_Data$`What is your age group?`),
    avg_spend = as.numeric(Micro_Data$`On average, how much do you spend per order on instant grocery apps?`)
  )
```
```

```
```{r}
summary(Micro_Data)
table(Micro_Data$income_group)
table(Micro_Data$household_type)
```
```

```{r}
# Convert relevant columns to factors
Micro_Data <- Micro_Data %>%
  mutate(
    income_group = factor(Micro_Data$`What is your monthly household income?`),
    household_type = factor(Micro_Data$`What is your household size?`),
    age_group = factor(Micro_Data$`What is your age group?`),
    avg_spend = as.numeric(Micro_Data$`On average, how much do you spend per order on instant grocery apps?`)
  )
```

```{r}
summary(Micro_Data)
table(Micro_Data$income_group)
table(Micro_Data$household_type)
```

```{r}
# Run Kruskal-Wallis Test: Hypothesis 1
Micro_Data %>%
  kruskal_test(Micro_Data$`How often do you purchase groceries just because of a discount or promotion?`~
Micro_Data$`What is your monthly household income?`)
```

A tibble: 1 x 6

n <int>	statistic <dbl>	df <int>	p <dbl>	method <chr>
254	3.265991	3	0.352	Kruskal-Wallis

1 row | 3-7 of 6 columns

```{r}

# Hypothesis 2: Chi Square test
# Convert frequency to ordered factor
Micro_Data <- Micro_Data %>%
  mutate(
    q_freq = factor(Micro_Data$`How often do you use instant grocery delivery services`)
  )

# Create contingency table
table(Micro_Data$`What is your household size?`, Micro_Data$`How often do you use instant grocery delivery services`)

# Run Chi-Square Test
chisq.test(table(Micro_Data$`What is your household size?`, Micro_Data$`How often do you use instant grocery delivery
services`))
```

```{r}
# Hypothesis 3:

# Kruskal-Wallis Test
Micro_Data %>%
  kruskal_test(Micro_Data$`How often do you buy items that you did not initially plan to purchase when using instant grocery apps?`~ Micro_Data$`What is your monthly household income?`)
```

A tibble: 1 x 6

n <int>	statistic <dbl>	df <int>	p <dbl>	method <chr>
254	2.266204	3	0.519	Kruskal-Wallis

1 row | 3-7 of 6 columns