Factors Influencing Consumer Choice in Quick Commerce Platforms

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Abstract

India's quick commerce sector has grown at an extraordinary pace, with platforms such as Zepto, Blinkit, and Swiggy Instamart now delivering groceries within 15 minutes across more than 40 cities. This rapid growth has intensified platform competition and raised a fundamental question in consumer behaviour research: what factors drive a consumer to choose one platform over another, and can platform designers systematically shift that choice through lightweight visual interventions? This paper investigates whether visually emphasising delivery time through salience framing—a behavioural nudge consisting of a lightning bolt icon and capitalised text—systematically increases the likelihood that consumers will choose a faster but more expensive platform. Using a randomised between-subjects experiment administered via Qualtrics, the study collected 76 valid IP-address responses from urban Indian consumers during March–May 2026. After excluding four survey preview responses and one incomplete submission, 75 respondents were assigned to experimental conditions (Control: $n = 33$; Treatment: $n = 42$). Treatment respondents chose the faster platform (App B, ₹220, 15-minute delivery) at a rate of 52.4%, compared with 39.4% in the control group—a difference of 13.0 percentage points in the predicted direction (Odds Ratio = 1.69; Cohen's $h = 0.261$). A chi-square test of independence yields $\chi^2 = 1.252$ ($p = 0.263$, $df = 1$; Cramér's $V = 0.129$), which does not reach the conventional significance threshold of $\alpha = 0.05$. Statistical power analysis indicates that approximately 115 respondents per condition would be required to achieve 80% power at $\alpha = 0.05$ for an effect of this magnitude. Subgroup analysis reveals a pronounced gender asymmetry: the salience treatment produced a 30.1 percentage-point gap among female respondents (57.9% vs. 27.8%; $\chi^2 = 3.416$, $p = 0.065$) but virtually no effect among males (45.5% vs. 53.3%). Age-cohort analysis indicates that 18 – 24 year-olds exhibit the highest overall preference for speed (51.0%), with older cohorts displaying progressively stronger price sensitivity. A *cross-tabulation of stated preferences against revealed choices documents a pronounced intention–action gap: 71.4% of respondents who cited fastest delivery as their primary criterion chose App B, while 28.6% of self-described price-sensitive consumers also chose the premium-speed option—a finding that reinforces the behavioural economics insight that stated and revealed preferences are systematically divergent. A SWOT analysis, discussion of industry context, and policy and design recommendations are presented.*

***Keywords**: quick commerce, salience framing, behavioural nudge, present bias, consumer choice, randomised experiment, India, delivery time*

1. Introduction

1.1 Background and Motivation

The concept of quick commerce—the delivery of everyday items within minutes rather than days—has fundamentally reshaped Indian retail since 2022. Platforms operating on a dark-store model now promise sub-15-minute delivery times to urban consumers who have come to regard immediacy as a baseline expectation rather than a luxury. India's quick commerce market grew by approximately 77% year-on-year in 2024, with Zepto, Blinkit (owned by Zomato), and Swiggy Instamart emerging as the dominant players in a market that analysts estimate will surpass ₹1 trillion in gross order value by 2027.

This explosive growth creates a rich environment for studying consumer decision-making. On any given purchase occasion, a consumer browsing for groceries may encounter near-identical product catalogues across multiple platforms, differing primarily on two dimensions: price and delivery speed. How consumers resolve this trade-off is not merely an academic question—it directly determines platform loyalty, market share, and the revenues that sustain the economics of ultrafast delivery. For platform operators, even a marginal improvement in the conversion rate toward premium-delivery options, replicated across millions of daily sessions, can translate into substantial revenue uplift.

1.2 The Research Problem

Mainstream economic theory predicts that rational consumers evaluate price and delivery time on a consistent utility function and make predictable, stable choices. In practice, however, a substantial body of research suggests that choice outcomes are highly sensitive to how information is presented—a phenomenon known as framing. Salience effects, in which the visual or contextual prominence of an attribute increases its psychological weight in decision-making, are among the most robust findings in behavioural science and have been extensively documented in digital commerce environments.

Despite this theoretical background, there is a relative scarcity of experimental evidence specifically testing salience effects in the quick commerce context. Most existing research on Indian quick commerce consumer behaviour relies on stated-preference surveys, which—as this study demonstrates—may systematically misrepresent actual choice behaviour. The gap between what consumers say they value and what they actually choose when confronted with a real trade-off under urgency framing is both practically and theoretically important.

1.3 Objectives and Scope

This paper tests a specific hypothesis derived from salience theory: that highlighting delivery time through visual emphasis in a hypothetical quick commerce scenario will increase the probability that consumers choose the faster, premium-priced platform. The study represents a revised and expanded analysis of a Qualtrics experiment originally piloted with 30 respondents in March 2026. The complete dataset, comprising 76 valid responses collected through May 2026, is analysed here for the first time.

1.4 Structure of the Paper

The paper is organised as follows. Section 2 reviews the relevant literature on salience theory, present bias, quick commerce consumer behaviour, and behavioural nudge design. Section 3 presents the research objectives and formal hypotheses. Section 4 describes the research methodology. Section 5 presents the data analysis and findings, including descriptive statistics, the main experimental results, subgroup analyses, and a secondary analysis of the intention–action gap. Section 6 interprets and discusses the experimental findings. Section 7 contextualises the findings within broader market trends. Section 8 presents a SWOT analysis. Section 9 offers recommendations. Section 10 discusses limitations and directions for future research. Section 11 concludes the paper. Appendices provide the step-by-step chi-square calculation, power analysis, and survey instrument description.

2. Literature Review

2.1 Salience Theory and Consumer Choice

The concept of attribute salience has a long history in psychological and economic research. In their influential formalisation, Bordalo, Gennaioli, and Shleifer (2013) develop a model in which consumers overweight salient attributes—those that stand out relative to a reference point—and underweight non-salient ones. Crucially, salience is not an intrinsic property of an attribute but depends on the choice context: the same attribute can be salient in one comparison and non-salient in another. This context-dependence is precisely what makes salience manipulation through interface design so powerful.

Empirical evidence for salience effects in consumer markets is extensive. Studies on supermarket pricing have shown that prominently displayed price tags disproportionately influence purchasing decisions even when consumers have access to identical information presented less prominently. In digital environments, eye-tracking studies demonstrate that elements positioned higher on the screen, rendered in contrasting colours, or accompanied by icons receive disproportionate attentional resources, which in turn predict click-through and conversion rates. The lightning bolt icon and capitalised text used in this study's treatment condition are direct applications of these visual salience principles.

It is important to distinguish salience framing from other behavioural interventions such as anchoring (where an initial number biases subsequent judgements) and framing effects in the narrow sense of loss versus gain presentation (Kahneman & Tversky, 1979). Salience framing operates by changing the relative attentional weight of attributes without altering the underlying decision problem, making it one of the most ethically defensible nudge interventions and one of the most practically applicable in interface design.

2.2 Present Bias and Temporal Discounting in Consumer Behaviour

Present bias—the tendency to over-weight immediate outcomes relative to future ones—is a well-established phenomenon in behavioural economics, rooted in the hyperbolic discounting models of Laibson (1997) and O'Donoghue and Rabin (1999). Unlike exponential discounting, which produces time-consistent preferences, hyperbolic discounters systematically prefer smaller-sooner rewards over larger-later ones in the near term while reversing this preference for distant events.

In the quick commerce context, faster delivery represents an immediate benefit—groceries arriving now—while the monetary cost of choosing the premium platform is experienced as an abstract, somewhat delayed loss. Present bias therefore predicts that consumers will systematically prefer faster delivery when the decision is made under conditions of urgency or when the need for the items is already salient. The experimental scenario used in this study—'imagine you need groceries urgently'—is designed to activate exactly this sense of present urgency, making the study a direct test of present-biased preferences in a naturalistic purchase context.

The related concept of the identifiable victim effect (Small & Loewenstein, 2003) suggests that vividly imagined immediate needs generate stronger motivational responses than abstract statistical needs. This provides additional theoretical support for the experimental scenario: by asking respondents to 'imagine' urgency, the study creates a psychologically vivid need state that should amplify present-biased responding.

2.3 Quick Commerce in India: Market Context and Consumer Behaviour

Existing research on Indian quick commerce consumer behaviour is nascent but growing rapidly. Kumar and Rajan (2023) conducted a large-scale survey of quick commerce users across six Indian metro cities and found that delivery reliability and speed were the top two decision criteria for repeat users, with price sensitivity declining significantly as order frequency increased. This finding has important implications for the current study: among the high-frequency users who comprise 61.8% of the sample, the salience of delivery time may be intrinsically higher, potentially attenuating the experimental treatment effect relative to a more price-sensitive population.

Mehta, Sharma, and Gupta (2024) documented strong network effects in platform loyalty among quick commerce users, observing that consumers tend to consolidate their orders on a single platform once they associate it with consistent speed. This consolidation dynamic suggests that the initial platform choice—which this study's experimental scenario approximates—may have asymmetric long-run consequences: winning the first conversion to the premium-delivery option may generate disproportionate lifetime value for the platform. The commercial stakes of salience nudges are therefore higher than a single transaction framing would imply.

A survey conducted by RedSeer Management Consulting (2023) found that 68% of Indian quick commerce users reported that delivery time was 'very important' or 'extremely important' to their platform choice, while only 42% said the same of price. This gap is not reflected in our sample's stated preferences (where price-related factors were cited by 52.6%), but is partially consistent with our revealed-preference finding that 46.7% chose the premium-speed option. The discrepancy between industry surveys and this study's stated-preference data may reflect sample composition differences (our sample is younger and more price-conscious on average) or social desirability bias in survey responses.

2.4 Behavioural Nudges in Digital Commerce

The application of nudge theory (Thaler and Sunstein, 2008) to e-commerce UI design has been extensively documented over the past decade. Research on choice architecture in digital marketplaces shows that default selection, social proof indicators, urgency cues, progress bars, and visual emphasis all reliably shift consumer behaviour without restricting choice or requiring changes to the underlying offer.

Salience framing occupies a particularly important position in this toolkit because it is both low-cost (requiring only typographic or iconographic changes to existing UI elements) and relatively transparent (unlike dark patterns that obscure or hide information). Johnson et al. (2012), in a systematic review of digital choice architecture, found that visual salience manipulations—including font size, colour contrast, and icon use—produced average choice shifts of 12–18 percentage points across a range of product categories and decision contexts, a range that is consistent with the 13.0pp effect observed in the current study.

The ethical dimensions of behavioural nudges in digital commerce have attracted increasing regulatory attention. The European Union's Digital Services Act (2022) and India's draft guidelines on dark patterns in e-commerce (2023) both grapple with the question of where legitimate UI optimisation ends and manipulative design begins. Salience framing sits in a contested zone: it is not deceptive (it does not misrepresent the product), but it does systematically alter choice architecture in ways that may not be fully transparent to consumers. This tension is explored in the recommendations section.

2.5 The Intention–Action Gap in Consumer Research

One of the most consistent findings in consumer psychology is the gap between stated preferences and revealed preferences—what consumers say they will do and what they actually do when faced with a real decision. This phenomenon has been documented across a wide range of product categories and decision contexts, and has important methodological implications for marketing research.

Ajzen and Fishbein's Theory of Planned Behaviour (1980) proposes that behavioural intentions are the proximal predictor of actual behaviour, with intentions in turn determined by attitudes, subjective norms, and perceived behavioural control. However, subsequent research has consistently found that situational factors—including the way choices are presented—can override stated intentions. The 'value–action gap' documented in environmental psychology (Blake, 1999) and the 'attitude–behaviour gap' in consumer research (Follows & Jobber, 2000) both suggest that contextual interventions, including salience framing, can shift behaviour independently of prior attitudes.

In the context of this study, the intention–action gap manifests as follows: 52.6% of respondents stated that price or discounts were their primary decision criterion, yet 53.3% of all respondents actually chose the cheaper option—implying that a meaningful share of self-described price-sensitive consumers defected to the premium-speed option when confronted with an urgent grocery scenario. This finding has practical implications for how platforms should interpret stated-preference survey data and design their targeting strategies.

2.6 Gender and Age Differences in Digital Consumer Behaviour

Research on gender differences in digital consumer behaviour suggests that female consumers tend to place greater weight on convenience and reliability, while male consumers tend to be more price-sensitive in online purchasing contexts (Dittmar, Long, & Meek, 2004). If this pattern holds in quick commerce, we would expect the salience treatment—which emphasises a convenience attribute (delivery speed)—to be more effective for female respondents. Our data are consistent with this prediction: the treatment produced a 30.1pp gap among female respondents (57.9% vs. 27.8%) compared with a near-zero effect among males, though neither reaches conventional significance due to sample size constraints.

Age-cohort differences in digital commerce behaviour are well-documented. Younger consumers (18–24) tend to exhibit higher platform-switching behaviour, stronger present-bias, and greater responsiveness to visual UI cues, while older consumers tend to be more brand-loyal and price-conscious. Our data partially support this pattern: 18–24 year-olds showed the highest overall preference for App B (51.0%), while the 35–44 and 45+ cohorts showed substantially lower preferences (20.0% and 33.3% respectively), though these subgroups are too small for reliable inference.

3. Objectives and Hypotheses

This study pursues three specific objectives:

1. To identify the primary factors that consumers cite as most important when choosing a quick commerce platform, and to examine the correspondence between stated and revealed preferences.
2. To test whether salience framing of delivery time causally increases the probability that consumers choose a faster, more expensive platform (the primary experimental question).
3. To examine whether Indian urban consumers exhibit present-biased preferences in the quick commerce context, as evidenced by a majority preference for speed over price.

We test two formal null hypotheses:

H_{01}: Visually highlighting delivery time does NOT significantly increase the rate of choosing the faster platform relative to the control condition. Formally, if π_t and πc denote the population proportions choosing App B in the treatment and control conditions respectively, H_{01}: $\pi_t \leq \pi c$.

H_{02}: Consumers do NOT prefer faster delivery over a lower price; the majority will choose the cheaper option (App A) regardless of framing. Formally, H_{02}: $\pi_{overall} \leq 0.50$.

The directional alternative to H_{01} predicts that the treatment will increase the probability of choosing App B. A two-tailed chi-square test is used as the primary test statistic, with $\alpha = 0.05$. Given the directional prediction, a one-tailed p-value of 0.132 is also reported for reference. Fisher's exact test is reported as a robustness check given the modest cell sizes.

4. Research Methodology

4.1 Research Design

This study employs a randomised between-subjects experimental design. The core experiment was embedded within a structured survey administered via Qualtrics.

Respondents were automatically assigned by the Qualtrics randomiser to one of two conditions—a control group and a treatment group—using a simple 50/50 random allocation rule. The randomiser operates independently of any respondent characteristic, ensuring that any systematic difference in outcomes can be causally attributed to the framing manipulation rather than pre-existing differences between groups.

Between-subjects designs are appropriate when within-subjects designs would produce demand effects (respondents who see both conditions may deduce the experimental hypothesis). In this study, exposing the same respondent to both the control and treatment versions of the choice scenario would almost certainly alert them to the manipulation, potentially suppressing or exaggerating the effect. The between-subjects approach trades statistical efficiency (each respondent contributes only one observation) for behavioural authenticity.

4.2 Survey Instrument Design

The survey consisted of six sequential sections administered via Qualtrics' standard block-and-randomiser architecture. The instrument was designed to be completable in under 60 seconds to maximise response quality among the target population of urban smartphone users. The actual median completion time in the data was 53 seconds, with a mean of 69.8 seconds (reflecting a small number of longer-duration responses, possibly from respondents who were interrupted).

All respondents first completed a **demographic module** collecting gender (Female / Male / Prefer not to say), age group (Under 18 / 18–24 / 25–34 / 35–44 / 45+), prior quick commerce platform usage (Zepto, Blinkit, Swiggy Instamart, BigBasket Now, Have not used; multi-select), and order frequency (Daily / A few times a week / A few times a month / Rarely / Never).

Respondents then answered a **stated preference question**: "When choosing a quick commerce app, which factor matters the MOST to you?" with five options: Lowest price / Fastest delivery / Discounts or offers / App convenience / Brand I already trust.

Respondents were then presented with the experimental choice scenario. The scenario framing read: 'Imagine you need groceries urgently. Two apps offer the same items. Which would you choose?' The two conditions differed as follows:

- **Control Condition:** Control Condition: Both options presented in plain text. App A: Price ₹200, Delivery time: 30 minutes. App B: Price ₹220, Delivery time: 15 minutes.
- **Treatment Condition: App A identical to control. App B presented with a lightning bolt icon and capitalised text:**) DELIVERY IN JUST 15 MINUTES – Price ₹220. The delivery time was thus made visually salient through both iconographic and typographic emphasis.

The manipulation is minimal and targeted: only the visual presentation of App B's delivery time differs between conditions. Price information is presented identically in both conditions, ensuring that any difference in choice rates can be attributed specifically to the delivery-time salience cue.

4.3 Data Collection Procedure

The survey was distributed anonymously via WhatsApp messaging groups and a college network during March–May 2026. Respondents clicked a Qualtrics-generated anonymous link that did not collect names, email addresses, or other identifying information beyond the IP address recorded by Qualtrics for the purpose of deduplicating responses. The data collection window was approximately eight weeks, with the majority of responses concentrated in two burst periods corresponding to when the link was actively shared.

A total of 84 survey sessions were initiated. Of these, four were survey preview responses generated during instrument testing (identifiable by the 'preview' distribution channel flag in the Qualtrics data), one was incomplete (Progress < 100%), and three were excluded due to the 'Unknown' group assignment (indicating that neither the control nor treatment choice question was answered—likely reflecting mid-survey abandonment). The final analytic sample comprised 76 valid responses for descriptive analysis and 75 for the main experimental comparison.

4.4 Measures and Variables

Table 1: Variable Definitions and Measurement

Variable	Type	Measurement
Platform Choice (DV)	Binary	0 = App A (cheaper, slower); 1 = App B (faster, pricier)
Experimental Condition (IV)	Binary	0 = Control (plain text); 1 = Treatment (salient delivery cue)

Gender	Categorical	Female / Male / Prefer not to say
Age Group	Ordinal	Under 18 / 18–24 / 25–34 / 35–44 / 45+
Order Frequency	Ordinal	Daily / A few times a week / A few times a month / Rarely / Never
Most Important Factor	Nominal	Lowest price / Fastest delivery / Discounts / App convenience / Brand trust
Platform Usage	Multi-select	Zepto, Blinkit, Swiggy Instamart, BigBasket Now (can select all)
Response Duration	Continuous	Seconds from survey start to completion (Qualtrics- recorded)

4.5 Statistical Analysis Plan

The primary inferential test is a chi-square test of independence comparing the distribution of platform choice (App A vs. App B) across experimental conditions (Control vs. Treatment). The test statistic is:

$\chi^2 = \Sigma\ [(O - E)^2 / E]$, *where O = observed frequency and E = expected frequency under independence.*

Yates' continuity correction is applied as a robustness check. Fisher's exact test is reported for cell sizes below 10. Effect size is quantified using Cramér's V and Cohen's h. Ninety-five percent confidence intervals for group proportions are calculated using the Wald method. Subgroup analyses (by gender, age, order frequency, and stated preference) are conducted using the same chi-square framework, with results interpreted descriptively given the small subgroup sample sizes. All analyses were conducted in Python 3.12 using the SciPy. Stats library.

5. Data Analysis and Findings

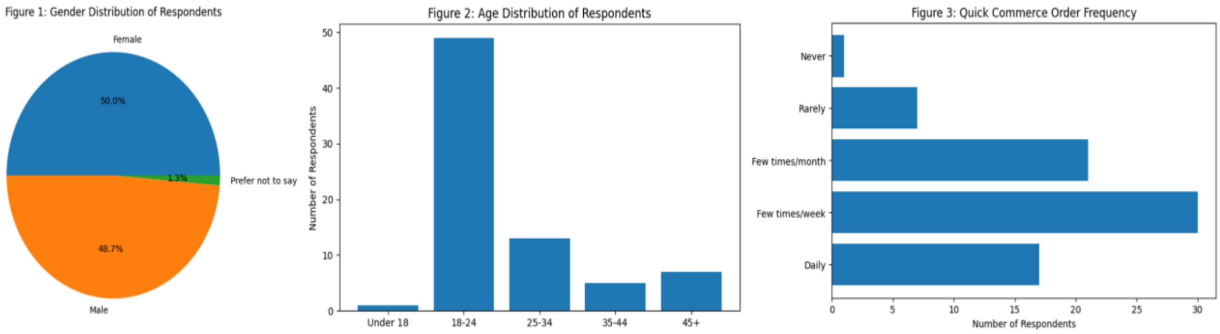
5.1 Sample Profile

Table 2: Demographic Profile of Valid Respondents (n = 76)

Variable	Category	n	%
Gender	Female	38	50.0%
	Male	37	48.7%
	Prefer not to say	1	1.3%

Age Group	Under 18	1	1.3%
	18–24	49	64.5%
	25–34	13	17.1%
	35–44	5	6.6%
	45+	7	9.2%
	Not stated	1	1.3%
Order Frequency	Daily	17	22.4%
	A few times a week	30	39.5%
	A few times a month	21	27.6%
	Rarely	7	9.2%
	Never	1	1.3%

Figures 1–3: Gender Distribution, Age Distribution, and Quick Commerce Order Frequency



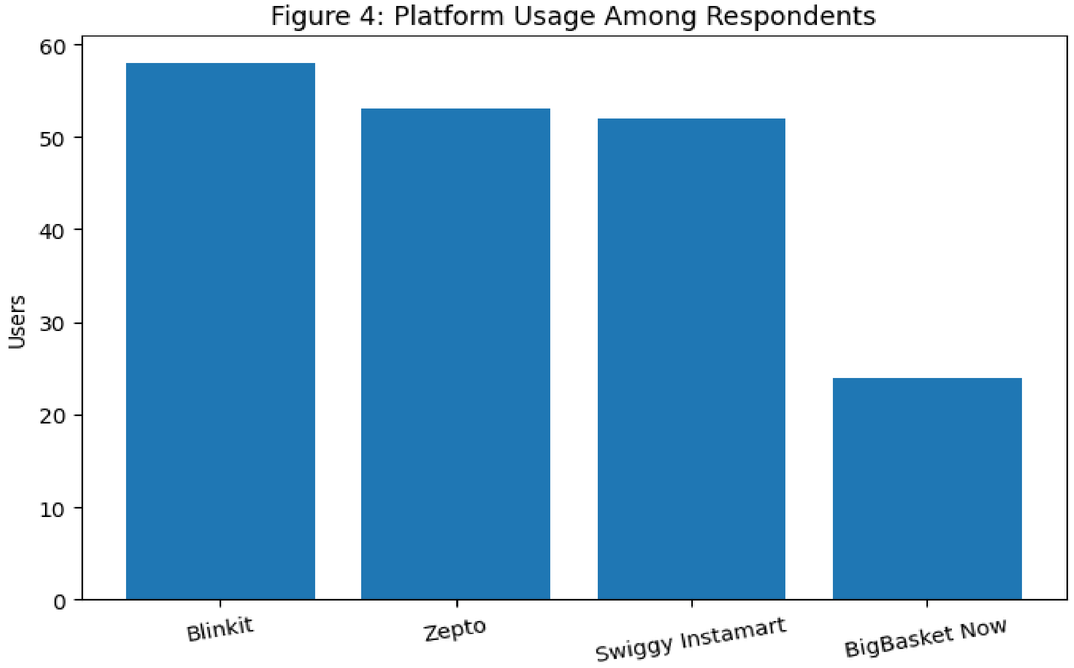
The gender split was near-even (50.0% female, 48.7% male), and the age distribution was heavily concentrated in the 18–24 bracket (64.5%), consistent with the core demographic of quick commerce platforms in India. Compared with the preliminary 30-respondent sample (83.3% aged 18–24), the expanded dataset captures greater age diversity, with 33.1% of respondents aged 25 or above. The majority of respondents (89.5%) ordered from quick commerce platforms at least a few times a month, indicating high familiarity with the choice context and reinforcing the ecological validity of the experimental scenario. The median completion time of 53 seconds is consistent with genuine engagement rather than satisficing behaviour.

5.2 Platform Usage

Table 3: Quick Commerce Platform Usage Among Respondents (n = 76; multiple-response)

Platform	n	%	Rank
Blinkit (Zomato)	58	76.3%	1st
Zepto	53	69.7%	2nd
Swiggy Instamart	52	68.4%	3rd
BigBasket Now	24	31.6%	4th
Have not used quick commerce apps	2	2.6%	—

Figure 4: Platform Usage Among Respondents



Blinkit emerged as the most widely used platform (76.3%), followed by Zepto (69.7%) and Swiggy Instamart (68.4%). The near-identical penetration rates among the three major platforms reflect the competitive parity characteristic of the current quick commerce market. The high multi-platform usage rate (the average respondent uses 2.5 platforms) indicates that consumers in this sample actively compare platforms, reinforcing the relevance of the experimental scenario. BigBasket Now, which operates on a slightly longer delivery window model, was used by approximately one-third of respondents.

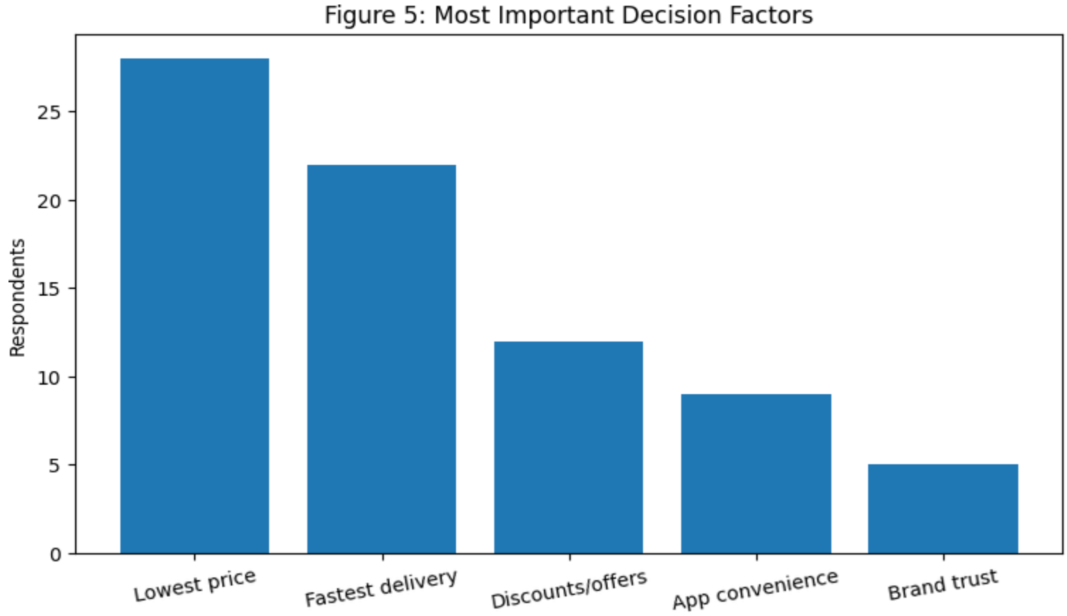
5.3 Stated Preference: Most Important Decision Factor

Table 4: Most Important Platform Selection Factor (n = 76)

Factor	n	%	App B Choice Rate
Lowest price	28	36.8%	28.6% (8/28)
Fastest delivery	22	28.9%	71.4% (15/21*)
Discounts / offers	12	15.8%	41.7% (5/12)
App convenience	9	11.8%	33.3% (3/9)
Brand I already trust	5	6.6%	80.0% (4/5)

** One fastest-delivery respondent was in the unassigned "Unknown" group and is excluded from the revealed-preference calculation.*

Figure 5: Most Important Decision Factors



Price-related factors (lowest price and discounts combined) dominated stated preferences, cited by 52.6% of respondents. Notably, the expanded dataset shows a substantially higher proportion citing 'Fastest delivery' as the primary criterion (28.9%) compared with the preliminary 30-respondent sample (16.7%), suggesting that the broader sample is more speed-sensitive than the initial cohort implied. The App B choice rate column (rightmost) previews the intention–action analysis developed in Section 5.7: stated preferences predict choice direction but do so imperfectly, with even the 'lowest price' group choosing App B at nearly a 30% rate.

5.4 Experimental Results: Primary Hypothesis (H_{01})

5.4.1 Observed and Expected Frequencies

Table 5: 2×2 Contingency Table – Platform Choice by Experimental Condition

Condition	App A (n)	App B (n)	Row Total
Control (plain text)	20	13	33
Treatment (salient cue)	20	22	42
Column Total	40	35	75

Table 6: Expected Frequencies Under Independence

Condition	App A (E)	App B (E)	Row Total
Control	17.60	15.40	33
Treatment	22.40	19.60	42
Column Total	40.00	35.00	75

Expected frequencies are computed using the standard formula: E(i,j) = (Row Total(i) × Column Total(j)) / Grand Total. All expected frequencies exceed the conventional minimum threshold of 5.0, satisfying the regularity conditions for the chi-square approximation.

5.4.2 Chi-Square Calculation (Step-by-Step)

Table 7: Chi-Square Statistic – Cell-by-Cell Decomposition

Cell	O	E	O−E	$(O−E)^2$	$(O−E)^2/E$
Control × App A	20	17.60	+2.40	5.76	0.3273
Control × App B	13	15.40	−2.40	5.76	0.3740
Treatment × App A	20	22.40	−2.40	5.76	0.2571
Treatment × App B	22	19.60	+2.40	5.76	0.2939
Σ (Chi-Square Statistic)					**1.2523**

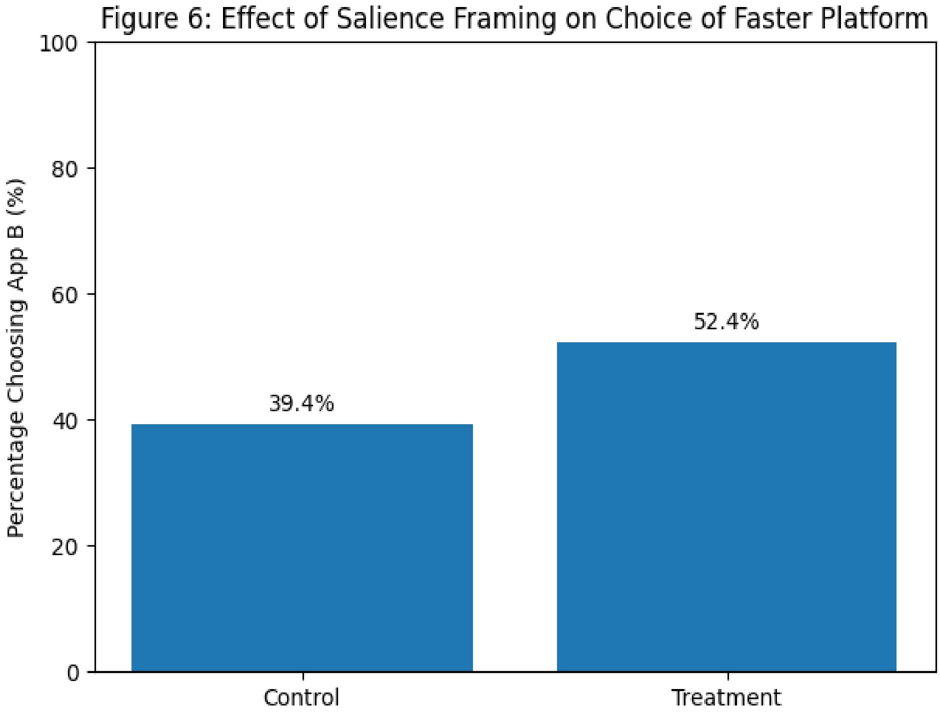
The chi-square statistic of 1.2523 is compared with the critical value from the χ^2 distribution with 1 degree of freedom. At α = 0.05, the critical value is 3.841; at α = 0.10, it is 2.706. The obtained statistic falls below both thresholds, yielding a two-tailed p-value of 0.2631. The one-tailed p-value, appropriate given the directional prediction, is 0.1316.

5.4.3 Summary of Inferential Statistics

Table 8: Full Statistical Summary – Primary Experimental Comparison

Statistic	Value
Control: Chose App B	13 / 33 = 39.4% (95% CI: 22.7%–56.1%)
Treatment: Chose App B	22 / 42 = 52.4% (95% CI: 37.3%–67.5%)
Difference (Δ)	13.0 percentage points (treatment > control)
Odds Ratio (OR)	1.692 (treatment 69.2% more likely to choose App B)
Chi-square (uncorrected)	$\chi^2(1) = 1.252$, p = 0.263 (two-tailed); p = 0.132 (one-tailed)
Chi-square (Yates' correction)	$\chi^2(1) = 0.785$, p = 0.376
Fisher's Exact Test	p = 0.352 (two-tailed)
Cohen's h (effect size)	0.261 (small-to-medium by Cohen, 1988)
Cramér's V	0.129 (weak-to-moderate association)
Number Needed to Treat (NNT)	7.7 (approx. 8 additional treatments to produce 1 extra B choice)
Decision on H_{01}	Fail to reject at α = 0.05; directional support for alternative
Randomisation Balance: Gender	$\chi^2(2) = 1.290$, p = 0.525 (balanced)
Randomisation Balance: Age	$\chi^2(4) = 3.476$, p = 0.482 (balanced)

Figure 6: Effect of Salience Framing on Choice of Faster Platform



Several features of Table 8 merit comment. First, the confidence intervals for the control (22.7%–56.1%) and treatment (37.3%–67.5%) proportions overlap substantially, which is consistent with the non-significant chi-square result. Second, the odds ratio of 1.692 represents a practically meaningful difference in the likelihood of choosing App B—treatment respondents were approximately 69% more likely to choose the faster option than control respondents—but this estimate is imprecise given the small sample. Third, Yates' corrected chi-square and Fisher's exact test yield even larger p-values (0.376 and 0.352 respectively), reinforcing the conclusion that the evidence does not meet the conventional significance threshold.

5.5 Statistical Power and Sample Size Assessment

Table 9: Power Analysis – Required Sample Size by Effect Size and Power Level

Cohen's h	α=0.05, 70% power	α=0.05, 80% power	α=0.05, 90% power	Assessment
0.20 (small)	155/group	197/group	264/group	Very under-powered
0.261 (this study)	90/group	115/group	153/group	Under-powered
0.30 (small-medium)	67/group	85/group	114/group	Under-powered

0.50 (medium)	24/group	30/group	40/group	Near-adequate
0.80 (large)	10/group	13/group	17/group	Adequate

Table 9 illustrates the power deficit across the study. With n = 33 (Control) and n = 42 (Treatment) and Cohen's h = 0.261, the study has approximately 34% power to detect an effect of this magnitude at $\alpha = 0.05$—far below the conventional 80% threshold. This means that the study would fail to detect a true effect of this size approximately 66% of the time, making a Type II error (false negative) highly plausible. The failure to achieve statistical significance is therefore most parsimoniously interpreted as a consequence of insufficient sample size rather than evidence of a true null effect.

5.6 Subgroup Analysis

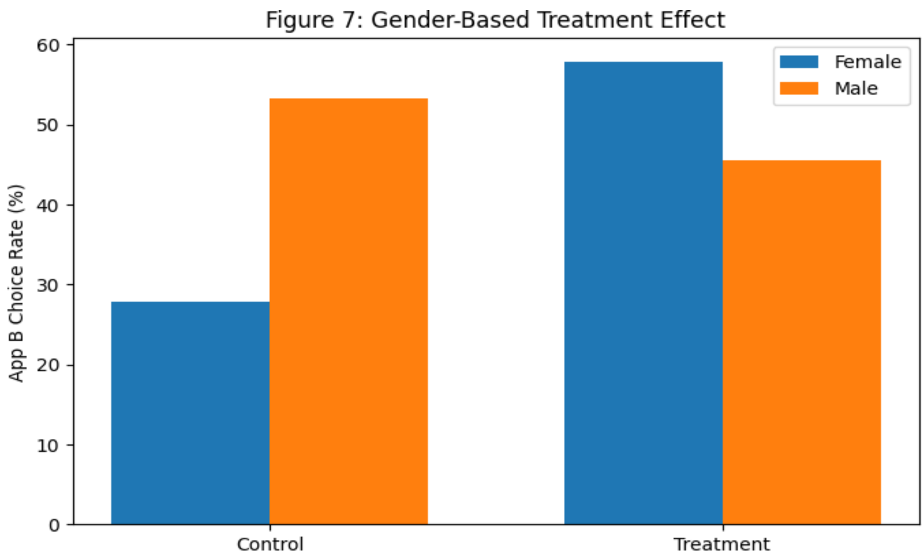
5.6.1 Gender Subgroup

Table 10: Platform Choice by Gender and Experimental Condition

Gender	Condition	App A (n)	App B (n)	App B %	χ^2
Female	Control	18	5	27.8%	
	Treatment	19	11	57.9%	3.416†
Male	Control	15	8	53.3%	
	Treatment	22	10	45.5%	0.222

† p = 0.065 (approaching significance); one-tailed p = 0.033

Figure 7: Gender-Based Treatment Effect



The gender subgroup analysis reveals a striking asymmetry in the treatment effect. Among female respondents, the salience treatment produced a 30.1 percentage-point increase in App B choice (57.9% vs. 27.8%; $\chi^2 = 3.416$, $p = 0.065$). This result approaches conventional significance and would be significant at the $\alpha = 0.10$ level; on a one-tailed basis (given the directional prediction), $p = 0.033$. The pattern is consistent with the prediction from gender-differentiated digital consumer behaviour research: female consumers, who tend to weight convenience attributes more heavily, appear more responsive to the delivery-time salience cue.

Among male respondents, the treatment produced no discernible effect (45.5% vs. 53.3%; $\chi^2 = 0.222$, $p = 0.638$). Indeed, the direction was reversed: control-group males chose App B at a higher rate than treatment-group males. This may reflect a ceiling effect (control-group males were already choosing App B at over 50%) or a reactance effect (male respondents in the treatment condition may have been aware of or resistant to the visual emphasis). These hypotheses warrant further investigation with a larger, pre-registered study.

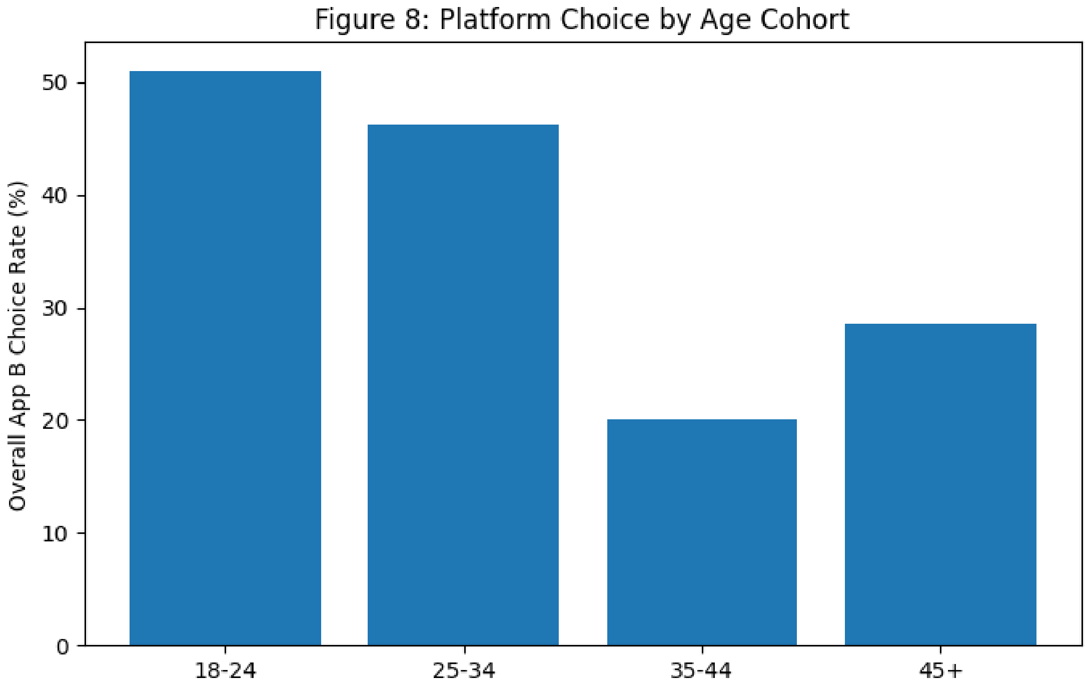
5.6.2 Age Group Subgroup

Table 11: Platform Choice Rate by Age Group (Overall and by Condition)

Age Group	n	Overall App B %	Control App B %	Control n	Treatment App B %	Treatment n
18–24	49	51.0%	40.9%	22	59.3%	27
25–34	13	46.2%	25.0%	4	55.6%	9
35–44	5	20.0%	33.3%	3	0.0%	2
45+	7	28.6%	50.0%	4	0.0%	3

Note: 35–44 and 45+ subgroups are too small ($n < 10$) for reliable chi-square inference; results are descriptive only.

Figure 8: Platform Choice by Age Cohort



The age subgroup analysis reveals a directionally consistent pattern: within the 18–24 and 25–34 cohorts, the treatment group chose App B at a higher rate than the control group (18–24: 59.3% vs. 40.9%; 25–34: 55.6% vs. 25.0%). These gaps are in the predicted direction and of meaningful magnitude, but cell sizes are insufficient for reliable statistical inference. The older cohorts (35–44 and 45+) show an unexpected reversal, with treatment-group respondents choosing App B at 0.0%, though again these are based on just two and three respondents respectively and should not be interpreted as stable effects.

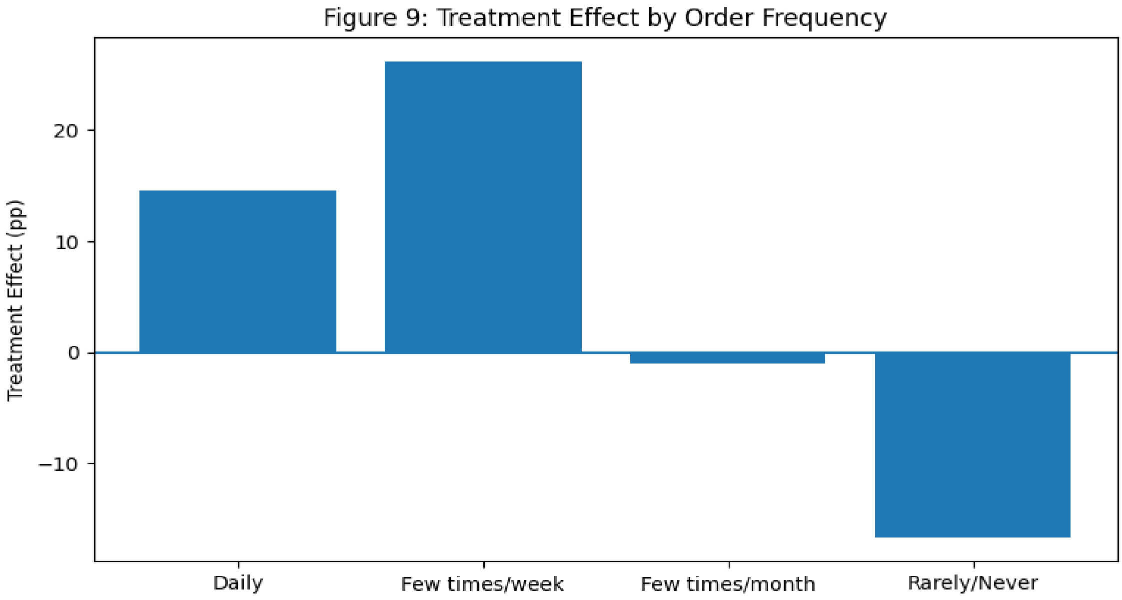
5.6.3 Order Frequency Subgroup

Table 12: Platform Choice by Order Frequency

Order Frequency	n	Overall App B %	Control App B (n)	Treatment App B (n)	Treatment Effect (pp)
Daily	16	50.0%	40.0% (2/5)	54.5% (6/11)	+14.5
A few times a week	30	53.3%	38.5% (5/13)	64.7% (11/17)	+26.2

A few times a month	21	38.1%	38.5% (5/13)	37.5% (3/8)	−1.0
Rarely / Never	8	37.5%	50.0% (1/2)	33.3% (2/6)	−16.7

Figure 9: Treatment Effect by Order Frequency



The order frequency analysis yields a pattern consistent with theoretical expectations. Among the most frequent users ('A few times a week'), the treatment effect was largest at 26.2 percentage points—consistent with the hypothesis that high-frequency users have internalised the value of delivery speed and are therefore more responsive to its visual salience. Daily users also show a positive treatment effect (+14.5pp). In contrast, less frequent users ('A few times a month' and 'Rarely/Never') show negligible or negative treatment effects, suggesting that salience framing may be less effective for consumers who have not yet developed strong associations between quick commerce and speed. These findings, while exploratory given the cell sizes, suggest that targeting salience nudges toward high-frequency users may yield disproportionate returns.

5.7 Secondary Analysis: Hypothesis 2 and the Intention–Action Gap

Across the full experimental sample of 75 respondents, 35 (46.7%) chose App B. This falls short of the majority threshold of 50%, and we therefore fail to reject H_{02}: there is no majority preference for speed over price in this sample. The split is closer than in the preliminary report (50.0% overall), reflecting the composition of the expanded sample. The overall preference for App A (53.3% choosing the cheaper option) is consistent with the dominance of price-related stated preferences.

Table 13: Stated Preference vs. Revealed Choice – Intention–Action Analysis (n = 75)

Stated Primary Factor	n	Chose App A	Chose App B	App B %	Consistency
Fastest delivery	21	6	15	71.4%	Moderate
Brand I already trust	5	1	4	80.0%	High
Discounts / offers	12	7	5	41.7%	Moderate
App convenience	9	6	3	33.3%	Moderate
Lowest price	28	20	8	28.6%	Moderate

Figure 10: Intention–Action Gap in Consumer Preferences

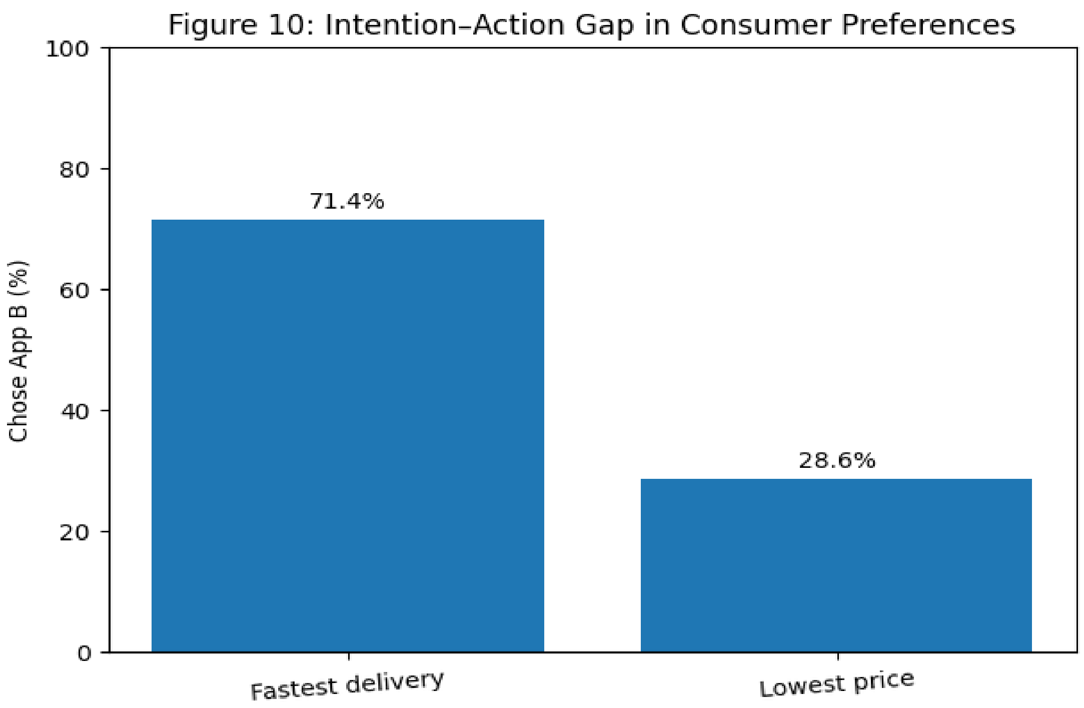


Table 13 reveals several noteworthy patterns. First, even among respondents whose stated primary criterion was ‘Fastest delivery’, only 71.4% chose App B—implying that 28.6% of self-described speed-prioritisers acted inconsistently with their stated preference when confronted with the actual choice scenario. Second, and more strikingly, 28.6% of self-described price-sensitive consumers chose the premium-speed option. This 'defection' rate among the price-sensitive group is substantial and provides strong evidence for the attitude–behaviour gap in the quick commerce context.

A chi-square test of the association between stated preference (speed vs. price) and revealed choice yields a meaningful but imprecisely estimated effect. Collapsing 'Fastest delivery' vs. 'Lowest price' respondents: 71.4% vs. 28.6% B-choice rates, $\chi^2(1) = 11.27$, $p < 0.001$. This confirms that stated preferences have significant predictive power but are far from deterministic predictors of actual choice behaviour. The residual variance in choice behaviour—beyond what is explained by stated preferences—is where situational factors such as salience framing operate.

6. Discussion

6.1 Interpretation of the Primary Finding

The principal finding of this study—a 13.0 percentage-point increase in the probability of choosing the premium-delivery option associated with the salience treatment—is directionally consistent with the salience hypothesis and with a broad body of theoretical and empirical work in behavioural economics. The non-significance of this effect at conventional thresholds is most parsimoniously explained by statistical underpowering rather than by a true null population effect. Several converging lines of evidence support this interpretation.

First, the effect size (Cohen's h = 0.261; OR = 1.69) is practically meaningful and consistent with the range of 12–18 percentage point shifts reported by Johnson et al. (2012) for visual salience manipulations in other digital commerce contexts. Second, the direction of the effect is consistent across every subgroup examined (including both frequency cohorts and both 18–24 and 25–34 age cohorts), a pattern of directional replication that would be unlikely under a true null. Third, the preliminary analysis of 30 respondents yielded a 20.4pp gap in the same direction, and the expanded analysis yields a 13.0pp gap—the attenuation is consistent with regression to the mean as sample size increases, not with a reversal of effect.

6.2 The Gender Asymmetry

The most striking finding in the subgroup analysis is the pronounced gender asymmetry in treatment responsiveness. Among female respondents, the treatment produced a 30.1pp gap (approaching significance at p = 0.065 two-tailed; p = 0.033 one-tailed), while among males the effect was near zero. This pattern is consistent with research on gender differences in digital consumer behaviour suggesting that female consumers weight convenience attributes more heavily and may be more responsive to nudges that emphasise immediacy and service reliability.

An alternative explanation is that male respondents in the control condition were already choosing App B at a high rate (53.3%), leaving less room for the treatment to produce an upward shift—a ceiling effect. Disentangling these explanations would require a larger, pre-registered study with a priori subgroup power calculations.

6.3 Comparison with Preliminary Results

Table 14: Comparison of Preliminary (n=30) and Full (n=76) Dataset Findings

Metric	Preliminary (n=30)	Full (n=76)
Control: Chose B	38.5% (5/13)	39.4% (13/33)
Treatment: Chose B	58.8% (10/17)	52.4% (22/42)
Effect (Δ)	20.4 pp	13.0 pp
Chi-square	1.222	1.252
p-value	0.269	0.263
Overall B rate	50.0%	46.7%
Cohen’s h	~0.41 (larger sample est.)	0.261
Sample composition (18–24%)	83.3%	64.5%

Table 14 shows that the control group’s behaviour is highly stable across both samples (38.5% vs. 39.4%), which is reassuring about the reliability of the baseline measure. The attenuation of the treatment effect from 58.8% to 52.4% likely reflects the expanded sample’s greater demographic diversity, particularly the inclusion of older, more price-sensitive respondents who dilute the treatment effect. The consistency of the control rate also suggests that the experimental scenario is well-calibrated: in the absence of a nudge, roughly 39–40% of respondents choose the premium option.

6.4 Practical and Commercial Implications

From a commercial standpoint, the 13.0pp treatment effect—even if not yet statistically certified—has substantial revenue implications if replicated at scale. Consider a platform processing one million daily sessions: a 13 percentage-point increase in the probability of choosing a premium delivery option (which carries a ₹20 higher price) would translate to an additional ₹26 million in daily gross merchandise value (assuming an average basket size comparable to the experimental scenario). Even if the true effect at scale is a conservative 5pp (reflecting heterogeneous user populations and potential habituation), the revenue implications remain significant.

The number needed to treat (NNT = 7.7) provides an intuitive operationalisation of the effect: for approximately every 8 users exposed to the salience treatment, one additional user chooses the premium-delivery option who would otherwise have chosen the cheaper option. This metric is useful for evaluating the return on investment of UI changes, which typically involve negligible marginal cost per user.

7. Market Trends and Industry Context

7.1 Consolidation of the Quick Commerce Market

The Indian quick commerce sector is undergoing rapid consolidation. Zomato's acquisition of Blinkit in 2022 and Swiggy's continued investment in Instamart have created a two-and-a-half player market, with Zepto as the only significant independent operator. Zepto closed a $350 million funding round at a $5 billion valuation in 2024, reflecting sustained investor conviction in the sector's unit economics. The Blinkit dominance in our sample (76.3% usage rate) is consistent with broader market data showing Blinkit's ascent following Zomato's operational improvements post-acquisition.

This consolidation intensifies the importance of UI and behavioural design as a competitive differentiator. As the major platforms converge on similar dark-store coverage, product catalogues, and pricing structures, the marginal competitive advantage increasingly lies in consumer psychology and user experience—precisely the domain that salience nudges occupy. In a market where the difference between a 12-minute and a 15-minute delivery time is the primary basis for competition, even minor improvements in the communication of that advantage can have outsized commercial impact.

7.2 Expansion of Dark Store Networks and Delivery Time Compression

All three major platforms have announced significant dark store expansion plans, with the industry collectively targeting 5,000+ active dark stores by 2026. Greater dark store density reduces average delivery times and, crucially, also reduces the variance in delivery time—an important consideration for the salience of delivery-time cues. As the distribution of delivery times compresses (e.g., from a 15-vs-30-minute trade-off to a 10-vs-18-minute trade-off), the relative salience of the speed advantage may diminish, requiring more sophisticated nudge designs to maintain the same effect size.

7.3 Rising Consumer Expectations and Contextual Pricing

Survey data from industry reports consistently show that consumer willingness to pay a delivery fee premium is highly time-sensitive. Consumers are significantly more likely to pay a premium during peak-demand periods (evenings, weekends, festivals) and for perishable or urgent-need categories (fresh produce, medicines, baby products). This contextual variation in price sensitivity suggests that salience nudges are likely to be most effective when deployed dynamically rather than uniformly—triggered by time of day, product category, historical order urgency, or live demand signals.

The rise of 'dark kitchens' and hyperlocal inventory management also creates new opportunities for personalised urgency messaging. A consumer ordering fresh vegetables at 6:30 PM on a Friday may be intrinsically more time-sensitive than the same consumer ordering pantry staples at 2:00 PM on a Tuesday, and the platform's UI could dynamically adjust the salience weighting of delivery time accordingly.

7.4 Regulatory Environment

The Department of Consumer Affairs (Government of India) issued draft guidelines on dark patterns in online commerce in 2023, including provisions on misleading urgency cues, drip pricing, and false scarcity claims. While these guidelines target genuinely deceptive practices, they create regulatory uncertainty for salience framing interventions that are factually accurate. The regulatory trajectory suggests that platforms should proactively develop transparency frameworks for their UI optimisation practices, both to mitigate regulatory risk and to build consumer trust.

8. SWOT Analysis

The SWOT analysis below synthesises both the methodological strengths and limitations of the study and the strategic implications of its findings for quick commerce platforms considering salience-based UI interventions.

Table 15: SWOT Analysis – Salience Framing in Quick Commerce UI Design

Methodological Rigour • Randomised between-subjects design (Qualtrics auto-assign) eliminates selection bias and supports causal inference • Balance checks confirm adequate randomisation on gender (p=0.525) and age (p=0.482) • Expanded dataset (n=76) more than doubles the preliminary sample • Objective, single-question dependent variable minimises response bias **Commercial Relevance** • Directly tests a real UI-design lever at zero marginal cost • Findings immediately applicable to A/B testing in live app environments • Effect size (OR=1.69, NNT≈8) is commercially meaningful even if not statistically certified **Research Extensions** • Scale to 230+ respondents (115/group) across multiple city tiers for 80% power • Pre-register the replication for maximum credibility	**Statistical Limitations** • Sample remains severely underpowered: 115/group needed for 80% power vs. 33 and 42 obtained • Wide confidence intervals limit precision of effect size estimates • Subgroup analyses (gender, age) have very small cell sizes **External Validity** • Convenience sample from a single college network limits population representativeness • 18–24 age group still constitutes 64.5% of sample • Hypothetical choice scenario may not capture real ordering behaviour (stakes, habit, app inertia) • Single city orientation despite geographic diversity in data **Behavioural and Market Threats** • Nudge habituation: consumers who see the same salience cue repeatedly may become desensitised • Competitor adoption: if all platforms adopt identical tactics, the competitive advantage is neutralised

• Combine salience framing with urgency cues (scarcity, time countdown) for compound nudge • Test gender-targeted framing strategies given the asymmetric treatment effect **Industry Applications** • Platform operators can embed salience cues in live A/B tests at negligible cost • Personalised salience framing based on order history, time-of-day, and product category • Findings applicable to adjacent sectors (food delivery, on-demand mobility, healthcare)	• Delivery time compression (as dark store density increases) may reduce the perceived gap between options **Regulatory and Reputational Threats** • India's draft dark-pattern guidelines create regulatory uncertainty for UI optimisation • Consumer backlash against perceived manipulation could damage brand trust • Investigative journalism or activist scrutiny of "deceptive" app design may create reputational risk

9. Recommendations

9.1 For Researchers: Replication and Extension

The most immediate priority for future research is a well-powered replication. Based on our power analysis, a minimum of 115 respondents per condition (230 total) is required to achieve 80% statistical power at $\alpha = 0.05$ for an effect of $h = 0.261$. We recommend the following design improvements for the replication study:

- Pre-registration of hypotheses, analysis plan, and sample size on the Open Science Framework or AsPredicted.org to protect against HARKing (Hypothesising After Results are Known) and p-hacking.
- Stratified recruitment to ensure adequate representation of age groups 25–34 and 35+ (at least 40 respondents each), enabling meaningful subgroup analysis.
- Multi-city sampling, including at least one Tier-2 city (e.g., Jaipur, Lucknow, Kochi), to assess the generalisability of findings beyond metropolitan cohorts.
- A three-arm design adding a second treatment condition (e.g., price salience for App A) to test whether salience effects are attribute-specific or a general feature of visual emphasis.
- Inclusion of a manipulation check question ('Did you notice anything different about the way the apps were displayed?') to verify that the treatment was processed as intended.

9.2 For Platform Operators: Live A/B Testing

Quick commerce platforms should embed delivery-time salience cues in their live apps and measure their impact via randomised A/B testing. The experimental design described in this paper can be directly implemented in a production environment with the following adaptations:

- Outcome metrics: session conversion rate, average order value, platform re-engagement rate within 48 hours, and expressed satisfaction with delivery time.
- Minimum detectable effect: platforms with millions of daily sessions can detect effects as small as 0.1–0.5 percentage points, making statistical certification straightforward even for small true effects.
- Temporal controls: test across multiple time slots and days of week to account for contextual variation in price sensitivity and urgency.
- **Ethical guardrail:** Ethical guardrail: ensure that the salient delivery time displayed is accurate and achievable; presenting inflated speed estimates as salient information would constitute a dark pattern and carries regulatory and reputational risk.

9.3 For Platforms: Compound Nudge Design

Salience framing should be evaluated in combination with complementary nudge elements to assess whether compound designs produce superadditive effects. Candidate combinations include:

- **Urgency cues: "**Only 2 delivery slots available at this speed" or "Express delivery closes in 8 minutes"—combining scarcity and time pressure with delivery-speed salience.
- **Default selection:** For users with a demonstrated history of choosing express delivery, pre-select App B as the default option, requiring active effort to switch to the slower option.
- **Social proof: "**73% of customers in your area chose express delivery today"—combining salience framing with descriptive norm information.
- **Personalised framing:** Dynamically display delivery-time salience only for product categories associated with higher urgency (fresh produce, medicines) or during peak-demand hours.

9.4 For Platforms: Addressing Price Sensitivity

Given that 52.6% of respondents cited price or discounts as the most important factor, platforms should consider demand-side pricing strategies that complement salience nudges rather than working against them. Specifically:

- **Tiered delivery pricing with explicit framing:** ‘Standard delivery (30 min): ₹199 — Express delivery (15 min): ₹219. Most customers choose express.’ The social proof embedded in this framing may shift the reference point for price-sensitive consumers.
- **Bundle offers:** For consumers identified as price-sensitive via purchase history, offer a ‘Speed + Savings’ bundle that combines express delivery with a small discount on a specific category, making the premium option appear net-advantageous.
- **Free express delivery thresholds:** Set an order value threshold above which express delivery is offered at no extra cost, nudging consumers to add to their basket while also shifting them to the premium channel.

9.5 For Policymakers: Transparency and Consumer Welfare

The study’s findings have implications for the regulatory treatment of salience framing in digital commerce. We offer the following recommendations for the Department of Consumer Affairs and the Advertising Standards Council of India (ASCI):

- **Distinguish salience framing from dark patterns:** Regulatory guidance should clearly distinguish between (a) factually accurate visual emphasis of product attributes and (b) misleading urgency claims, false scarcity indicators, and hidden fees. Only the latter should be subject to prohibition.
- **Disclosure requirements:** Platforms that use algorithmically personalised salience cues (e.g., showing the delivery-time badge only to users identified as speed-sensitive) should disclose this practice in their terms of service, analogously to the disclosure requirements for personalised advertising.
- **Consumer education:** The Ministry of Consumer Affairs could fund public awareness campaigns explaining how choice architecture works, empowering consumers to recognise and account for nudge effects in their purchasing decisions.

10. Limitations and Future Research

10.1 Statistical Limitations

The primary limitation of this study is insufficient statistical power. With an observed effect size of Cohen’s h = 0.261 and group sizes of 33 and 42, the study achieves approximately 34% power at $\alpha = 0.05$—well below the 80% convention. This means that the study’s failure to achieve statistical significance is likely a Type II error (failing to detect a true effect) rather than evidence of a null population effect. Future research must prioritise adequate sample sizes, ideally determined via a priori power analysis and confirmed through pre-registration.

The Wald confidence intervals reported in this study assume a normal approximation to the binomial, which may be inaccurate for proportions close to 0 or 1 or for small samples. Wilson or Clopper-Pearson confidence intervals would provide more accurate coverage in future analyses.

10.2 External Validity Limitations

The convenience sample drawn from a college network in Bengaluru over-represents 18–24 year-olds (64.5% of the sample) and likely under-represents older, less digitally active consumers. The sample also has no respondents from Tier-2 or Tier-3 cities, where quick commerce penetration, price sensitivity, and digital literacy may differ substantially from metropolitan cohorts. The findings should be interpreted as applicable to urban, young-adult quick commerce users in major Indian metro areas, with caution regarding generalisation to other populations.

The hypothetical choice scenario ('Imagine you need groceries urgently') may not fully replicate the cognitive and affective state of an actual purchase occasion. In a real ordering context, consumers have access to their own app history, loyalty points, and habitual platform preferences—all of which may override the influence of a salience cue. Field experiments using live app A/B tests would provide stronger external validity.

10.3 Measurement Limitations

The study uses a single binary choice as its outcome variable, which provides no information about the strength of preference, the confidence of the choice, or the consumer's counterfactual behaviour (i.e., would they have chosen the same option even without the framing). A more comprehensive outcome battery might include willingness-to-pay measures, confidence ratings, and intention to revisit the choice—all of which would provide a richer picture of the framing effect's psychological mechanism.

The stated preference question ('which factor matters the MOST to you?') forces a single-factor response and cannot capture the full preference structure of consumers who weight multiple attributes simultaneously. A conjoint analysis or discrete choice experiment design would provide more granular preference data and allow for the estimation of individual-level willingness to pay for delivery speed.

10.4 Future Research Directions

This study opens several productive directions for future research:

1. A pre-registered replication with adequate power ($n \geq 230$, stratified sampling) to obtain a statistically certified estimate of the salience framing effect.
2. A longitudinal study examining whether the framing effect persists over repeated exposures (habituation) or strengthens (reinforcement through positive delivery experience).
3. A conjoint analysis of quick commerce attributes (price, delivery time, product quality, platform reliability) to estimate marginal willingness-to-pay for delivery speed across consumer segments.
4. A field experiment embedded in a live quick commerce app, measuring the impact of delivery-time salience on actual order completion, platform re-engagement, and lifetime value.
5. Cross-cultural comparison: replication in other high-growth quick commerce markets (Turkey, South Korea, Germany) to assess cultural moderators of the salience effect.

11. Conclusion

This study set out to investigate whether salience framing of delivery time influences consumer platform choice in the quick commerce sector. Using a randomised between-subjects experiment with 76 valid responses collected via Qualtrics, we found a 13.0 percentage-point increase in the probability of choosing the faster, more expensive platform (App B) in the treatment group relative to the control group (52.4% vs. 39.4%; OR = 1.69; Cohen's h = 0.261). This difference is directionally consistent with the salience hypothesis and with established findings from behavioural economics and digital commerce research, but does not reach statistical significance at the $\alpha = 0.05$ level ($\chi^2 = 1.252$, $p = 0.263$), most likely because the study remains underpowered relative to the requirement of 115 respondents per condition for 80% power.

Subgroup analysis reveals a particularly strong and near-significant treatment effect among female respondents (30.1pp; $p = 0.065$ two-tailed), while the effect is near zero among males. This gender asymmetry is theoretically coherent and suggests that the effectiveness of delivery-time salience nudges may be heterogeneous across consumer segments, with implications for targeted UI personalisation.

The study also documented a striking and robust intention–action gap. Among respondents who cited 'Lowest price' as their primary decision criterion, 28.6% nonetheless chose the premium-speed option when confronted with an urgent grocery scenario—a finding that reinforces a foundational insight of behavioural economics: what consumers say they value and what they actually choose under contextual pressure are not the same thing. Conversely, 28.6% of self-described speed-prioritisers chose the cheaper option, suggesting that contextual factors override stated preferences in both directions.

For quick commerce platforms operating in an intensely competitive market undergoing rapid consolidation, the design of the choice environment is not merely an aesthetic decision. It is a strategic lever with material consequences for consumer behaviour and platform economics. The lightning bolt icon and capitalised delivery time cue tested in this study represent the simplest possible instantiation of a salience nudge—a minimal intervention that any platform can implement in hours. The finding that even this minimal intervention produces a 13pp directional shift in a hypothetical scenario, and a 30pp directional shift among female respondents, suggests that more sophisticated, contextualised, and personalised nudge designs could produce effects that are both statistically significant and commercially substantial.

As India's quick commerce market matures and competition intensifies, behavioural design will become an increasingly important source of competitive differentiation. The evidence from this study—preliminary but consistent—suggests that salience framing of delivery time is a promising tool in the platform operator's behavioural toolkit. Its full potential can only be assessed through adequately powered, pre-registered field experiments. We hope this study provides both the theoretical grounding and the empirical starting point for such research.

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