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Impact of Personalized Digital Marketing Strategies (Offers and App Notifications) on Purchase Decisions in Quick Commerce: A Study among Generation Z Consumers in Andhra Pradesh.

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ABSTRACT :

The rapid growth of quick commerce has changed the way consumers purchase groceries and daily essentials by providing fast and convenient delivery through mobile applications. Digital marketing strategies such as personalized offers, discount alerts, and app notifications are increasingly used by quick commerce platforms to attract and influence consumers. This study focuses on the impact of personalized digital marketing strategies, particularly offers and app notifications, on the purchase decisions of Generation Z consumers in Andhra Pradesh.

The main purpose of this study is to understand how personalized offers and app notifications influence consumers' decisions to make purchases through quick commerce applications. The study considers Generation Z consumers as the target group and examines their responses to different types of digital marketing strategies, including personalized discounts, promotional offers, reminder notifications, and product-related alerts. The study also aims to identify which type of personalized strategy has a greater influence on purchase decisions.

The research will use primary data collected from Generation Z consumers in Andhra Pradesh through a structured questionnaire. The collected data will be analysed to understand consumer preferences, responses, and purchasing behaviour.

Keywords: Personalized Digital Marketing, Offers, App Notifications, Purchase Decisions, Quick Commerce, Generation Z, Consumer Behaviour, Andhra Pradesh, Digital Marketing Strategies.

Introduction

The growth of digital technology has changed the way consumers search for products, compare prices, and make purchasing decisions. The increasing use of smartphones, mobile applications, digital payments, and internet services has encouraged consumers to purchase products online. Along with traditional e-commerce, a new form of online shopping known as quick commerce (Q-commerce) has become popular. Quick commerce mainly focuses on delivering groceries, household products, and daily essentials to customers within a short period of time.

Quick commerce platforms use mobile applications to provide customers with convenience, easy product selection, multiple payment options, discounts, and fast delivery. Platforms such as Blinkit, Zepto, Swiggy Instamart, and BigBasket Now use different digital marketing techniques to attract and retain customers. As competition increases in the quick commerce sector, companies are focusing not only on providing fast delivery but also on understanding individual customer preferences.

Among the different personalized strategies, offers and app notifications play an important role in attracting consumer attention. Discount offers, promotional coupons, limited-time deals, cashback offers, and personalized product recommendations can encourage customers to consider a purchase. Similarly, app notifications can inform consumers about new offers, price reductions, products, reminders, and special promotions. These messages may influence consumers to make planned purchases as well as unplanned or impulse purchases.

Generation Z, generally referring to young consumers who have grown up with digital technology, represents an important group for digital businesses. They are familiar with smartphones, mobile applications, social media, online payments, and digital shopping platforms. Their regular interaction with digital platforms makes them an important consumer group for quick commerce companies. Understanding how Generation Z responds to personalized offers and app notifications can help businesses improve their digital marketing strategies.

In Andhra Pradesh, the increasing use of smartphones, internet services, digital payments, and online shopping has created opportunities for quick commerce platforms. Consumers in urban and developing areas can use mobile applications to order groceries and daily essentials without visiting

physical stores. However, consumer responses to digital marketing messages may differ depending on their preferences, shopping habits, perceived value of offers, and convenience.

Therefore, this study titled “Impact of Personalized Digital Marketing Strategies (Offers and App Notifications) on Purchase Decisions in Quick Commerce: A Study among Generation Z Consumers in Andhra Pradesh” focuses on understanding the relationship between personalized digital marketing strategies and consumer purchase decisions

1.2 Problem Statement

Quick commerce platforms such as Blinkit, Zepto, Swiggy Instamart, and BigBasket Now use personalized digital marketing strategies such as special offers, discounts, coupons, and app notifications to attract consumers. These strategies are designed to create interest and encourage consumers to make purchases. Generation Z consumers are active users of mobile apps and may respond differently to personalized offers and notifications. However, there is a need to understand how these personalized marketing strategies influence their purchase decisions in the quick commerce sector.

2. REVIEW OF LITERATURE

Varnali, K., and Toker, A. (2010) conducted a study titled “Mobile Marketing Research: The-State-of-the-Art.” The study reviewed existing research on mobile marketing and examined its role in consumer communication and behaviour. The authors highlighted the importance of mobile devices in reaching consumers, delivering marketing messages, and building customer relationships. The study helps explain how mobile marketing strategies can influence consumer responses and supports further research on personalized app notifications and purchase decisions in quick commerce.

Pappas et al. (2017) conducted a study on personalized e-commerce to understand how personalized recommendations and customer emotions influence purchase intentions. The study examined the role of personalization quality, message quality, recommendation benefits, and customer emotions in online shopping. The researchers collected data from 582 experienced online customers. The findings highlighted the importance of relevant and high-quality personalized recommendations in influencing customers' purchase intentions.

Iyer and Zhong (2022) conducted a study titled "Pushing Notifications as Dynamic Information Design," listed under Marketing Science / SSRN. The purpose of the study was to understand how push notifications influence consumer behaviour. Push notifications were treated as the independent variable and purchase behaviour as the dependent variable.

The findings show that notifications increase consumer engagement and raise the probability of purchase. The main contribution of the study is its strong theoretical model of push notifications.

Sruthiya and Aswani Sasikumar (2025) conducted a study titled "Consumer Perception and App Loyalty Through Personalized Push Notifications," published in the International Journal of Research in Commerce and Management Studies (IJRCMS). The study aimed to analyse how consumers respond to personalized notifications. Personalized notifications were the independent variable and app loyalty was the dependent variable.

The study found that personalization improves consumer satisfaction and repeat usage of the application. Its distinctive focus is on app personalization as a way of building loyalty.

Mukhopadhyay (2024) conducted a study titled "From Click to Quick: Drivers of Quick Commerce," available on SSRN. The study examined the factors behind the growth of quick commerce. Convenience and speed were the independent variables and buying behaviour was the dependent variable. The study found that faster delivery increases impulse buying. It contributes an explanation of the quick commerce business model.

Jose and Mathews (2025) conducted a study titled "Quick Commerce and Impulse Buying Behaviour of Consumers," available on SSRN. The study aimed to understand consumer buying behaviour in quick commerce. Convenience was the independent variable and impulse buying was the dependent variable. The findings show that quick commerce increases unplanned purchases. The study focuses on the buying behaviour of consumers in fast-moving consumer goods (FMCG)..

Jain et al. (2026) conducted a study titled "Push-to-Purchase: Impact of Notifications and Offers in Quick Commerce Apps," published in the International Journal of Scientific Development and Research (IJS DR). The study analysed how promotional offers and app notifications affect consumers. Offers and notifications were the independent variables and purchase decisions were the dependent variable.

Tong, Luo, and Xu (2020) conducted a study titled “Personalized Mobile Marketing Strategies,” published in the *Journal of the Academy of Marketing Science*. The study developed a framework for personalized mobile marketing by examining how personalization can be applied to product, price, promotion, place, and prediction strategies. The authors highlighted the importance of using mobile data to deliver relevant marketing messages and targeted offers to consumers.

Park, Park, and Schweidel (2018) conducted a study titled “The Effects of Mobile Promotions on Customer Purchase Dynamics,” published in the *International Journal of Research in Marketing*. The study examined the effects of price discounts and free-sample coupons on customer purchase behaviour over time. The findings showed that both types of mobile promotions increased purchase likelihood and spending during the coupon redemption period. Free-sample coupons also had longer-lasting effects on purchasing behaviour.

Bleier and Eisenbeiss (2015) conducted a study titled “*Personalized Online Advertising Effectiveness: The Interplay of What, When, and Where,*” published in *Marketing Science*. The researchers examined how advertisement content, timing, and placement affect the effectiveness of personalized online advertising. The findings showed that personalization can improve advertising effectiveness, but its impact depends on when and where the advertisement is displayed

Research Objectives

- **To study** the impact of personalized digital marketing strategies, particularly offers and app notifications, on the purchase decisions of Generation Z consumers in Andhra Pradesh.
- **To examine** the influence of personalized offers, discounts, coupons, and app notifications on the purchase decisions of Generation Z consumers in quick commerce.
- **To analyze** which personalized digital marketing strategy has the strongest influence on the purchase decisions of Generation Z consumers in quick commerce.
- **To suggest** suitable personalized digital marketing strategies that quick commerce platforms can use to influence the purchase decisions of Generation Z consumers.

2.2 Research Gap

Existing studies on digital marketing mainly focus on general e-commerce platforms, while limited attention has been given to personalized digital marketing strategies in quick commerce. Personalized offers, discounts, coupons, and app notifications are important marketing tools used by quick commerce platforms such as Blinkit, Zepto, and Swiggy Instamart. However, further research is needed to understand how these strategies influence consumers' purchase decisions in the quick commerce market.

Another important research gap is the limited focus on Generation Z consumers. As this generation actively uses mobile applications for shopping, it is important to examine how they respond to personalized offers and app notifications. In addition, the geographical scope of the present study focuses on Generation Z consumers in Andhra Pradesh.

Previous research has examined different aspects of online promotions, personalization, and mobile marketing. However, the combined influence of personalized offers and app notifications on purchase decisions in quick commerce requires further investigation. It is also important to understand whether these strategies influence consumers' actual purchase decisions rather than only their interest or purchase intention.

Therefore, the present study aims to address these research gaps by examining the impact of personalized digital marketing strategies, particularly offers and app notifications, on the purchase decisions of Generation Z consumers in Andhra Pradesh's quick commerce market.

RESEARCH METHODOLOGY

Research Design

The study follows a descriptive and analytical research design based on a cross-sectional quantitative survey. Primary data were collected once from respondents using a structured questionnaire.

Population, Sample and Data Collection

The population consists of Generation Z consumers in Andhra Pradesh who use quick commerce applications. A non-probability convenience sampling method was used, and the questionnaire was circulated online through Google Forms. Responses were received between 23 August 2026 and 29 September 2026. A total of 72 responses were received. All 72 responses are used for the respondent profile, and 70 respondents with complete purchase decision scores are used for the chi-square and ANOVA tests. 70 respondents with complete scores on all three scales are used for the regression analysis.

Research Instrument

The questionnaire has two sections. Section A collects the respondent profile and usage pattern (age group, gender, district, occupation, quick commerce apps used, frequency and duration of use, products purchased, monthly spending and main reason for use). Section B contains 20 statements measured on a five-point Likert scale (1 = Strongly disagree, 5 = Strongly agree), grouped into three constructs:

- Personalized Offers (PO): 6 statements on attention, relevance, discounts, coupons, recommendations and frequency of app use.
- App Notifications (AN): 6 statements on noticing, attention, motivation to open the app, promotional messages, relevance and urgency.
- Purchase Decision (PD): 8 statements on the influence of offers and notifications on purchase decisions, purchase intention, unplanned purchases and overall influence.

Data Preparation and Statistical Tools

A score for each construct was calculated as the mean of its statements, so every score lies between 1 and 5. Reliability was checked with Cronbach's alpha. For the chi-square test, respondents were classified by their PD score as Low influence (below 2.5) or Moderate/High influence (2.5 and above); this two-level classification was used so that expected cell counts remained adequate in a small sample. To avoid very small groups, age groups 24-26 and 27-30 were combined (24-30), occupations Business/Self-employed and Other were combined, usage frequency below twice a week was combined,

and monthly spending was grouped into three bands.

The tools used were: (i) chi-square test of independence with Cramér's V; (ii) one-way ANOVA with eta squared, supported by Levene's test, Welch's test and the Kruskal-Wallis test as robustness checks; and (iii) multiple linear regression with standardized coefficients, VIF, Durbin-Watson statistic and Shapiro-Wilk test of residuals. The analysis was carried out using MS Excel (formulas and LINEST) and cross-checked with the SciPy statistical library in Python.

Hypotheses of the Study

Null hypotheses are stated first, followed by the corresponding alternative hypotheses. All hypotheses are tested at the 5 per cent level of significance.

- H01: There is no significant association between the respondent profile (gender, age group, occupation, usage frequency, monthly spending, usage duration and main app used) and the level of influence of personalized digital marketing on purchase decisions.
- H1: There is a significant association between the respondent profile (gender, age group, occupation, usage frequency, monthly spending, usage duration and main app used) and the level of influence of personalized digital marketing on purchase decisions.
- H02: There is no significant difference in the mean purchase decision score across the groups of each profile variable.
- H2: There is a significant difference in the mean purchase decision score across the groups of each profile variable.
- H03: Personalized offers have no significant effect on purchase decisions.
- H3: Personalized offers have a significant effect on purchase decisions.
- H04: App notifications have no significant effect on purchase decisions.
- H4: App notifications have a significant effect on purchase decisions.
- H05: The regression model with personalized offers and app notifications as predictors does not significantly explain purchase decisions.
- H5: The regression model with personalized offers and app notifications as predictors significantly explains purchase decisions.

DATA ANALYSIS AND INTERPRETATION

4.1 Profile of the Respondents

Table 4.1: Demographic profile of respondents (N = 72)

Variable	Category	Respondents	Per cent
Gender	Female	60	83.3
	Male	12	16.7
Age group (years)	18-20	35	48.6
	21-23	30	41.7
	24-26	3	4.2
	27-30	4	5.6
Occupation	Student	49	68.1
	Salaried Employee	14	19.4
	Business/Self-employed	7	9.7
	Other	2	2.8
District / city	Vijayawada	37	51.4
	Guntur	12	16.7
	Visakhapatnam	9	12.5
	Nellore	7	9.7
	Other districts / not stated	7	9.7

Gender of respondents (N = 72)

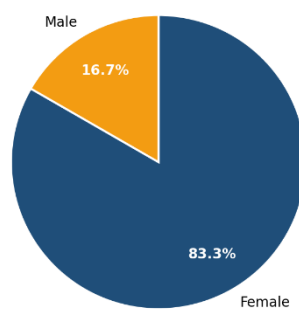


Figure 4.1: Gender of respondents (Table 4.1)

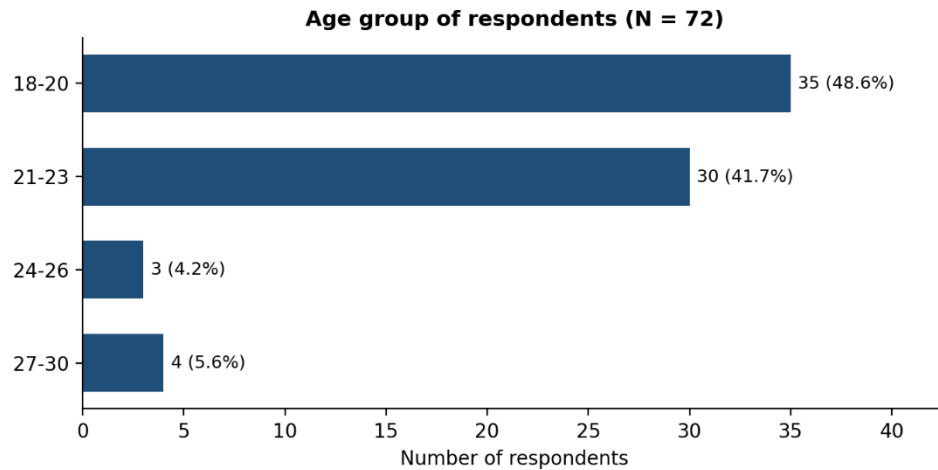


Figure 4.2: Age group of respondents (Table 4.1)

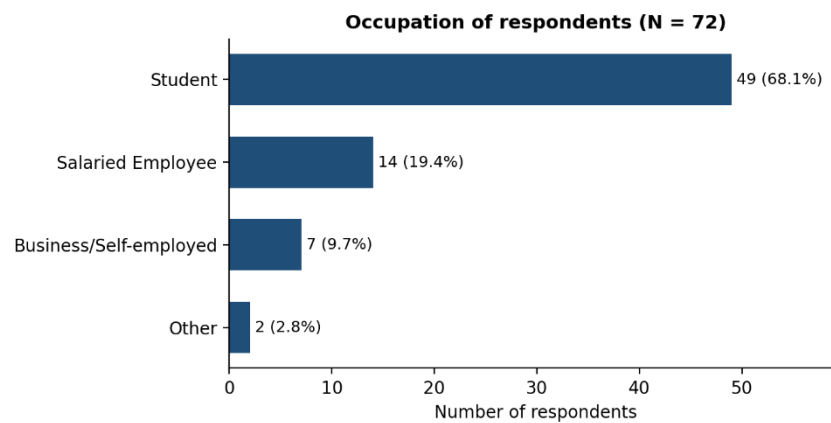


Figure 4.3: Occupation of respondents (Table 4.1)

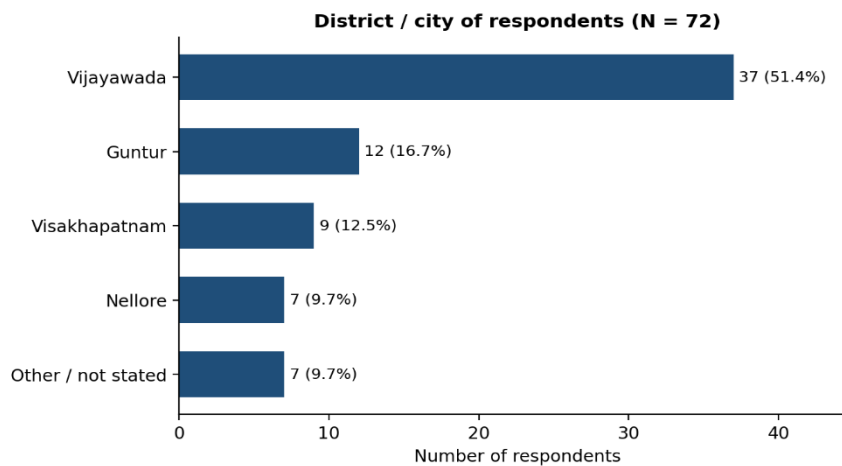


Figure 4.4: District / city of respondents (Table 4.1)

Table 4.2: Quick commerce usage pattern of respondents (N = 72)

Variable	Category	Respondents	Per cent
Quick commerce app	Blinkit	32	44.4
	Swiggy Instamart	16	22.2
	Zepto	14	19.4
	BigBasket	10	13.9
Frequency of use	Daily	14	19.4
	2-3 times a week	30	41.7

Variable	Category	Respondents	Per cent
Duration of use	Once a week	15	20.8
	2–3 times a month	7	9.7
	Rarely	6	8.3
	Less than 6 months	10	13.9
	6 months–1 year	25	34.7
	1–2 years	21	29.2
Main products bought	More than 2 years	16	22.2
	Snacks and beverages	28	38.9
	Groceries	15	20.8
	Household products	14	19.4
	Personal care products	7	9.7
	Fruits and vegetables	6	8.3
Monthly spending	Other	2	2.8
	Below ₹500	16	22.2
	₹500–₹1,000	19	26.4
	₹1,001–₹2,000	21	29.2
	₹2,001–₹3,000	7	9.7
	Above ₹3,000	9	12.5
Main reason for use	Fast delivery	35	48.6
	Convenience	14	19.4
	Easy ordering	9	12.5
	Discounts and offers	8	11.1
	Saves time	4	5.6
	Wide variety of products	2	2.8

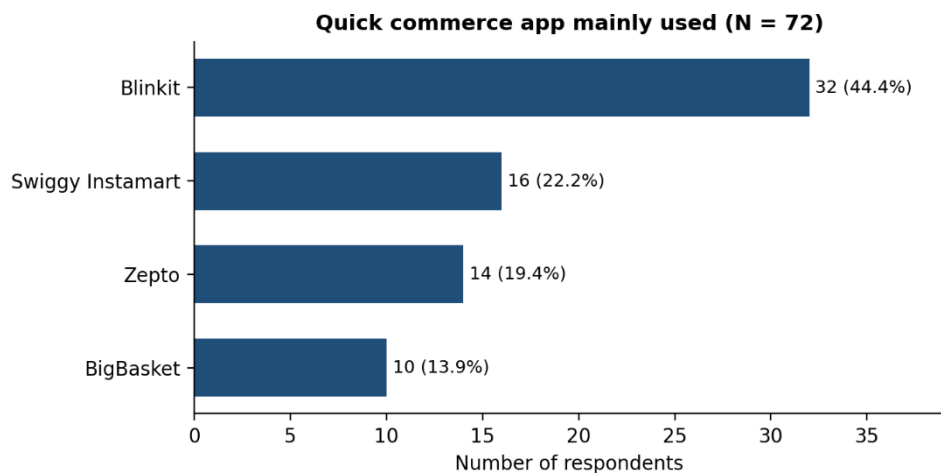


Figure 4.5: Quick commerce app mainly used (Table 4.2)

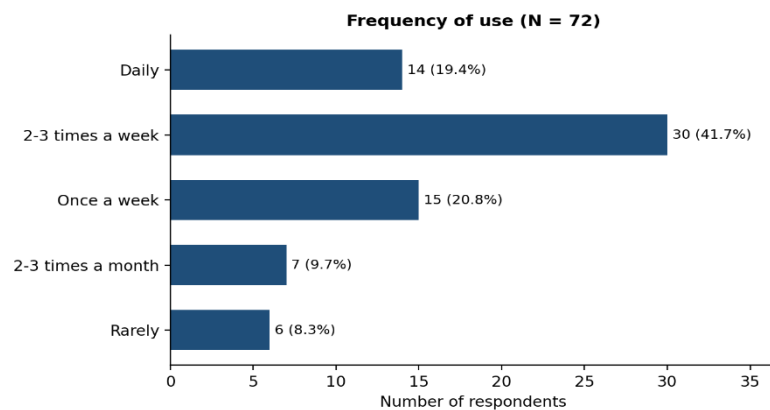


Figure 4.6: Frequency of quick commerce use (Table 4.2)

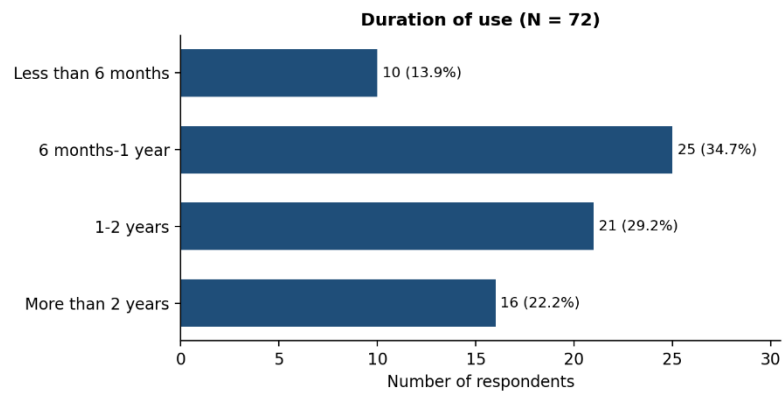


Figure 4.7: Duration of quick commerce use (Table 4.2)

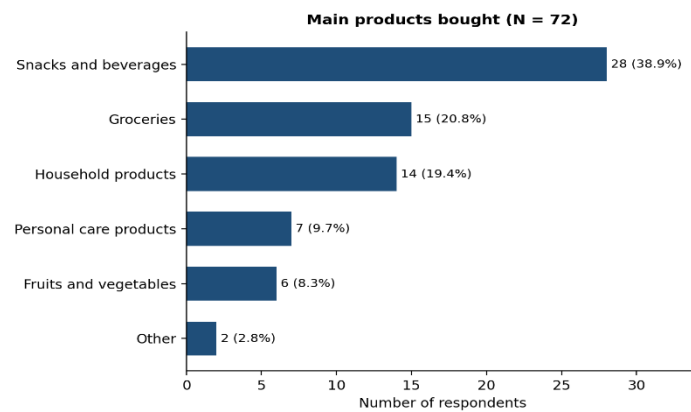


Figure 4.8: Main products bought (Table 4.2)

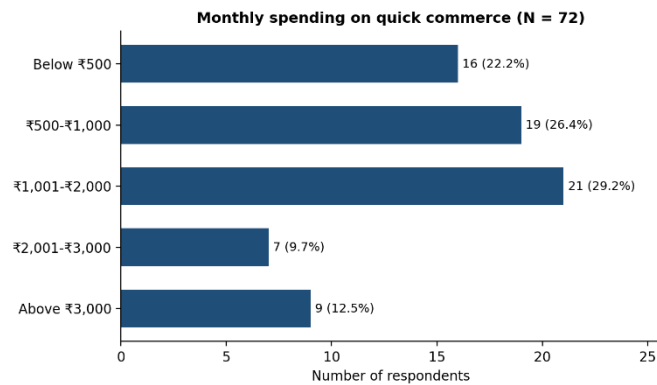


Figure 4.9: Monthly spending on quick commerce (Table 4.2)

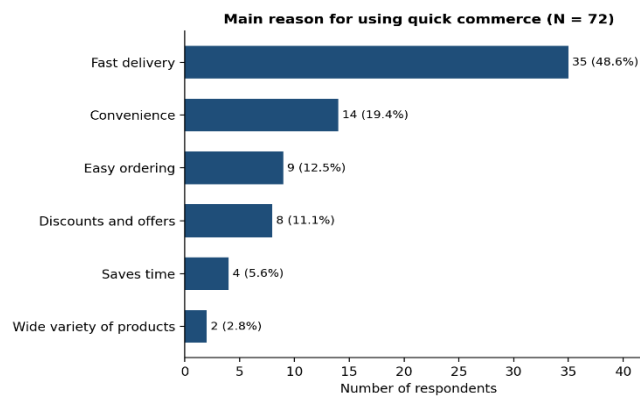


Figure 4.10: Main reason for using quick commerce (Table 4.2)

The sample is predominantly female (60 respondents, 83.3 per cent) and young: 65 respondents (90.3 per cent) are aged 18-23, and 49 (68.1 per cent) are students. Vijayawada accounts for 51.4 per cent of responses. Blinkit is the most used application (44.4 per cent), followed by Swiggy Instamart and Zepto. Most respondents order two to three times a week (41.7 per cent), buy mainly snacks and beverages, and spend between ₹500 and ₹2,000 a month. Fast delivery is the main reason for using quick commerce (48.6 per cent); only 8 respondents (11.1 per cent) name discounts and offers as their main reason.

4.2 Reliability of the Scales

Table 4.3: Cronbach's alpha

Construct	Items	Cases	Cronbach's alpha
Personalized Offers (PO)	6	71	0.889
App Notifications (AN)	6	71	0.868
Purchase Decision (PD)	8	70	0.909

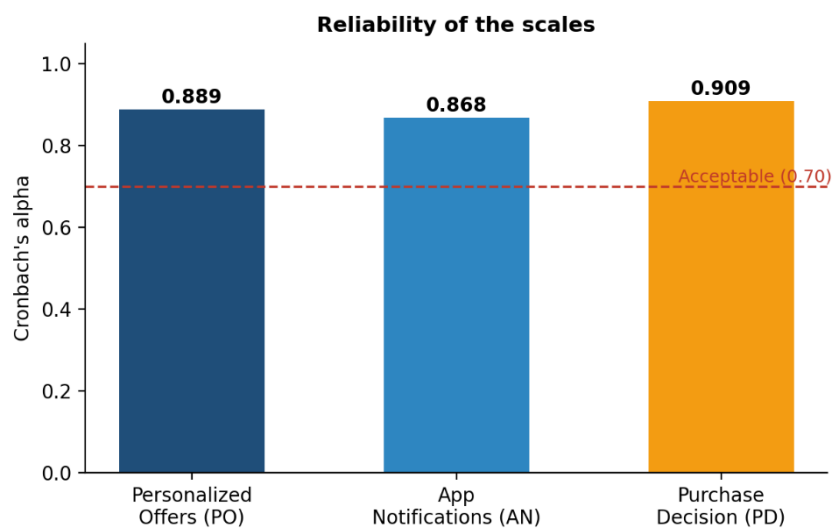


Figure 4.11: Cronbach's alpha of the three constructs (Table 4.3)

All three alpha values are above 0.80, which indicates good internal consistency (a value of 0.70 or above is normally considered acceptable). The item scores can therefore be averaged into construct scores.

4.3 Descriptive Analysis of Personalized Marketing Statements

Table 4.4: Item-wise mean scores (1 = Strongly disagree, 5 = Strongly agree)

Code	Statement	Mean	SD	% Agree (4-5)	% Disagree (1-2)
PO1	Personalized offers on quick commerce apps attract my attention.	2.24	1.06	8.5	59.2
PO2	Offers based on my previous purchases are relevant to my interests.	2.27	1.12	12.7	59.2
PO3	Personalized discounts make me more likely to purchase a product.	2.38	1.20	16.9	53.5
PO4	Personalized coupons encourage me to make purchases.	2.42	1.27	22.5	52.1
PO5	Personalized product recommendations increase my interest in purchasing a product.	2.44	1.18	19.7	52.1
PO6	Personalized offers encourage me to use quick commerce apps more frequently.	2.24	1.22	18.3	60.6
AN1	I regularly notice notifications from quick commerce apps.	2.40	1.26	18.1	54.2
AN2	Personalized app notifications attract my attention.	2.64	1.20	23.6	48.6
AN3	Notifications about products or offers that encourage me to open the app.	2.60	1.26	22.2	43.1
AN4	Discount and promotional notifications encourage me to make purchases.	2.65	1.26	26.4	45.8

Code	Statement	Mean	SD	% Agree (4-5)	% Disagree (1-2)
AN5	Notifications based on my previous purchases or interests are more useful to me.	2.69	1.29	25.0	43.1
AN6	Limited-time offer notifications create a sense of urgency to purchase.	2.79	1.24	26.8	40.8
PD1	Personalized offers influence my purchase decisions.	2.31	1.14	17.1	62.9
PD2	App notifications influence my decision to purchase products.	2.69	1.23	27.1	47.1
PD3	Personalized digital marketing increases my intention to purchase.	2.63	1.12	17.1	42.9
PD4	Personalized offers or notifications encourage me to purchase products that I had not planned to buy.	2.79	1.12	27.1	40.0
PD5	I am more likely to purchase a product when it is personally recommended to me.	2.50	1.11	17.1	48.6
PD6	I have made an unplanned purchase because of a personalized offer or app notification.	2.83	1.23	27.1	38.6
PD7	Personalized offers and app notifications make quick commerce shopping more attractive to me.	2.37	1.12	14.3	58.6
PD8	Overall, personalized offers and app notifications significantly influence my purchase decisions on quick commerce apps.	2.23	1.17	12.9	61.4

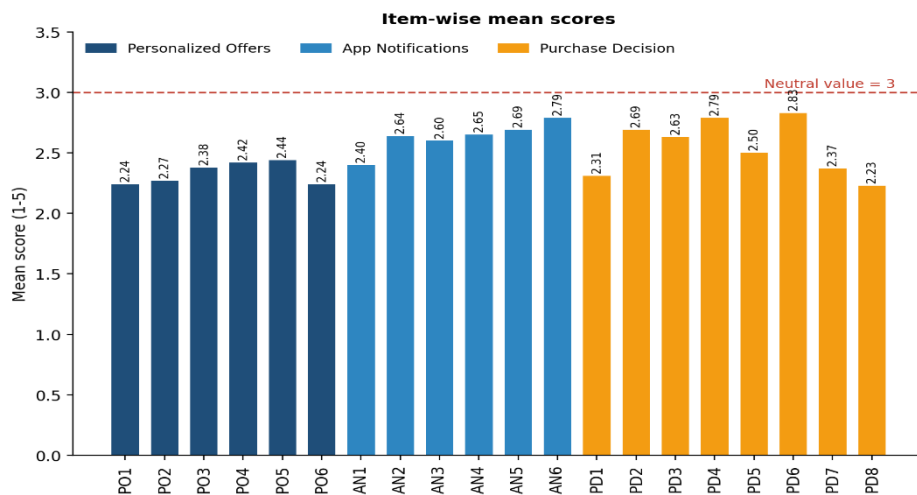


Figure 4.12: Item-wise mean scores of PO, AN and PD statements (Table 4.4)

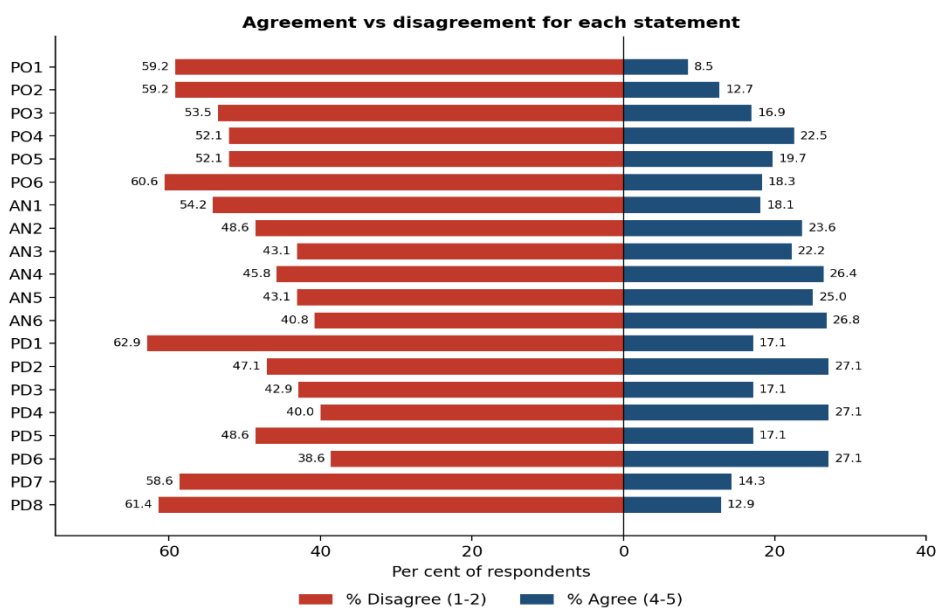
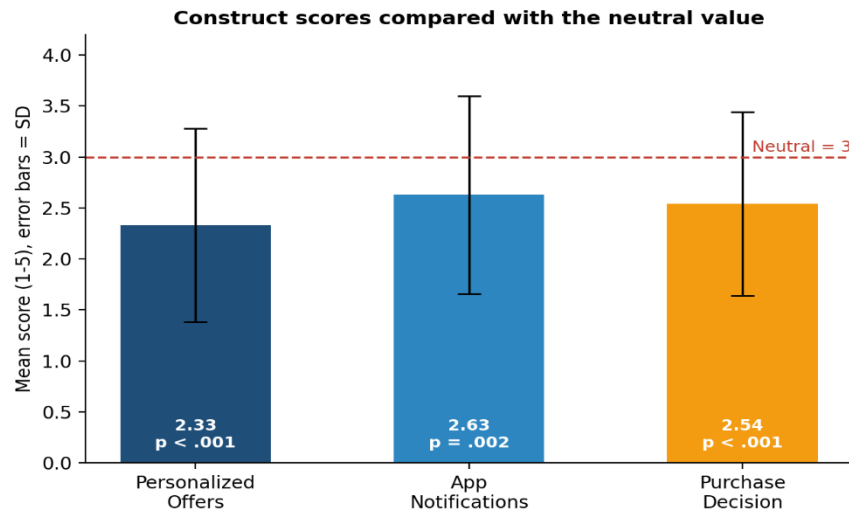


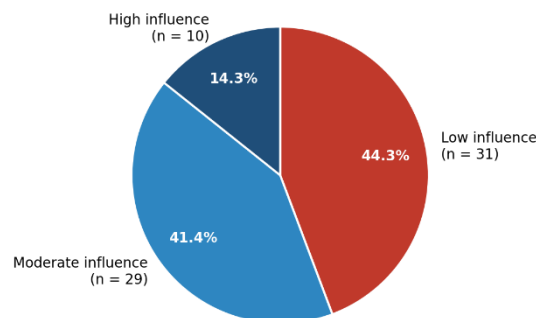
Figure 4.13: Per cent agreeing (4-5) and disagreeing (1-2) with each statement (Table 4.4)

Table 4.5: Construct scores compared with the neutral value of 3

Construct	N	Mean	SD	t	p-value
Personalized offers	71	2.33	0.95	-5.96	< .001
App notifications	72	2.63	0.97	-3.26	.002
Purchase decision	70	2.54	0.90	-4.24	< .001

**Figure 4.14: Mean construct scores against the neutral value of 3 (Table 4.5)**

Every item has a mean below the neutral value of 3, and each construct mean is significantly below 3 (Table 4.5). Respondents therefore lean towards disagreement on average: they report only a modest influence of personalized marketing on their buying. Notifications (mean 2.63) score higher than offers (mean 2.33). The highest-scoring item is the statement on having made an unplanned purchase (2.83), followed by the unplanned-purchase encouragement and time-limited urgency statements (both 2.79), while the lowest are the overall influence statement (2.23) and the statements that personalized offers attract attention and increase app use (both 2.24). Based on the PD score, 31 respondents (44.3 per cent) show low influence, 29 (41.4 per cent) moderate influence and 10 (14.3 per cent) high influence.

Level of influence of personalized marketing (N = 70)**Figure 4.15: Level of influence based on Purchase Decision score (Section 4.3)**

4.4 Chi-Square Test: Respondent Profile and Level of Influence

H01 was tested for each profile variable by cross-tabulating it with the level of influence (Low or Moderate/High).

Table 4.6: Chi-square test results (N = 70)

Profile variable	χ^2	df	p-value	Cramér's V	Min. expected count	H01
Gender	0.04	1	.841	0.02	5.31	Not rejected
Age group	2.25	2	.324	0.18	2.66	Not rejected
Occupation	1.22	2	.544	0.13	3.99	Not rejected
Usage frequency	1.95	2	.377	0.17	5.76	Not rejected
Monthly spending	2.80	2	.246	0.20	7.09	Not rejected
Usage duration	0.78	3	.853	0.11	3.99	Not rejected
Main app used	0.27	3	.966	0.06	4.43	Not rejected

Note: Cross-tabulation with Low vs Moderate/High influence. Age group has 2 of 6 cells (33 per cent) with expected count below 5, and occupation has 1 of 6; interpret these two tests with caution.

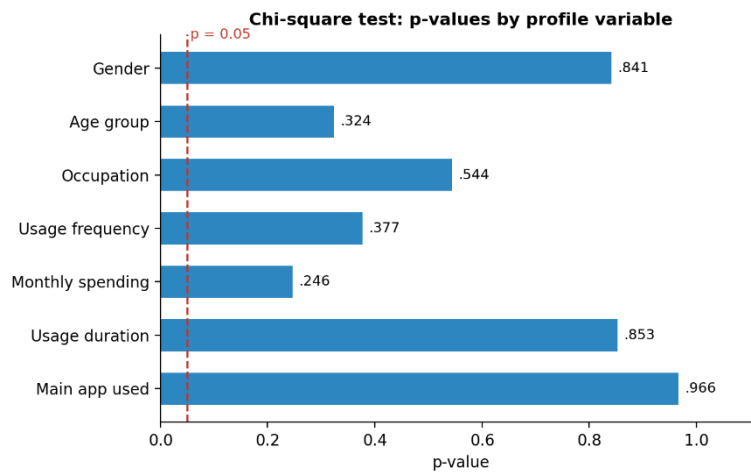


Figure 4.16: Chi-square p-values for each profile variable; all exceed 0.05 (Table 4.6)

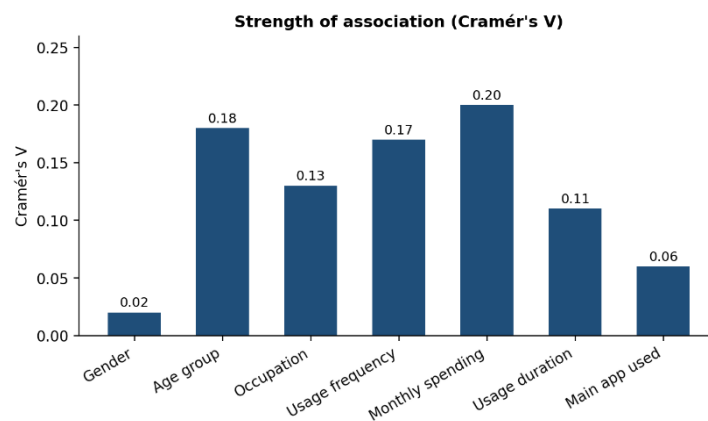


Figure 4.17: Cramér's V for each profile variable (Table 4.6)

Table 4.7: Cross-tabulation of usage frequency and level of influence

Usage frequency	Low influence	Moderate/High influence	Total
Daily	8	5	13
2-3 times a week	12	17	29
Once a week or less	11	17	28

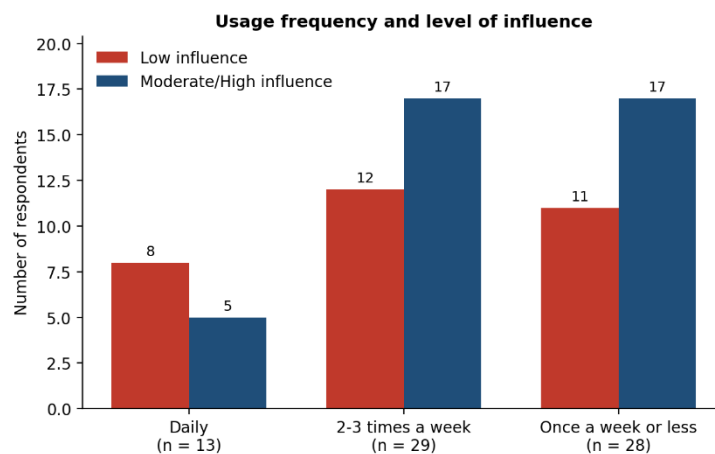
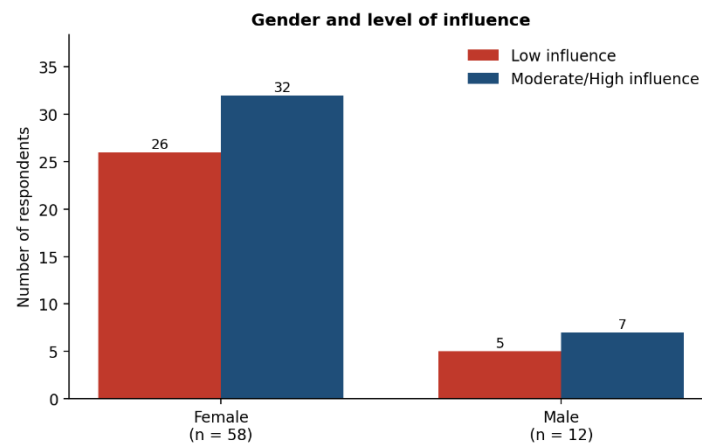


Figure 4.18: Cross-tabulation of usage frequency and level of influence (Table 4.7)

Table 4.8: Cross-tabulation of gender and level of influence

Gender	Low influence	Moderate/High influence	Total
Female	26	32	58
Male	5	7	12

**Figure 4.19: Cross-tabulation of gender and level of influence (Table 4.8)**

All seven p-values are above 0.05, so H01 is not rejected for any profile variable: the level of influence of personalized digital marketing is statistically independent of gender, age group, occupation, usage frequency, monthly spending, usage duration and the app used. The strength of association is small in every case (Cramér's V of 0.02 to 0.20). Usage frequency comes closest to significance (Table 4.7): 8 of 13 daily users fall in the Low group, compared with 12 of 29 users who order two to three times a week. Using the three-level classification (Low, Moderate, High) gave the same conclusions, with usage frequency again the smallest p-value ($p = .079$).

4.5 One-Way ANOVA: Purchase Decision Scores across Respondent Groups

H02 was tested by comparing the mean PD score across the groups of each profile variable.

Table 4.9: Mean purchase decision score by respondent group

Profile variable	Group	N	Mean PD	SD
Gender	Female	58	2.50	0.80
	Male	12	2.77	1.32
Age group	18-20	34	2.57	0.98
	21-23	30	2.52	0.86
	24-30	6	2.52	0.77
Occupation	Business/Other	9	2.49	1.01
	Salaried Employee	13	2.47	0.64
	Student	48	2.57	0.96
Usage frequency	2-3 times a week	29	2.77	0.97
	Daily	13	2.25	1.19
	Once a week or less	28	2.45	0.61
Monthly spending	Above ₹2,000	16	2.44	1.11
	Up to ₹1,000	34	2.58	0.88
	₹1,001–₹2,000	20	2.56	0.80
Usage duration	1–2 years	21	2.67	0.72
	6 months–1 year	25	2.35	0.85
	Less than 6 months	9	2.74	0.67
	More than 2 years	15	2.58	1.29
Main app used	BigBasket	10	2.38	0.51
	Blinkit	31	2.50	0.88
	Swiggy Instamart	15	2.67	1.13
	Zepto	14	2.62	0.97

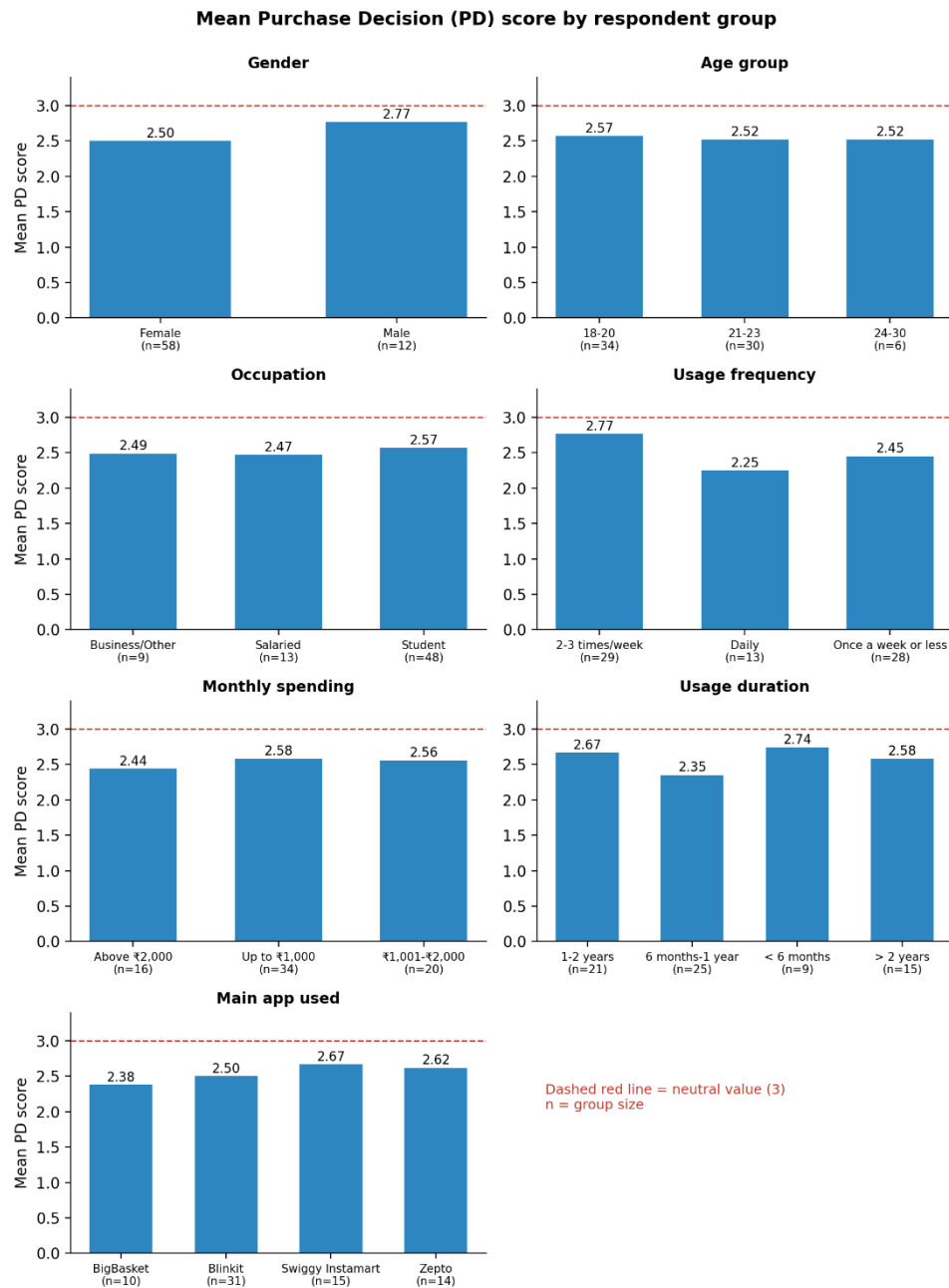


Figure 4.20: Mean purchase decision score by respondent group (Table 4.9)

Table 4.10: One-way ANOVA results

Profile variable	df (between, within)	F	p-value	η^2	Kruskal-Wallis p	Levene p	H02
Gender	1, 68	0.92	.340	0.013	.482	.043	Not rejected
Age group	2, 67	0.02	.979	0.001	.880	.466	Not rejected
Occupation	2, 67	0.08	.920	0.002	.976	.369	Not rejected
Usage frequency	2, 67	1.78	.177	0.050	.140	.038	Not rejected
Monthly spending	2, 67	0.14	.866	0.004	.641	.272	Not rejected
Usage duration	3, 66	0.68	.568	0.030	.558	.173	Not rejected
Main app used	3, 66	0.25	.861	0.011	.889	.523	Not rejected

Note: $\eta^2 = SS \text{ between} / SS \text{ total}$. Levene $p < .05$ indicates unequal variances; Welch's test is reported below for those variables.

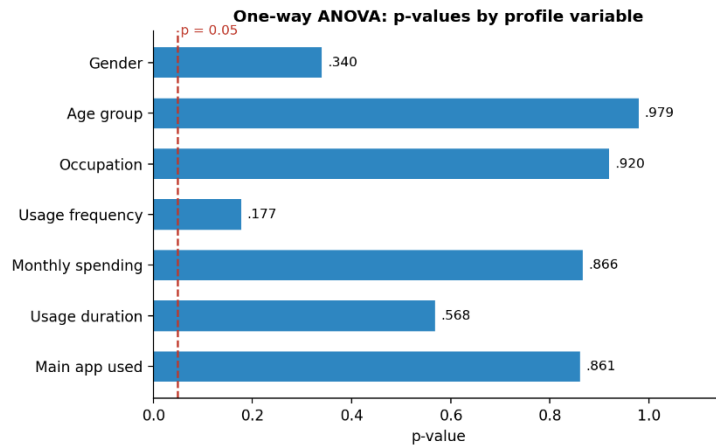


Figure 4.21: ANOVA p-values for each profile variable; all exceed 0.05 (Table 4.10)

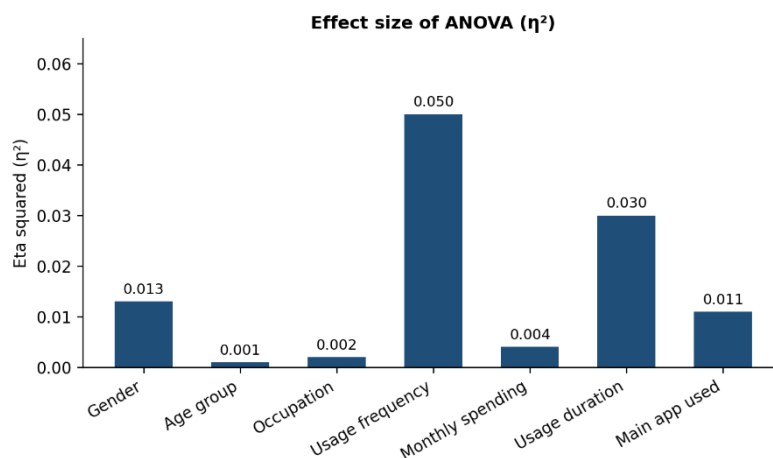


Figure 4.22: Eta squared (effect size) for each profile variable (Table 4.10)

None of the seven ANOVA tests is significant (all $p > 0.05$), so H02 is not rejected: mean purchase decision scores are similar across gender, age groups, occupations, usage-frequency bands, spending bands, usage duration and apps. Effect sizes are very small (η^2 of 0.001 to 0.05). Levene's test showed unequal variances for gender and usage frequency; Welch's test, which does not assume equal variances, again gave non-significant results for gender (Welch $F = 0.48$, $p = .500$) and usage frequency (Welch $F = 1.45$, $p = .253$). The non-parametric Kruskal-Wallis test agreed in every case. Because no ANOVA was significant, post-hoc comparisons were not required. In practice, the influence of personalized marketing is fairly uniform across this sample. It should be noted that with only 6 respondents in the 24-30 age group, 12 males, and 9 respondents each in the business/other occupation and shortest-usage groups, the tests have limited power to detect small differences.

4.6 Linear Regression: Effect of Personalized Offers and App Notifications on Purchase Decisions

Table 4.11: Correlation between the constructs (N = 70)

	PO	AN	PD
Personalized offers (PO)	1.000	0.634	0.621
App notifications (AN)	0.634	1.000	0.777
Purchase decision (PD)	0.621	0.777	1.000

All correlations are significant at $p < .001$.

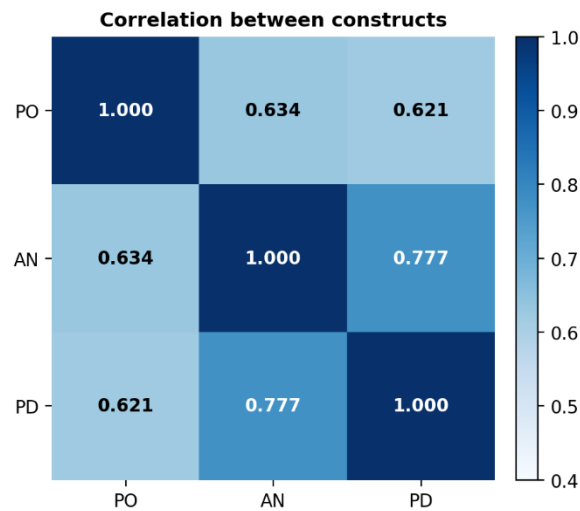
Figure 4.23: Correlation matrix of PO, AN and PD; all significant at $p < .001$ (Table 4.11)

Table 4.12: Model summary

Model	Predictor(s)	R ²	Adjusted R ²	F	Significance
1	PO	0.386	0.377	42.72	< .001
2	AN	0.603	0.597	103.27	< .001
3	PO and AN	0.631	0.620	57.19	< .001

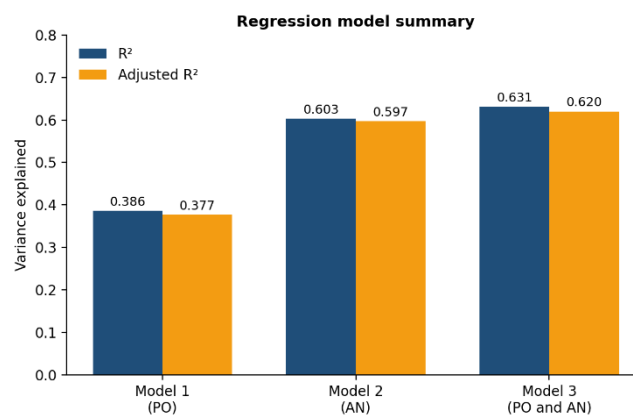
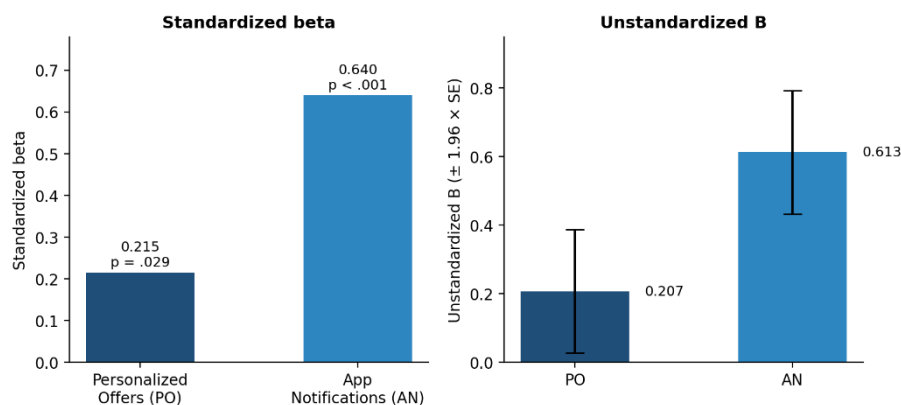
Figure 4.24: R² and adjusted R² of the three regression models (Table 4.12)

Table 4.13: Regression coefficients, Model 3 (dependent variable: PD; N = 70)

Predictor	B	Std. error	Std. beta	T	p-value	H0
Constant	0.418	0.210	-	1.99	.051	-
Personalized offers (PO)	0.207	0.092	0.215	2.24	.029	Rejected
App notifications (AN)	0.613	0.092	0.640	6.66	< .001	Rejected

Figure 4.25: Regression coefficients of personalized offers and app notifications (Table 4.13)

Effect of PO and AN on Purchase Decision (Model 3)



The regression equation is: $PD = 0.418 + 0.207 (PO) + 0.613 (AN)$. The model is statistically significant, $F(2, 67) = 57.19$, $p < .001$, and explains 63.1 per cent of the variation in purchase decision scores (adjusted $R^2 = 0.620$). H05 is therefore rejected.

App notifications have the stronger effect: the standardized beta for AN (0.640) is about three times that of PO (0.215). Used alone, AN explains 60.3 per cent of the variance and PO explains 38.6 per cent; adding PO to a model that already contains AN raises R^2 only from 0.603 to 0.631. A paired comparison also shows that respondents rate notifications (2.67) significantly higher than offers (2.35), $t(69) = 3.36$, $p = .001$. On the ordinary least squares results, both H03 and H04 are rejected.

Diagnostic checks: the two predictors are correlated ($r = 0.63$) but multicollinearity is not a concern ($VIF = 1.67$); residuals are independent (Durbin-Watson = 2.01). The Shapiro-Wilk test indicates that residuals depart from normality ($p = .001$), which is common with five-point scale data. As a robustness check, the model was re-estimated with heteroskedasticity-robust (HC3) standard errors and a 5,000-sample bootstrap. The effect of app notifications remains clearly significant (robust $p < .001$; bootstrap 95 per cent CI 0.32 to 0.89). The unique effect of personalized offers, however, is not robust (robust $p = .172$; bootstrap 95 per cent CI -0.05 to 0.47, which includes zero). The rejection of H03 should therefore be treated as tentative, while the rejection of H04 is firmly supported.

4.7 Summary of Hypothesis Testing

Table 4.14: Summary of results

Hypothesis	Test	Result	Decision
H01: Profile and level of influence are independent (7 variables)	Chi-square	All p between .246 and .966 (none below .05)	Not rejected
H02: Mean PD score equal across profile groups (7 variables)	One-way ANOVA	All p between .177 and .979 (none below .05)	Not rejected
H03: Personalized offers have no effect on PD	Regression (t)	$t = 2.24$, $p = .029$; not robust to HC3 / bootstrap	Rejected (tentative)
H04: App notifications have no effect on PD	Regression (t)	$t = 6.66$, $p < .001$; robust	Rejected
H05: Regression model is not significant	Regression (F)	$F = 57.19$, $p < .001$	Rejected

FINDINGS, SUGGESTIONS AND CONCLUSION

5.1 Findings

- The sample of 72 respondents is young, mostly female (83.3 per cent) and mostly students (68.1 per cent); Vijayawada accounts for over half of the responses. Blinkit is the most used app, and fast delivery, not discounts, is the main reason for using quick commerce.
- Respondents report only a modest influence of personalized marketing. The mean scores for personalized offers (2.33), app notifications (2.63) and purchase decision (2.54) are all significantly below the neutral value of 3. Between 12.9 and 27 per cent of respondents agree with the individual purchase decision statements, and about 44.3 per cent show low overall influence.
- App notifications are rated higher than personalized offers, and the strongest notification items are time-limited offer urgency (2.79) and notifications based on previous purchases (2.69).
- The level of influence is not associated with gender, age group, occupation, usage frequency, monthly spending, usage duration or app used (chi-square), and mean purchase decision scores do not differ across these groups (ANOVA).

5.2 Suggestions

- Quick commerce companies should give priority to well-timed, relevant notifications, especially those linked to previous purchases and to time-limited deals, since these show the strongest link with purchase decisions.
- Personalized offers should be used to support notifications rather than as a stand-alone tool, and their relevance to each customer's buying history should be improved, because respondents rate the relevance and attention value of offers low.
- Because respondents choose quick commerce mainly for fast delivery, marketing messages should stress speed and convenience along with discounts.
- Since the response pattern is similar across gender, age, occupation and spending groups, a single well-designed personalization approach may serve Generation Z users broadly, and more detailed segmentation should be based on behavioural data rather than demographics.

5.3 Scope for Further Research

- The sample is small (N = 72; 70 complete cases) and was collected by convenience sampling, so the findings cannot be generalised to all Generation Z consumers in Andhra Pradesh.
- The sample is heavily female (83 per cent) and student (68 per cent), and concentrated in Vijayawada. Some comparison groups (male, 24-30 years, business/other occupations) contain very few respondents, which limits the power of the chi-square and ANOVA tests.
- The 24-30 age group includes respondents at the upper edge of the Generation Z age range.
- The data are self-reported perceptions, not observed purchase behaviour, and the study is cross-sectional, so the regression results show association and not proven causation.

5.4 Conclusion

This study examined how personalized offers and app notifications influence the purchase decisions of Generation Z consumers on quick commerce applications in Andhra Pradesh. The results show that respondents perceive only a moderate influence, and that this influence is similar across gender, age, occupation, spending and usage groups. Personalized digital marketing together explains a substantial share of the variation in purchase decisions, and app notifications are clearly the more influential strategy; the additional effect of personalized offers is small and less reliable. For quick commerce companies, the findings suggest that relevant, timely and controlled notifications are the most effective way to influence Generation Z purchase decisions, with personalized offers acting as a supporting element. Given the small and unbalanced sample, these conclusions should be confirmed with a larger study.

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