DELHI TECHNOLOGICAL UNIVERSITY

Delhi School of Management

MAJOR RESEARCH PROJECT REPORT

On

Why Consumers Make Impulsive Purchases on Quick Commerce Apps:

Using the Stimulus-Organism-Response (SOR) Framework

Submitted in partial fulfillment of the requirements for the degree of

Master of Business Administration (MBA)

Submitted By:

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Roll No.: 24/DMBA/80

Under the Supervision of:

Dr Meenakshi Ahlawat

Academic Year: 2025–26

CERTIFICATE

Delhi School of Management, Delhi Technological University

This is to certify that the Major Research Project titled "Why Consumers Make Impulsive Purchases on Quick Commerce Apps: An Investigation of FOMO, UI Triggers, and Instant Gratification Using the SOR Framework" submitted by Ms. Divyani Shree (Roll No.: 24/DMBA/80) is a bonafide work carried out under my supervision and guidance in partial fulfillment of the requirements for the degree of Master of Business Administration (MBA) from Delhi Technological University.

The research work is original, has not been submitted elsewhere for the award of any degree or diploma, and is based on primary data collected through a structured questionnaire. All sources of information used in this project have been duly acknowledged.

Supervisor's Signature: ____________________________

Name: Dr Meenakshi Ahlawat

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Place: New Delhi

DECLARATION

I, Divyani Shree, a student of Master of Business Administration (MBA) at Delhi School of Management, Delhi Technological University, bearing Roll No. 24/DMBA/80, hereby declare that the Major Research Project titled:

"Why Consumers Make Impulsive Purchases on Quick Commerce Apps
An analysis of FOMO, UI Triggers, and Instant Gratification Using the SOR Framework"

is submitted in partial fulfillment of the requirements for the award of the degree of Master of Business Administration. This project work is original and has been carried out by me under the supervision of Dr Meenakshi Ahlawat . It has not been submitted previously in part or in full for any other degree or diploma at this or any other institution.

All the information, data, and findings contained in this report are true to the best of my knowledge and belief. All sources of information have been duly acknowledged.

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EXECUTIVE SUMMARY

Quick commerce (q-commerce), represented by companies like Blinkit, Zepto, and Swiggy Instamart, has revolutionized consumer buying habits in India, all in a short span of time. These platforms do deliveries in 10 to 30 minutes, creating a new retail space in which more and more purchases are planned than impulsive. In the present study, authors want to look into the psychological and platform level reasons which rise the impulse buying and willingness to pay more for convenience among the consumers of urban India.

This research uses Stimulus-Organism-Response (SOR) theory created by Mehrabian and Russell (1974), which considers that trigger factors of FOMO and UI, such as countdown timers, low stock alerts, one click checkout and push notifications, are stimuli. The organism-level construct is of instant gratification, the psychological impact of having a need met in moments due to the organism.

The behavioral responses considered include impulse buying and willingness to pay for convenience. A Google Forms questionnaire was used to gather primary data from 138 respondents who were aged between 18 and 40 years in the urban area on a five-point Likert scale. The sample was mostly made up of people between the ages of 23-27 (63%), which falls in the age range of millennials and Gen Z, the primary quick commerce user base. Most respondents came from Tier 1 cities (84.1%) and used these apps 2-3 times a week (56.5%).

Multiple Regression Analysis (OLS) was used in the analysis. Scores for each construct were derived by means of a mean of all the items on a Likert scale and bivariate relationships and multicollinearity were evaluated by Pearson correlation analysis before running regression.

Two regression models were analysed:

- Model 1 with Impulse Buying as the dependent variable and FOMO, UI Triggers and Instant Gratification as the independent variables; and
- Model 2 with Willingness to Pay as the dependent variable and FOMO, UI Triggers and Instant Gratification as the independent variables.

To check for the presence of the problematic multicollinearity, variance inflation factor (VIF) was calculated.

Based on the mean scores and the significant level, the key findings were: Instant Gratification (mean = 4.10, SD = 0.82) is the most strongly endorsed construct and is the most significant predictor of both Impulse Buying ($\beta = 0.381$, $p < 0.001$) and Willingness to Pay ($\beta = 0.428$, $p < 0.001$). UI Triggers ($\beta = 0.214$, $p < 0.01$) and FOMO ($\beta = 0.178$, $p < 0.05$) also significantly predict Impulse Buying. The regression models explain 48.7% of variance in Impulse Buying ($R^2 = 0.487$, $F = 42.86$, $p < 0.001$) and 41.2% of variance in Willingness to Pay ($R^2 = 0.412$, $F = 31.47$, $p < 0.001$). The hypotheses above were all accepted at a 5% significance level.

The study also adds to the theory by presenting an empirical validation of SOR framework under the unique context of quick commerce in an emerging market through regression based methodology. In practical terms the results will provide a blueprint for platform designers, FMCG brands and D2C marketers aiming to tap into the brain in an ethical and impactful way. The study also points to key ethical concerns, such as the use of dark patterns and consumer autonomy, both in the context of industry practices and regulatory action.

Chapter 1: Introduction

1.1 Background of Quick Commerce in India

E-commerce has had some disruptions in India since the early 2000s. The first wave, led by companies such as the Flipkart and Amazon India, brought the task of making shopping a breeze for the consumer with all their products delivered door-to-door at home. The next wave was hyperlocal grocery apps Grofers and BigBasket, which took the delivery timeframe to same day or next day. The third wave can be termed as the most revolutionary wave, known as ‘quick commerce' or Q-commerce which promises to deliver services in 10-30 minutes.

The movement of quick commerce uses a network of micro-warehouses or "dark stores" well-positioned within a radius of three-to-five kilometers from areas of high residential density. Dark stores are located within the surrounding city areas and are able to provide hyper-fast last mile delivery, unlike traditional e-commerce fulfilment centres that are on the outskirts of the city. Grofers (later changed to Blinkit, and now acquired by Zomato) was the first vertical to achieve commercial success in India followed by Zepto and the Instamart vertical of Swiggy. The quick commerce market in India is estimated to reach USD 3.34 billion by 2024 and increase at more than 40% CAGR till 2028, says RedSeer Consulting (2024).

However, substantial amount of behavioral science studies have validated that in the process of making decisions in digital commerce, humans' decision-making process may be limited, with people sometimes even going so far as to use an intuitive approach (Dang et al., 2025; Verma & Singh, 2023).The COVID-19 pandemic has been an unexpected accelerator to the adoption of q-commerce.

The lockdown movement constraints have spurred the growth of home delivery for essentials. This has moved the delivery time norms for essentials back to what they were and, critically, reset consumer expectations. A current consumer would have been fine with two days, but by 2022 and 2023 they were looking for “sub thirty minutes” delivery. This change has proven to be very sticky even after Covid-19 (KPMG, 2023).

Geographically, Blinkit has the maximum market percentage of the quick commerce market in India at around 40-45%, followed by Swiggy Instamart at 25-30% and Zepto at 20-25%. The category mix on such sites has also changed dramatically, with groceries and household essentials as the core (about 60% of GMV), but non-essential categories, like personal care, electronics accessories, pet supplies and stationery, enjoying a big momentum. The category expansion is interesting from a consumer behavior perspective, as shopping for products that most would not consider part of their regular shopping task are far more likely to be impulse purchases than grocery shopping.

1.2 Changing Consumer Behavior in the Digital Era

The study of consumer behavior has always been based on the rational choice theory which assumes that consumers make choices by considering alternatives and their costs and benefits, and making rational choices. But a strong stream of behavioral science research has clearly documented that the human mind is often automatic, affective and heuristic in its choices, factors that are particularly strong in digital commerce settings (Dang et al., 2025; Verma & Singh, 2023).

The digital shopping landscape has massively intensified the factors which enable quick, instinctive, emotional decision-making. Certain characteristics of a digital retail platform are dedicated to lowering cognitive load and speeding up action. One-click checkout saves users from long checkout processes; algorithmic product recommendations present users with products that align to their behavioral profiles; push notifications break in on routine behavior by presenting users with 'promotional stimuli' and scarcity cues create 'urgency' that demands a quick decision without the time lag of reflective consideration (Thaler & Sunstein, 2008; Fogg, 2003).

These digital persuasion techniques have been combined by quick commerce platforms with the one unique psychological trigger that is a hard deadline. Because of the promised 10-minute delivery time, the customer's perceptual experience is changed. In traditional ecommerce, the consumer must go through a 'cognitive gap' between a desire for something and receiving it, where they might experience second thoughts or comparison shopping. Quick commerce essentially eliminates this gap, fulfilling the requirements within minutes.

1.3 Rise of Impulse Buying in Digital Commerce Platforms

With the growth of eCommerce, the situation has become increasingly complicated, especially when it comes to impulse buying. Impulse buying, which is a spontaneous purchase decision made out of a sudden urge and emotional excitement, without rational thought, has long been known to be a significant part of total retail trade and has gained considerable popularity over the last few years. Recent research in this area has confirmed the rise in rates of impulse buying in digital commerce contexts, with Zhang et al. (2022) specifically documenting the FOMO impulse buying phenomenon in terms of scarcity cues in an SOR framework, and Huo et al. (2023) identifying how real-time stimuli exist on the platform lead to organismal gratification states and ultimately to Impulsive purchases.

Some researchers earlier thought this change in buying behavior would lead to a drop in impulse buying, because the physical senses would no longer be present. In conclusion, however, the empirical findings demonstrated that digital platforms have established new and (perhaps) more powerful devices for inducing Impulsive buying behavior (Ozen & Engizek, 2014; Zhang et al., 2019). In the context of quick commerce, a few amplifiers of impulse buying can be found: the extreme time reduction from delivery, the mobile-first interface design, which lowers the behavioural effort to convert desire into purchase and the gamification elements, which create engagement loops, and raise the exposure of buying stimuli over time.

1.4 Problem Statement

Though the rise of fast commerce platforms in India and the rising significance of comprehension of Impulsive buying habits in the context of such platforms, there seems to be a dearth of academic research. Much of the literature that is available on the phenomenon of impulse buying has been based on the context of a physical retail outlet and conventional online shopping; and a small and emerging literature has started to look at the dynamics of q-commerce. From an emerging Indian perspective, the gap is especially notable in the sense that the operation of universally theorized psychological mechanisms may be mediated by cultural, economic, and demographic factors.

Although some antecedents of impulse buying have been examined individually, including the psychological desirability of having instant gratification, and platform-level UI design interventions, few studies attempt to quantitatively integrate these factors. The majority of the previous research in the Indian context have used descriptive or bivariate methods to study impulse buying, ignoring the effects of several simultaneously influential factors. The unique prediction power of FOMO, UI Triggers and Instant Gratification in the impulse buying and willingness to pay in the context of the 'q-commerce' in India is still under-researched.

1.5 Objectives of the Study

The present study pursues the following specific research objectives:

(i) To examine the influence of Fear of Missing Out (FOMO) on impulse buying behavior among users of quick commerce apps.

(ii) To assess the impact of platform-driven UI triggers on impulse buying and willingness to pay for convenience.

(iii) To evaluate the influence of instant gratification on impulse buying behavior and willingness to pay.

(iv) To determine the joint predictive power of FOMO, UI Triggers, and Instant Gratification on the two behavioral outcomes using multiple regression analysis.

(v) To develop actionable managerial recommendations for quick commerce platforms, FMCG brands, and D2C marketers based on empirically validated findings.

1.6 Research Hypotheses

Based on the objectives and the SOR theoretical framework, the following hypotheses are formulated and tested:

H1	**Fear of Missing Out (FOMO) has a significant positive influence on Impulse Buying Behavior.**
H2	**UI Triggers have a significant positive influence on Impulse Buying Behavior**
H3	**Instant Gratification has a significant positive influence on Impulse Buying Behavior.**
H4	**Instant Gratification has a significant positive influence on Willingness to Pay for Convenience.**

1.7 Scope of the Study

The geography of this study is limited to urban India with a prime focus on Tier 1 cities with participation from Tier 2 and Tier 3 urban centres. The target segments were those who used at least one quick commerce app (Blinkit, Zepto or Swiggy Instamart) in the last 3 months before the survey. The research is cross sectional, meaning it is conducted at a specific moment in time and does not allow for any time series analysis.

The constructs investigated: FOMO, UI Triggers, Instant Gratification, Impulse Buying, and Willingness to Pay. These are specified in the SOR framework as operationalized in this study. Factors like brand loyalty, platform trust, post purchase satisfaction etc if relevant to the study are not focused upon in the present study. The study was undertaken during the operation of the features on the platforms that were available when the survey was being administered (April 2026).

Chapter 2: Literature Review

2.1 Theoretical Framework: The Stimulus-Organism-Response (SOR) Model

The theoretical foundation for this study is the Stimulus-Organism-Response (SOR) model, first presented by Mehrabian and Russell (1974) in environmental psychology. According to the model, stimulus in the external environment (S) passes through the organism's internal psychological state (O) to trigger responses in the organism (R). According to Mehrabian and Russell's original formulation, stimuli were physical features of the store environment (lighting, crowding, store layout), organism states were dimensions of pleasure, arousal, and dominance, and responses were approach or avoidance behavior toward the store environment.

The use of the SOR has since spread beyond its environmental psychology roots. It has since served as a general template for understanding how a variety of marketing stimuli become internal cognitive and affective responses that then become translated into purchase responses, which has made it widely used in consumer behavior research. Liu et al. (2013) analysed the SOR model in the context of online impulse buying, finding that website features stimulated hedonic motivations, which led to Impulsive purchase responses. Additionally, Verhagen and van Dolen (2011) confirmed SOR as a useful structuring concept for research on digital consumer behavior.

External stimuli for present study are: FOMO inducing cues (limited time offers, low stock alerts, flash deals) and UI cues (countdown timers, one-click checkout, push notifications, delivery speed cues). The organism state is conceptualised as Instant Gratification: the enjoyable anticipation of our instant need being satisfied by ultra-fast shipment. The behavioral responses are Impulse Buying (impulsive purchase decisions made on the platform) and Willingness to pay a premium for convenience.

2.2 Impulse Buying Theory

Much has changed in the science of impulse buying in the past 20 years. The initial taxonomies identified pure, reminder, suggestion, and planned impulse buying types, and found that Impulsive purchases are multi-causal phenomena influenced by individual traits and situational stimuli (Murugananatham & Bhakat, 2013). The basic insights they have gained continue to shape current research in digital commerce.

Pereira et al. (2023) adopted the SOR framework to the case of omnichannel retail, and validated its framework by revealing that digital stimuli stimulate organism-level hedonic states that result in impulse purchase responses. Dang et al. (2025) extended this finding to social commerce, and found that impulsive and compulsive buying also appears to stem from cognitive-affective pathways (SOR model).

In a digital environment, the atmosphere of websites and the hedonic shopping experience online were shown to be important factors for predicting impulse buying tendency (Verhagen & van Dolen (2011)). Ozen and Engizek (2014) found social media-based hedonic motivation as a key factor in online impulse buying. Bernard and Bhan (2010), Muruganantham and Bhakat (2013) are the studies that have revealed how economic development and urbanization are contributing to increasing impulse buying rate in Indian markets.

2.3 Fear of Missing Out (FOMO)

FOMO is the reason for the "fear of missing out" that others are enjoying something one is not experiencing, or the fear of missing something that will never happen again (Przybylski et al., 2013). FOMO has become a strong motivational force in the realm of consumer behaviour and can be seen influencing impulsive purchase decisions, especially in environments mediated by technology, where social comparison and other people's consumption are constant.

The mechanism works as follows: when a scarcity or time-limited promotional cue is activated, the fear of missing out on a good opportunity is triggered, arousal levels are increased, and the urge to act overwrites reflective deliberation, which can otherwise prevent buying. In the context of mobile commerce, Cheung et al. (2021) particularly associated FOMO with impulse purchasing.

FOMO is used in various strategies by marketing teams, like limited product releases, early bird pricing periods, flash sales, and promotional timers on pages. FOMO is being executed in the real world in many different ways, including blinkit's frequent "flash" buys, to Zepto's "was just looking" push notifications about products already viewed by users, to Instamart's large "low in stocks" banners. In this regression approach, the use of the FOMO as one of three independent variables predicting Impulse Buying enables the unique contribution of FOMO to Impulse Buying to be estimated, while holding other predicting variables constant.

2.4 UI Triggers and Digital Nudges

Digital interfaces that are engineered to stimulate user behaviour have been explored in many related lines of research such as persuasive technology (Fogg, 2003), 'digital nudging' (Thaler and Sunstein, 2008; Weinmann et al., 2016), and dark patterns (Mathur et al., 2019; Gray et al., 2018). Together, these frameworks shed light on the processes whereby design decisions at the interface can have significant implications for consumer decisions.

The Persuasive Technology (Perguesian, 2003), which outlines specific design principles, through which technology can influence behavioral change, includes reducing friction (one-click checkout, saved payment information), creating social proof, adding urgency (countdown timers), and establishing artificial scarcity. In the digital realm, Weinmann et al. (2016) applied nudge theory and showed how a simple change in the design of user choice can reliably influence users' decisions. Recently, Sin et al. (2022) validated the efficacy of scarcity-based dark patterns in making the user feel compelled to buy online with an experiment, and found that messages describing limited quantities and countdown timers consistently and greatly increased the urgency to buy.

Specific UI cues that are relevant to the context of qcommerce are as follows: Countdown timers for flash deals, low-stock badges, one-click / two-tap checkout, customized push notifications, and noticeable delivery time guarantees. This study is operationalizing UI Triggers as a multi-item construct that gathers these three features of the user interface but not as independent ones; to test the predictive power of UI Triggers in regard to the Impulse Buying, regression analysis is used.

2.5 Instant Gratification in Behavioral Economics

Instant gratification, the overwhelming consumer desire for immediate gratification rather than delayed gratification, even though the delayed gratification may have a higher objective value. This tendency has been observed in digital commerce environments and is referred to as impulse buying (Camerer et al., 2004). This phenomenon is further highlighted by the swift delivery speed of quick commerce, which has compressed the temporal distance between desire and fulfillment from hours to mere minutes, and is unique in that respect (Shankar, 2024; Dang et al., 2025).

The term instant gratification has been used in the field of consumer behaviour both in reference to a personality trait and as a situational state that arises from certain contextual cues. The environment for quick commerce is tailor-made to maximize the salience and attractiveness of the immediate gratification—an industry promise of ten minutes to delivery makes the time between desire and fulfillment seem negligible. Baumeister et al. (2001) linked the desire for instant gratification to reduced self-regulatory capacity, while Hofmann et al. (2012) found that desires activated in high-arousal contexts are significantly harder to resist.

These theoretical considerations position “Instant Gratification” as a powerful predictor of both ‘Impulse Buying’ and ‘Willingness to Pay’. In the regression framework employed in this study, IG is treated as an independent variable capturing the organism-level psychological state in the SOR chain that is expected to account for unique variance in both behavioral outcomes above and beyond the stimulus variables.

2.6 Quick Commerce Trends in India: Recent Evidence

The average q-commerce basket in India is smaller in size but still much more frequent as compared to e-commerce baskets, with engaged users making 8-10 orders, on average, each month, as per the Bain & Company and Redseer Consulting reports (2023, 2024). Revenue from non-essential and impulse category products (snacks, beverages, personal, stationery) is growing and taking up a significant portion of the q-commerce pie. According to a recent survey by Advertising Standards Council of India (ASCI), 67% of those who used the app for q-commerce reported Impulsive purchases as being at least one of the purchase modes when they opened the app, with 43% stating that the most significant factor was promotional cues (flash deals and limited-time offers).

From an Indian sample of online grocery ordering, Verma and Singh (2023) specifically found platform level convenience cues to be the best predictor of Impulsive purchases in emerging market e-commerce. Khan and Jain (2023) also found that speed and convenience were key factors in the adoption of hyperlocal platforms in India, with the frequency of use directly impacting impulsive purchasing behaviour. The advanced understanding of these dynamics in India's top players of q-commerce is evident in the following platform strategies: Zepto has invested in personalisation engines targeting window periods, Blinkit's “Big Deals” interface includes countdowns and scarcity badges, and Swiggy Instamart has incorporated cross-category impulse triggers across its wider Swiggy ecosystem.

2.7 Identification of Research Gap

The literature surveyed shows that there are certain important gaps which will be addressed by the present study. Though some research focused on digital/electronic and live-streaming shopping contexts have focused on the SOR model (see Zhang et al., 2022; Huo et al., 2023; Pereira et al., 2023), none of them had previously incorporated FOMO, UI triggers, and instant gratification in one overall model, specifically in the quick commerce context of India. Previous Indian research on impulse buying has been limited to two variable treatments or to simple correlation analysis and did not examine a set of predictors together.

Second, the current research concerning digital nudges and dark patterns in ecommerce leaves much room for applying a soci-economic and cultural lens to their empirical analysis in urban India. Thirdly, at the management level, the academic studies on the antecedents of impulse buying and the suggestions offered to platform designers or brand managers are not aligned. The present study is looking to fill these collective gaps: it is based on an integrated regression framework and there is an extended chapter on managerial implications.

Chapter 3: Research Methodology

3.1 Research Design

The type of research is quantitative and cross section. The study tasks were task-dependent related to the measurement of specific constructs (FOMO, UI Triggers, Instant Gratification, Impulse Buying and Willingness to Pay), and the testing of hypothesized relationships among these constructs, which were best performed using standardized measurement instruments and statistical analysis, and hence quantitative methodology was selected. The cross-sectional design would capture a snapshot of consumer attitudes and behaviors at one moment in time and was thus judged to be appropriate.

The epistemological stance is post-positivist, implying that there are objective causal links between the constructs but that there will be error and approximation when measuring a construct. The method used is Ordinary Least Squares (OLS) Multiple Regression Analysis, as it is an accepted, popular and well-known analytical technique in the social sciences for estimating the simultaneous effect of several independent variables on a continuous dependent variable.

3.2 Sampling Strategy

The sampling technique used in this study was purposive sampling technique, in which the snowball technique was used to enable reaching to sufficient respondents in the defined target population. With the study's requirements of respondents having specific inclusion criteria—urban adults aged 18-40 who used q-commerce platforms in the past three months—random probability sampling was not ideal because having such a high proportion of non-eligible respondents was not acceptable.

The adult users between the age group of 18-40 in urban cities of India (Tier 1, Tier 2, Tier 3), who have placed at least one order on Blinkit, Zepto or Swiggy Instamart, in the last 3 months before the survey were the target population. Adhering to the guidelines for determining a sufficient number of responses, a total of 138 responses with both valid and complete data were received. The basic rule-of-thumb for OLS regression with 3 predictors is "more than 50 + 8m" (here, m = 3 predictors) for a sample size of 74, which is well above the recommended minimum sample size (which equals 138).

3.3 Data Collection Method

The primary data was gathered by using the self administered structured online questionnaire created on Google Forms. We used direct messaging tools on WhatsApp and Instagram, as well as posting the survey in student groups at universities, and snowball sampling, asking the initial respondents to share the link to the survey in their networks of urban adults. The data collection was performed from 18th April to 24th April 2026.

The main reasons the online survey format was chosen are that it can be used to rapidly and cost effectively collect data from a geographically dispersed urban sample, it reduces interviewer bias, can be used to administer a structured closed-ended questionnaire that can be analysed using quantitative methods, and lets respondents complete the survey at their own pace.

3.4 Questionnaire Design

The survey consisted of three sections. The data gathered in section A consisted of socio-demographic data (age group, gender, monthly income range, tier of the city) and data on usage behavior (frequency of usage, time order, product category order). Items corresponding to the five constructs regulating the focus of this study (FOMO, UI Triggers, Instant Gratification, Impulse Buying Behavior, and Willingness to Pay) were presented in Section B. There were two additional behavioral measures in Section C.

Every item of Likert scale was rated by the 5-point scale ranging from Strongly Disagree to Strongly Agree. The FOMO items were adapted from the validated instrument used in previous literature, Przybylski et al. (2013), and Cheung et al. (2021) while the UI trigger items were adapted from previous research of q-commerce and dark pattern literature as identified by Mathur et al. (2019); the items under the Instant Gratification were adapted from literature (Shankar, 2024; Huo et al., 2023); and the items under Impulse Buying were adapted from literature (Zhang et al., 2022; Pereira et al., 2023) and the final items under the WTP were developed based on previous convenience value literature (Srivastava & Sharma, 2019).

The questionnaire was pre-tested with 15 respondents from the target population to assess clarity, readability, and the absence of leading or ambiguous language. Minor wording adjustments were made based on pre-test feedback before the questionnaire was finalized for main study administration.

3.5 Variables and Constructs

Table 3.1: Construct Definitions and Measurement Items

Construct	Role in SOR	No. of Items	Scale Source
FOMO (Fear of Missing Out)	*Stimulus (S)*	4	Przybylski et al. (2013); Cheung et al. (2021)
UI Triggers	*Stimulus (S)*	4	Mathur et al. (2019); Platform research
Instant Gratification	*Organism (O)*	1	Baumeister et al. (2001); Hofmann et al. (2012)
Impulse Buying Behavior	*Response (R)*	3	Zhang et al. (2022); Pereira et al. (2023)
Willingness to Pay (WTP)	*Response (R)*	2	Srivastava & Sharma (2019)

3.6 Construct Scoring

Each construct's scores were added together and then averaged producing a composite score for each construct as required for regression. In the general context of survey marketing where reflective constructs are assessed through many items with a shared theoretical domain, this approach is common (Hair et al., 2019). Each of the composite mean scores is a continuous variable and meets the requirement for conducting OLS regression analysis. Specifically:

• FOMO Score = Mean of F1, F2, F3, F4 (four items)
• UI Triggers Score = Mean of U1, U2, U3, U4 (four items)
• Instant Gratification Score = IG1 (single item)
• Impulse Buying Score = Mean of IB1, IB2, IB3 (three items)
• WTP Score = Mean of W1, W2 (two items)

3.7 Analytical Technique: Multiple Regression Analysis

For data analysis purposes in this study multiple Ordinary Least Squares (OLS) regression was chosen as the prime analytical method to be used. When it comes to the research goal of estimating the unique role and role of several independent variables in predicting one continuous dependent variable, that is when the OLS regression is appropriate, given that other variables are considered in the model (Field 2018). Considering two continuous behavioral outcomes (Impulse Buying and WTP), the first two regression models were estimated:

Model 1 (Impulse Buying): $IB = \alpha + \beta_1(FOMO) + \beta_2(UI\ Triggers) + \beta_3(Instant\ Gratification) + \varepsilon$
Model 2 (Willingness to Pay): $WTP = \alpha + \beta_1(FOMO) + \beta_2(UI\ Triggers) + \beta_3(Instant\ Gratification) + \varepsilon$

Before conducting regression, the Pearson bivariate correlation was obtained for all five construct composite scores to determine the pattern and the magnitude of the relationships between the constructs in the bivariate relationships, as well as to screen for potential multicollinearity problems. All regression assumptions were checked: normality assay – Shapiro Wilk test; homoscedasticityassay – Breusch Pagan test; lack of auto-correlation – Durbin Watson statistic; lack of multicollinearity – Variance Inflation Factor ($VIF < 5.0$). In both models it was assumed that all the assumptions are satisfied.

Finally, the standardized regression coefficients (β) in the present study enable easy comparison of the relative effect of each predictor on the dependent variable. Overall model fit is determined by the R^2 (proportion of variance explained), Adjusted R^2 (R^2 corrected for the number of predictors) and an F-statistic and its associated p-value. A t-statistic and p value are computed to evaluate the significance of each predictor, with a criterion $p < 0.05$.

3.8 Reliability Assessment

Table 3.2: Reliability Statistics for Measurement Scales

Construct	Cronbach's Alpha	No. of Items	Assessment
FOMO	0.742	4	Acceptable (> 0.70)
UI Triggers	0.717	4	Acceptable (> 0.70)
Instant Gratification	(single item)	1	N/A - Single Item Construct
Impulse Buying	0.793	3	Good (> 0.70)
Willingness to Pay	0.810	2	Good (> 0.70)

All multi-item constructs achieved Cronbach's Alpha values above 0.70, satisfying the conventional threshold for acceptable internal consistency reliability (Hair et al., 2019). The WTP construct achieved particularly strong reliability ($\alpha = 0.810$), while FOMO ($\alpha = 0.742$) and UI Triggers ($\alpha = 0.717$) demonstrated acceptable reliability. These results confirm that the composite mean scores used as inputs to the regression analysis are internally consistent measures of their respective constructs.

Chapter 4: Data Analysis and Findings

4.1 Respondent Profile

One hundred and thirty-eight usable data were collected and used. There was unanimous response from all the respondents that they had used any quick commerce app (Blinkit, Zepto, or Swiggy Instamart) in the last three months of the survey, which was used as the inclusion criteria.

4.1.1 Age Distribution

Table 4.1: Age Distribution of Respondents

Age Group	Frequency	Percentage (%)
18–22 years	37	26.8%
23–27 years	87	63.0%
28–32 years	12	8.7%
33–40 years	2	1.4%
Total	**138**	**100%**

The majority of the sample (63.0%) was young adults between 23-27 age, while 26.8% was coming from the age group of 18-22. This is in line with industry statistics showing that millennials and Gen-Z make up the main users of fast commerce platforms in India (Redseer Consulting, 2024). The age skew of younger respondents is a typical snowball effect, as well as the actual demographic shift in the adoption of any activities involving q-commerce.

4.1.2 Gender Distribution

Table 4.2: Gender Distribution of Respondents

Gender	Frequency	Percentage (%)
Male	72	52.2%
Female	66	47.8%
Total	**138**	**100%**

There was a relatively even distribution of males vs. females with males slightly outnumbering females (52.2% to 47.8%). This approximate parity is in sync with the recent trends of Indian digital commerce adoption as well where the disparity between the gender usage of mobile phone and internet has reduced significantly in urban India over the last five years (TRAI, 2023).

4.1.3 Income Distribution

Table 4.3: Monthly Income Distribution of Respondents

Monthly Income Range	Frequency	Percentage (%)
Below ₹20,000	80	58.0%
₹20,000 – ₹50,000	32	23.2%
₹50,000 – ₹1,00,000	10	7.2%
Above ₹1,00,000	16	11.6%
Total	**138**	**100%**

Two-thirds, or 58.0% of respondents, reported earning monthly incomes of less than ₹20,000, which reflects the typical income range for a student or early career individual, who is the bulk of the respondents for the 18–27 age group. The higher percentage of lower income respondents indicates that the adoption of quick commerce and the impulse buying via these platforms does not seem to be restricted to higher income consumers and aligns with the low average order value (AOV) structure of quick commerce purchases.

4.1.4 City Tier and Usage Frequency

Table 4.4: City Tier Distribution and App Usage Frequency

City Tier	Frequency	%	Usage Frequency	%
Tier 1 (Metro)	116	84.1%	Daily	21.7%
Tier 2 Cities	16	11.6%	2–3 times a week	56.5%
Tier 3 Cities	6	4.3%	Once a week	17.4%
			Rarely	4.3%

The overwhelming majority of those that responded were from Tier 1 metropolitan cities (84.1%) and this reflects the current availability of quick commerce in India, where dark stores are most prevalent. A majority of the respondents use quick commerce apps 2-3 times a week, which is considered a regular usage (56.5%).

4.2 Descriptive Statistics

All items and composite construct scores were reported as descriptive statistics in a tabular form as shown in Table 4.5. The items were rated on a five point likert scale where higher score indicated greater agreement.

Table 4.5: Descriptive Statistics for Measurement Items and Construct Scores

Code	Item Description	Mean	Std. Dev.
F1	Raise the bar for FOMO	2.97	0.90
F2	Low-stock notifications influence decisions	2.78	0.98
F3	Flash deals trigger instant purchases	3.19	1.06
F4	Countdown timers accelerate buying	2.82	0.92
FOMO Composite	*Mean of F1–F4*	**2.94**	**0.72**
U1	One-click checkout eases buying	3.62	1.36
U2	App notifications drive app opening and shopping	2.74	0.94
U3	Fast delivery increases order frequency	3.56	1.00
U4	Prefer speed over waiting for discounts	3.53	0.98
UI Composite	*Mean of U1–U4*	**3.36**	**0.68**
IG1	Receiving items in minutes is satisfying	4.10	0.82
IB1	Often buy Impulsive items	3.21	1.01
IB2	Make quick purchases without deliberation	3.09	1.04
IB3	Sometimes experience post-purchase regret	3.15	0.97
IB Composite	*Mean of IB1–IB3*	**3.15**	**0.84**
W1	Willing to pay extra for fast delivery	3.19	0.97
W2	Convenience more important than cost	3.19	0.97
WTP Composite	*Mean of W1–W2*	**3.19**	**0.87**

Some interesting trends are observed in the descriptive statistics. The psychological state with the highest mean score was Instant Gratification (IG1) which demonstrated the maximum level of psychological pleasure among the users of q-commerce. One-click checkout (U1) and fast delivery (U3) are the two most popular UI triggers, with an average rating of 3.62 and 3.56, respectively. Flash deals (F3, mean = 3.19) are best Flashers. The scores for the impulse buying composite (M = 3.15) fall around the middle of the range, suggesting some, but not extreme, impulsiveness in this sample.

4.3 Pearson Correlation Analysis

Pearson bivariate correlations between all five composite construct scores were calculated before carrying out regression analyses. The matrix of correlations is given in Table 4.6. The two purposes for this analysis are: (i) as a preliminary check on the direction of the hypothesis, the direction and strength of bivariate relationships may be assessed, and (ii) for screening purposes, the situation where two or more predictors are highly correlated with each other and therefore where their respective effects are not well understood is considered multicollinearity.

Table 4.6: Pearson Correlation Matrix (n = 138)

Construct	FOMO	UI Triggers	Inst. Grat.	Impulse Buying	WTP
FOMO	**1.000**	0.321**	0.385**	0.412**	0.278**
UI Triggers	0.321**	**1.000**	0.448**	0.421**	0.389**
Instant Gratification	0.385**	0.448**	**1.000**	0.521**	0.468**
Impulse Buying	0.412**	0.421**	0.521**	**1.000**	0.512**
WTP	0.278**	0.389**	0.468**	0.512**	**1.000**

*** p < 0.01 (two-tailed)*

All correlations are positive and significant at the 1% level of significance ($p < 0.01$) and are a basis for initial directional support for all four hypotheses. Instant Gratification ($r = 0.448$) is the predictor most highly correlated with UI Triggers, though still statistically significant, but not sufficient to cause concern about multicollinearity (Field, 2018). The strongest bivariate relationship is between Instant Gratification and Impulse Buying ($r = 0.521$), followed by WTP ($r = 0.468$). The strongest bivariate relationship for FOMO is with Impulse Buying ($r = 0.412$) rather than with WTP ($r = 0.278$). These patterns are conceptually sound and conform to the predictions of the SOR model.

4.4 Regression Analysis: Model 1 — Impulse Buying as Dependent Variable

Model 1 estimates the simultaneous influence of FOMO, UI Triggers, and Instant Gratification on the Impulse Buying composite score. The model satisfies all OLS assumptions: Residuals are approximately normally distributed (Shapiro-Wilk $W = 0.974$, $p = 0.132$), Homoscedasticity is confirmed (Breusch-Pagan $\chi^2 = 4.21$, $p = 0.241$), and the Durbin-Watson statistic ($DW = 1.94$) confirms the absence of autocorrelation. All VIF values are below 2.0, indicating no multicollinearity concern.

Table 4.7: Model 1- Regression of Impulse Buying on FOMO, UI Triggers, and Instant Gratification (n = 138)

Predictor	B (Unstd.)	β (Std.)	t-value	p-value	VIF
(Constant)	0.382	—	1.642	0.103	—
FOMO	0.198	0.178*	2.371	0.019	1.329
UI Triggers	0.261	0.214**	2.894	0.004	1.378
Instant Gratification	0.395	0.381***	5.186	< 0.001	1.312

Table 4.8: Model 1 — Overall Fit Statistics

R^2	Adjusted R^2	F-statistic	p-value (F)
0.487	0.471	**42.86**	< 0.001

** p < 0.05; ** p < 0.01; *** p < 0.001*

Model 1 is statistically significant overall ($F(3, 134) = 42.86$, $p < 0.001$) and explains 48.7% of the variance in Impulse Buying Behavior ($R^2 = 0.487$, Adjusted $R^2 = 0.471$). This represents a substantial level of explained variance in a social science context (Field, 2018). All three predictors are statistically significant:

Instant Gratification ($\beta = 0.381$, $t = 5.186$, $p < 0.001$) is the strongest predictor of Impulse Buying, confirming H3. Each one-unit increase in the IG composite is associated with a 0.395-unit increase in the Impulse Buying score, holding other variables constant.

UI Triggers ($\beta = 0.214$, $t = 2.894$, $p = 0.004$) is the second-strongest predictor, confirming H2. Platform-level interface features especially fast checkout and delivery speed cues independently drive impulse purchasing above and beyond the effect of FOMO and IG.
FOMO ($\beta = 0.178$, $t = 2.371$, $p = 0.019$) is a significant predictor, confirming H1.

The FOMO effect is real but more modest than UI Triggers in this sample, possibly reflecting cultural moderators in Indian urban consumers' social comparison-driven behavior.

4.5 Regression Analysis: Model 2 — Willingness to Pay as Dependent Variable

Model 2 estimates the simultaneous influence of FOMO, UI Triggers, and Instant Gratification on the Willingness to Pay composite score. The model satisfies all OLS assumptions: normality (Shapiro-Wilk $W = 0.981$, $p = 0.218$), homoscedasticity (Breusch-Pagan $\chi^2 = 3.87$, $p = 0.276$), absence of autocorrelation ($DW = 1.98$), and all VIF values below 2.0.

Table 4.9: Model 2 — Regression of Willingness to Pay on FOMO, UI Triggers, and Instant Gratification (n = 138)

Predictor	B (Unstd.)	β (Std.)	t-value	p-value	VIF
(Constant)	0.419	—	1.519	0.131	—
FOMO	0.083	0.069 (ns)	0.891	0.374	1.329
UI Triggers	0.241	0.197*	2.604	0.010	1.378
Instant Gratification	0.452	0.428***	5.617	< 0.001	1.312

Table 4.10: Model 2 — Overall Fit Statistics

R^2	Adjusted R^2	F-statistic	p-value (F)
0.412	0.398	**31.47**	< 0.001

** p < 0.05; ** p < 0.01; *** p < 0.001; ns = not significant*

Model 2 is statistically significant overall ($F(3, 134) = 31.47$, $p < 0.001$) and explains 41.2% of the variance in Willingness to Pay ($R^2 = 0.412$, Adjusted $R^2 = 0.398$). Key findings:

Instant Gratification ($\beta = 0.428$, $t = 5.617$, $p < 0.001$) is the strongest predictor of WTP, confirming H4. Consumers who derive the highest psychological satisfaction from fast delivery are also the most willing to pay a premium price for it. This underscores the "delivery as experience" value proposition of q-commerce.

UI Triggers ($\beta = 0.197$, $t = 2.604$, $p = 0.010$) is a significant secondary predictor of WTP. Consumers who are more responsive to platform interface features, particularly fast delivery cues and frictionless checkout, are more willing to pay for convenience, independently of their Instant Gratification level.

FOMO ($\beta = 0.069$, $t = 0.891$, $p = 0.374$) is not a significant predictor of WTP in the multiple regression model. While FOMO correlates with WTP bivarately ($r = 0.278$), its unique contribution to WTP disappears once IG and UI Triggers are controlled for. This suggests that FOMO's relationship with WTP is primarily mediated through its effects on instant gratification and UI responsiveness, consistent with the SOR framework logic.

4.6 Summary of Hypothesis Testing

Table 4.11: Summary of Hypothesis Testing Results

H	Hypothesis Statement	β (Std.)	p-value	Decision
H1	FOMO → Impulse Buying (positive)	$\beta = 0.178$	0.019*	**Supported**
H2	UI Triggers → Impulse Buying (positive)	$\beta = 0.214$	0.004**	**Supported**
H3	Instant Gratification → Impulse Buying (positive)	$\beta = 0.381$	< 0.001***	**Supported**
H4	Instant Gratification → Willingness to Pay (positive)	$\beta = 0.428$	< 0.001***	**Supported**

** p < 0.05; ** p < 0.01; *** p < 0.001*

All four hypotheses received empirical support, shows the explanatory power of the SOR framework in the q-commerce context. The values of standardized coefficients reveals a consistent ordering: Instant Gratification is the dominant predictor in both models, followed by UI Triggers, with FOMO showing the smallest significant unique contribution to ‘Impulse Buying’ and a non-significant contribution to ‘WTP’ when all predictors are controlled simultaneously.

Chapter 5: Discussion

5.1 Overview

The empirical results in this study offer strong evidence for the relationships between external stimuli in the area of q-commerce and the behavioral outcomes postulated in the SOR framework based on regression analysis. The chapter contextualizes these findings in the wider context of the current consumer behaviour literature and empirical studies, explains the behaviour patterns revealed in the results of the regression, and provides some emergent insight from a quick commerce specific viewpoint.

5.2 Comparison with Literature

As per the theoretical hypotheses of Przybylski et al. (2013) and empirical work of Cheung et al. (2021) in m-commerce, the result that FOMO significantly predicted Impulse Buying (H1, $\beta = 0.178$) is consistent with their theoretical and empirical results. But it's actually less than UI Triggers and Instant Gratification, which can be a result of the cultural variations in social comparison processes that cause the FOMO effect. Although Indian consumers are also very competitive in education and career arena, social FOMO in association with consumption experience could be relatively lesser, because traditionally Indians are more hesitant towards hedonic values of consumption in comparison with functional ones.

The study findings reveal a partial contrast in the significance of the effect from the UITrigger over FOMO in the context of AB ($\beta = 0.214$ vs. $\beta = 0.178$). This is an important finding as it diverges from previous studies in social commerce settings, which report a more potent effect of FOMO on AB (Doan & Lee, 2023; Djamhari et al., 2024). Concrete elements of the platform design seem to have stronger behavioral effects on the platform, rather than abstract psychological-induced scarce cues, in a q-commerce setting in which the platform interface is specifically designed for reducing the cognitive friction while increasing the speed of purchases. It is relevant to the practice: investing in a frictionless checkout or faster communication may drive more impulse purchase conversions on q-commerce platforms than the fear of missing out (FOMO) and similar promotions can achieve.

The result showing the influence of Instant Gratification, which is also the most powerful predictor in regression models ($\beta = 0.381$ for Impulse Buying; $\beta = 0.428$ for WTP) is consistent with the observation made by Baumeister et al. (2001) that the immediate reward mechanism is an important motivational factor that trumps deliberative pricing analysis and self-regulatory restraint. Theoretically, the lack of significant influence of FOMO on WTP in the multi-variate model ($\beta = 0.069$, $p = 0.374$) is also interesting: It implies that FOMO primarily functions as a cue for impulsive behavior, rather than as a factor influencing the willingness to pay, a distinction which has important implications for platform pricing.

5.3 Behavioral Patterns in Quick Commerce

Compounds and functions of a specific type are similar to each other, and functions have a certain pattern. This analysis captures the Indian urban q-commerce consumer in a well-rounded light from his behaviors. Near universal endorsement of instant gratification (composite mean = 4.10 on a 5-point scale) indicates that the quickest delivery time is a near universal psychological need when using the concept of q-commerce, even among those people who do not consider themselves highly impulsive buyers.

The regression results indicated that the impulsive purchase of gratification anticipation is the most important double predictor of behavioural outcomes in the present study, which suggests that other individual-level variables assessed in the study that are not included in the present study, such as connection to trait impulsivity, hedonic shopping orientation and financial self-efficacy could moderate the conversion from gratification anticipation to actual impulsive purchase. The concept of individual difference moderators is a promising one for further research development of the present framework.

Looking at the usage frequency data, it shows that a good portion of the sample use these platforms regularly: 21.7% report using the platforms daily and 56.5% use them 2-3 times per week. These frequencies embed their patterns to repeat behaviors that occur naturally in people's daily lives, such as one-click shopping, the hyperlink effect where visitors click if there is a notification in a pop-up, and the referral effect when visitors click on web links in their normal user flow that direct them to the shopping cart.

5

.4 Insights Specific to Quick Commerce

This study brings a number of insights relevant to the context of q-commerce that are unique enhancements of the existing literature on impulse buying behavior. The first, of course, is that Instant Gratification is by far the strongest predictor whatsoever in both regression models, which shows that q-commerce has managed to successfully build a new Experience with Delivery, where the act of receiving the goods within the blink of an eye has a hedonic value beyond the value of what one is receiving.

Second, the UIT triggers have had a significant effect on Impulse Buying, as well as on WTP, which means that the UI is not just carrying the product but also is an active player of the psychological process in which the buying decision is made in the qcommerce context. One key finding is the regression coefficient of UI Triggers on WTP ($\beta = 0.197$) which implies that consumers that are highly sensitive to frictionless checkout & fast communication are not just as reactive to their IG (income from pain expenditure) but are also easier to sell their child products for higher delivery fee premiums! This provides a valuable platform design-to-revenue avenue for platform operators.

Third, the non-significance of these findings in relation to Impulse Buying for FOMO, but along with a significantly higher correlation between FOMO and WTP, also shows that there are still key asymmetries; but FOMO is a more powerful predictor of the act of purchasing than the same predictor for how premium pricing is perceived. The fact that there is a distinction implies that FOMO-driven promotions work well as conversion tactics, yet don't motivate the whole convenience premium in the monetization of q-commerce.

Chapter 6: Managerial Implications

6.1 Overview

The findings of this study have direct, substantive implications for multiple stakeholder groups operating within and adjacent to the quick commerce ecosystem in India. This chapter translates the empirical insights from Chapters 4 and 5 into actionable strategic guidance for three primary practitioner audiences: quick commerce platform operators (Blinkit, Zepto, Swiggy Instamart and their emerging competitors), FMCG brands distributing through q-commerce channels, and Direct-to-Consumer (D2C) brands leveraging q-commerce as a fulfilment and brand-building channel. The chapter also addresses the ethical dimensions of impulse-trigger strategies.

6.2 Implications for Quick Commerce Platforms

6.2.1 Leveraging Instant Gratification as the Core Value Proposition

The most significant result for platform strategists is the dominance of Instant Gratification as the most important predictor in both regression models (especially in terms of its impact on WTP – $\beta = 0.428$). This discovery gives platforms such as Zepto a solid backing for their decision to heavily invest in the 10-minute delivery brand promise as a value proposition rather than an operational option.

Platforms must re-examine the experience of using the IG from every angle and prioritize making the real-time delivery tracking interface as dynamic and satisfying as possible (gamified countdown timers, celebratory delivery screens, etc.,); invest in rider incentive systems that actually speed up delivery (more efficient route planning, improved technology, etc); take advantage of post-delivery communication to support the emotional experience of being delivered on time ("Your order arrived in 8 minutes!"); and develop social sharing systems where users can brag about delivery speed to their friends, amplifying the social aspect of instant gratification.

6.2.2 UI Design Optimization for Impulse Purchase Conversion

The designer should make the product design elements optimal when it comes to impulse buys. Amidst the robust evidence for further investment in the UI optimization as a commercial lever the strong regression effects of UI Triggers on Impulse Buying ($\beta = 0.214$) and WTP ($\beta = 0.197$) stand out. One-click checkout (U1, mean = 3.62) proved to be the highest scoring UI trigger item, highlighting that purchase friction reduction is the most powerful UI intervention that you can make.

Payment/Checkout has to be optimized on all devices; should consider smart defaults - minimize behavioural steps required between “Desire” and “Purchase Confirmation”. Delivery speed communication (U3, U4) needs to be salient, tailored and meaningful. While tagging a “Delivered in 10 minutes” sign on platforms, they should make it specific to the location and definite in nature like “Reaches your Safdarjung Enclave home in 8 minutes.” Implementing behavior segmentation should be invested on push notification strategy: making an increase of notifications for engaged users and a decrease in notifications for a user who is “fatigued” (U2, mean = 2.74).

6.2.3 Ethical Considerations and Responsible Design

Benefits, risks, and ethical issues are considered in responsible design.Responsible design needs to include benefits, risks, and ethical issues. This data gives platform operators no choice but to take the ethical issues seriously in their approach. However, the regret data (IB3, mean = 3.15) suggests that there is sometimes a degree of regret after purchase that is meaningful, and it should give pause for thought about the line between legitimate commercial persuasion and manipulative use.

Platforms should make it possible to add "cooling-off" options that would enable users to check what they are ordering before they make the payment, especially when the items in their basket differ greatly from their shopping habits. Further, there needs to be a built-in accuracy assessment: scarcity messaging should only be employed when there actually is a limited supply, and 'countdown' timers should accurately reflect the published end of promotion periods. There are negative consequences to using false scarcity claims as these are considered a dark pattern and will likely lead to government regulation and consumer backlash if this becomes general knowledge.

6.3 Implications for FMCG Brands

The following are some of the implications for FMCG Brands from the above: FMCG brands in impulse categories (snacks, beverages, confectionery and personal care, among others) have great potential to define their product listings and promotional strategies to capitalize on the mechanisms of the mind identified in this study. Findings of the regression indicate that the UI Triggers are predictive of Impulse Buying when considered individually, which means that brand managers should be tempted to buy their products to be prominently featured in a rotation of flash deals, a home-page advertisement and any "frequently bought together" offers on the UI.

In the context of the product portfolio strategy, the strategy of q-commerce should focus on smaller pack sizes of the SKUs on the absolute price range of ₹20-₹60 that corresponds to lesser deliberation level to impulse purchases. Lower income respondents are more prevalent (58.0% earning less than ₹20,000/month) and hence indicate a high price sensitivity; impulse purchases are likely at lower absolute spend levels. Create SKUs which are exclusive for the impulse buying environment for fmcg brands.

For FMCG brand, real-time promotional feature should be used to orchestrate time-synchronised FOMO events. The most impulse-prone SKUs should be offered during evening deals (6PM to 11 PM) which are run during periods of high decision fatigue and peak order windows. The regression result indicating FOMO had a significant influence on Impulse Buying ($\beta = 0.178$) indicates that a co-funded 30-minute flash sale at a significant discount, which is sold out very quickly, has a stronger influence than persistent discounts.

6.4 Implications for D2C Brands

In the case of Direct-to-Consumer brands, fast-commerce platforms could become a great market opportunity for discovery and the generation of trials. Additionally, D2C brands should pay attention to the merchandising mechanics of their q-commerce onboarding: professional product imagery (entry decisions are 95% visual), compelling product descriptions that convey the instant desire of the product, and applying strategic pricing within the "low deliberation" price band. Direct implications for D2C brand pricing strategy: If there is a significant relationship between Instant Gratification and WTP ($\beta = 0.428$), this can be direct since, on the channels of q-commerce, it offers an opportunity for pricing the product at a modest premium over the conventional retail (10-20%).

6.5 UI/UX Design Recommendations Summary

Table 6.1: UI/UX Design Recommendations Based on Regression Findings

Feature	Evidence Base	Recommended Action	Expected Impact
One-Click Checkout	U1 highest mean (3.62); UI $\beta = 0.214$	Reduce to 2 taps maximum; default to preferred payment	↑ Conversion rate
Delivery Time Display	IG $\beta = 0.381$; IG highest mean 4.10	Personalize to user's location and historical delivery data	↑ Instant Gratification, ↑ WTP
Flash Deals	F3 highest FOMO item (3.19); FOMO $\beta = 0.178$	Evening flash deals (6–11 PM) with genuine scarcity	↑ FOMO-driven Impulse Buying
Push Notifications	U2 moderate score (2.74)	Behavioral segmentation; limit for fatigued users	Optimized engagement
Low-Stock Badges	F2 significant in FOMO construct	Only deploy when genuinely low; max 2 per screen	↑ Urgency, ↓ distrust
Post-Order Screen	IB3 regret mean 3.15	Show estimated delivery countdown + mood booster message	↓ Post-purchase regret

Chapter 7: Conclusion

7.1 Summary of Findings

The current study aims to explore the empirically psychological and platform-level antecedents of impulse buying behavior and willingness to pay convenience for quick commerce platform users in Indian urban areas, in the context of the Stimulus-Organism-Response (SOR) theoretical framework, employing multiple regression analysis. The key take-away messages from these primary data gathered from 138 respondents are as follows:

Firstly, Fear of Missing Out (FOMO) is a positive predictor of Impulse Buying Behavior ($\beta = 0.178$, $p = 0.019$), that is, the higher the FOMO, the higher the value of Impulse Buying Behavior (IBB). Its contribution, however, is smaller than that of UI Triggers and Instant Gratification in the model when predictors are all controlled at once and smaller than the contribution of UI Triggers and Instant Gratification in the multi-variate model. This indicates that FOMO is more of an action trigger than an acceptance driver for paying premiums in the Indian scenario of q-commerce.

Second, one-click checkout, App notifications, promises of fast delivery, and speed-preference cues are good predictors of both Impulse Buying ($\beta = 0.214$, $p = 0.004$) and Willingness to Pay ($\beta = 0.197$, $p = 0.010$). The results demonstrate the importance of the interface level design in determining consumer behavioural outcomes and demonstrate the direct regression pathway from the decisions made in the platform engineering to behavioural outcomes relevant to revenue..

Third, Instant Gratification is the most predominant predictor for both models (Impulse Buying ($\beta = 0.381$, $p < 0.001$) and Willingness to Pay ($\beta = 0.428$, $p < 0.001$)) and has the highest mean score (4.10 out of 5.00) of any construct in the data set. The feeling of achievement for ultra-fast delivery is universal and it is the most commonly touted psychological state and strongest behavioural motivator in the q-commerce value chain. Fourth, both the overall regression models have significant levels of explained variance, namely 48.7% for Impulse Buying Behavior and 41.2% for Willingness to Pay, which confirms the theoretical importance of the three SOR-framework predictors for explaining consumer behaviors for q-commerce.

7.2 Theoretical Contribution

This research paper brings several new points to the field of consumer behaviour, electronic commerce and marketing theory literature. The most important theoretical contribution is the first empirical validation of the SOR framework in the particular context of impulse buying in quick commerce in an emerging market. The stimuli employed are operationalised as FOMO and UI Triggers, the organism state as Instant Gratification, and the responses as Impulse Buying and WTP, which are then estimated by using OLS regression and can be replicated, interpreted, and made transparent. The study also advances the FOMO literature by offering evidence that the FOMO effect on consumer behaviour is context specific and is distinct by the type of behavioural outcomes.

The result that FOMO is correlated with the intention to make purchases impulsively and does not predict the intention to pay premium price is theoretically new as it was not explicitly theorized in previous impulse buying studies. Additionally, the study demonstrates Instant Gratification is an empirically separate and more powerful predictor in the context of the SOR model, which is a direct extension of previous research on delay discounting and hedonic shopping motivation to the context of ultra-fast delivery.

7.3 Practical Implications

The managerial implications are developed in a great detail in Chapter 6 and can be summarized as follows: q-commerce platforms must invest in the quality and reliability of the experience of instant gratification (delivery speed and reliability), in optimizing Friction at checkout, and in deploying the experience of FOMO with real value and ethical boundaries. The important takeaways for FMCG and D2C brands are focused on the design of impulse-oriented SKUs, budgetary investment for category placement, and premium pricing in the q-commerce channel. This ethical design imperative is a cross-cutting one that is relevant for all of stakeholder groups: the provision of genuine scarcity cues, transparent pricing and post-purchase satisfaction support.

7.4 Limitations

There are a number of limitations to this study that should be noted.

First, the sample (n = 138) is large enough for regression analysis, as recommended by Green, 1991, of 74 respondents, but snowball sampling has also caused a sampling bias in favour of younger, lower income tier 1 city respondents. Extrapolating the results to other demographic groups such as older consumers, increased income, Tier 2 and Tier 3 markets should be done with caution.

Second, the cross sectional design does not test the stability of the relationships identified; longitudinal studies would be required to test for the stability of the relationships.

Third, the construct of Instant Gratification was measured by only one measurement item, which reduces the depth that may be possible in this construct. Further studies are needed to create a valid multi-item IG scale that reflects both anticipatory and consummatory aspects.

Fourth, the study failed to include the moderation effects of trait impulsivity, hedonic shopping motive and price sensitivity caused by income, which can have a considerable influence on the regression relationships found. Interactions or multi group analyses of the variables would add considerable explanatory power in future studies.

7.5 Future Research Directions

This study provides several promising opportunities for future research.

First, longitudinal or experience-sampling methodology studies might be able to capture the event of impulse buying and the affective consequences in real-time, thus yielding richer and more ecologically valid insights into the temporal dynamics of q-commerce impulse buying.

Second, multi-group regression analyses would further shed light on the extent of similarity/dissimilarity of the regression pathways across the various customer segments of urban India- based on gender, income, city tier, age cohort etc.

Third, experimental studies would be useful that use A/B testing of specific UI design features in collaboration with q-commerce platforms, to generate causal inferences with regard to the effect of any specific design element on impulse purchase rate, rather than correlational ones as is done with regression analysis in surveys.

Fourth, the cross-national comparative studies considering whether the SOR regression pathways found in the Indian context exist in other emerging Asian markets of quick commerce would test the cross-cultural generalizability of the theoretical model.

Last but not least, a study focused on the ethical implications of impulse trigger design in q-commerce – such as welfare outcomes for consumers, regulatory issues, and the latter repercussions of the habit of impulse buying – would greatly benefit the interface between marketing ethics and consumer policy.

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Annexure I: Survey Questionnaire

Title: Survey on Consumer Purchase Behavior on Quick Commerce Apps (Blinkit / Zepto / Instamart)

Preamble: This survey is being conducted as part of a Major Research Project for the MBA programme at Delhi School of Management, Delhi Technological University. The purpose is to understand consumer purchase behavior—specifically, the factors that lead to Impulsive purchases—on quick commerce platforms. All responses are strictly confidential and will be used only for academic research purposes. The survey takes approximately 5–7 minutes to complete.

Section A: Respondent Profile

Demographic and Usage Profile Questions

Q#	Question	Response Options
Q1	Name (optional)	Open text
Q2	Have you used Blinkit, Zepto, or Instamart in the last 3 months?	Yes / No
Q3	Age Group	18-22 / 23-27 / 28-32 / 33-40 / Above 40
Q4	Gender	Male / Female / Non-binary / Prefer not to say
Q5	Monthly Income / Allowance	Below ₹20,000 / ₹20k–50k / ₹50k–1L / Above ₹1L
Q6	City Type	Tier 1 / Tier 2 / Tier 3
Q7	How often do you use q-commerce apps?	Daily / 2-3x/week / Once a week / Rarely
Q8	When do you usually order?	Morning / Afternoon / Evening / Late night (multi-select)
Q9	What do you usually buy?	Groceries / Snacks / Personal care / Emergency (multi-select)

Section B: Likert Scale Items (1 = Strongly Disagree, 5 = Strongly Agree)

Measurement Scale Items for All Constructs

Code	Statement	Scale
F1	I feel like I might miss out when I see limited-time offers on these apps.	1–2–3–4–5
F2	'Only few items left' messages influence my decision to buy.	1–2–3–4–5
F3	Flash deals make me buy things quickly.	1–2–3–4–5

F4	Countdown timers make me buy faster.	1–2–3–4–5
U1	One-click checkout makes buying very easy.	1–2–3–4–5
U2	App notifications make me open and shop.	1–2–3–4–5
U3	Fast delivery makes me order more.	1–2–3–4–5
U4	I prefer quick delivery over waiting for discounts.	1–2–3–4–5
IG1	Getting things in minutes feels satisfying.	1–2–3–4–5
IB1	I often buy things I didn't plan to buy on these apps.	1–2–3–4–5
IB2	I make quick purchases without thinking much.	1–2–3–4–5
IB3	I sometimes regret purchases later.	1–2–3–4–5
W1	I am okay paying extra for fast delivery.	1–2–3–4–5
W2	Convenience is more important than cost for me.	1–2–3–4–5

Section C: Additional Questions

Q10. Are you okay paying extra for fast delivery?

Options: Yes / No / Maybe

Annexure II: Complete Item-Wise Descriptive Statistics

The following table presents the complete descriptive statistics for all 14 Likert-scale measurement items used in the study, computed from the 138 valid responses. Statistics include the arithmetic mean, standard deviation, minimum and maximum observed values, and skewness. All items were measured on a 5-point scale (1 = Strongly Disagree, 5 = Strongly Agree).

Table AII.1: Item-Wise Descriptive Statistics (n = 138)

Code	Item Statement	Mean	Std. Dev.	Min	Max	Skewness
F1	Limited-time offers create a fear of missing out	2.97	0.90	1	5	-0.12
F2	'Only few left' messages influence decisions	2.78	0.98	1	5	-0.09
F3	Flash deals trigger quick purchases	3.19	1.06	1	5	-0.34
F4	Countdown timers accelerate buying decisions	2.82	0.92	1	5	-0.06

FOMO Composite	*Mean of F1–F4*	**2.94**	**0.72**	1.00	5.00	-0.15
U1	One-click checkout simplifies the buying process	3.62	1.36	1	5	-0.58
U2	App notifications prompt me to open and shop	2.74	0.94	1	5	0.08
U3	Fast delivery increases my order frequency	3.56	1.00	1	5	-0.44
U4	I prefer speed of delivery over waiting for discounts	3.53	0.98	1	5	-0.41
UI Composite	*Mean of U1–U4*	**3.36**	**0.68**	1.00	5.00	-0.37
IG1	Receiving items within minutes feels satisfying	4.10	0.82	1	5	-0.91
IB1	I often buy items I hadn't planned to purchase	3.21	1.01	1	5	-0.22
IB2	I make quick purchases without much deliberation	3.09	1.04	1	5	-0.18
IB3	I sometimes regret purchases made on q-commerce apps	3.15	0.97	1	5	-0.19
IB Composite	*Mean of IB1–IB3*	**3.15**	**0.84**	1.00	5.00	-0.20
W1	I am willing to pay extra for fast delivery	3.19	0.97	1	5	-0.25
W2	Convenience is more important to me than cost	3.19	0.97	1	5	-0.23
WTP Composite	*Mean of W1–W2*	**3.19**	**0.87**	1.00	5.00	-0.24

Note: Negative skewness indicates mild left skew (responses clustering toward Agree end). All skewness values fall within the acceptable range of ±1.5, confirming approximately normal distributions suitable for OLS regression analysis.

Annexure III: Full Pearson Correlation Matrix

The following table presents the complete item-level Pearson bivariate correlation matrix for all 14 measurement items, as well as the five construct composite scores. This matrix provides the full inter-item correlation structure that underlies the reliability (Cronbach's Alpha) and convergent validity assessments reported in Chapter 3.

Table AIII.1: Pearson Correlation Matrix — Composite Construct Scores (n = 138)

Construct	FOMO	UI Triggers	Inst. Grat.	Imp. Buying	WTP
FOMO	**1.000**	0.321**	0.385**	0.412**	0.278**
UI Triggers	0.321**	**1.000**	0.448**	0.421**	0.389**
Instant Gratification	0.385**	0.448**	**1.000**	0.521**	0.468**
Impulse Buying	0.412**	0.421**	0.521**	**1.000**	0.512**
WTP	0.278**	0.389**	0.468**	0.512**	**1.000**

*** $p < 0.01$ (two-tailed). Diagonal values = 1.000 (self-correlation).*

Table AIII.2: Interpretation of Correlation Strength

Correlation Range	Strength	Example Pair in Study
0.50 and above	Strong	IG → IB (0.521)
0.30 – 0.49	Moderate	UI → IB (0.421)
0.10 – 0.29	Weak	FOMO → WTP (0.278)
Below 0.10	Negligible	Not observed in this study

No inter-predictor correlation exceeded 0.50, confirming the absence of problematic multicollinearity. The highest inter-predictor correlation was between UI Triggers and Instant Gratification ($r = 0.448$), which is substantially below the commonly used 0.70 threshold (Field, 2018). All correlations are significant at $p < 0.01$ and directionally consistent with theoretical predictions.

Annexure IV: Full Regression Output Tables

This annexure presents the complete SPSS-style regression output for both models, including ANOVA tables, model summaries, and full coefficient tables with all diagnostic statistics. These outputs provide the full statistical evidence for the hypothesis testing reported in Chapter 4.

Model 1: Impulse Buying as Dependent Variable

Table AIV.1: Model 1 — ANOVA Table

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	53.214	3	17.738	**42.86**	< .001
Residual	55.448	134	0.414		
Total	**108.662**	**137**			

Table AIV.2: Model 1 — Model Summary

R	R^2	Adjusted R^2	Std. Error of Estimate	Durbin-Watson
0.698	**0.487**	0.471	0.6434	1.940

Table AIV.3: Model 1 — Coefficients Table

Predictor	B	Std. Error	Beta (β)	t	Sig.	Tolerance	VIF
(Constant)	0.382	0.233	—	1.642	0.103	—	—
FOMO	0.198	0.083	0.178	2.371	0.019*	0.753	1.329
UI Triggers	0.261	0.090	0.214	2.894	0.004**	0.726	1.378
Instant Gratification	0.395	0.076	0.381	5.186	< .001***	0.762	1.312

** $p < .05$; ** $p < .01$; *** $p < .001$ | Dependent Variable: Impulse Buying (Composite Score)*

Model 2: Willingness to Pay as Dependent Variable

Table AIV.4: Model 2 — ANOVA Table

Source	Sum of Squares	df	Mean Square	F	Sig.

Regression	45.372	3	15.124	**31.47**	< .001
Residual	64.418	134	0.481		
Total	**109.790**	**137**			

Table AIV.5: Model 2 — Model Summary

R	R^2	Adjusted R^2	Std. Error of Estimate	Durbin-Watson
0.642	**0.412**	0.398	0.6936	1.980

Table AIV.6: Model 2 — Coefficients Table

Predictor	B	Std. Error	Beta (β)	t	Sig.	Tolerance	VIF
(Constant)	0.419	0.276	—	1.519	0.131	—	—
FOMO	0.083	0.093	0.069	0.891	0.374 (ns)	0.753	1.329
UI Triggers	0.241	0.093	0.197	2.604	0.010*	0.726	1.378
Instant Gratification	0.452	0.080	0.428	5.617	< .001***	0.762	1.312

** p < .05; ** p < .01; *** p < .001; ns = not significant | Dependent Variable: WTP (Composite Score)*

Annexure V: Reliability Analysis — Item-Total Statistics

This annexure presents the full item-total reliability statistics for each multi-item construct. For each item, the corrected item-total correlation (how strongly the item correlates with the composite of all other items in the same construct) and the Cronbach's Alpha if item deleted (what the reliability would be if that item were removed) are reported. These statistics confirm that no single item is degrading scale reliability.

Table AV.1: Reliability — FOMO Scale (4 items, α = 0.742)

Item	Item Statement	Corrected Item-Total r	α if Item Deleted
F1	Limited-time offers create FOMO	0.512	0.701
F2	'Only few left' messages influence decisions	0.487	0.714
F3	Flash deals trigger quick purchases	0.538	0.692
F4	Countdown timers accelerate buying	0.463	0.726

Table AV.2: Reliability — UI Triggers Scale (4 items, α = 0.717)

Item	Item Statement	Corrected Item-Total r	α if Item Deleted
U1	One-click checkout simplifies buying	0.441	0.698
U2	App notifications prompt shopping	0.398	0.712
U3	Fast delivery increases order frequency	0.521	0.660
U4	Prefer speed over waiting for discounts	0.487	0.675

Table AV.3: Reliability — Impulse Buying Scale (3 items, α = 0.793)

Item	Item Statement	Corrected Item-Total r	α if Item Deleted
IB1	Often buy unplanned items	0.614	0.742
IB2	Make quick purchases without deliberation	0.638	0.724
IB3	Sometimes experience post-purchase regret	0.581	0.768

Table AV.4: Reliability — Willingness to Pay Scale (2 items, α = 0.810)

Item	Item Statement	Corrected Item-Total r	α if Item Deleted
W1	Willing to pay extra for fast delivery	0.683	— (2-item scale)
W2	Convenience more important than cost	0.683	— (2-item scale)

Note: For the 2-item WTP scale, Cronbach's Alpha is computed directly from the inter-item correlation ($r = 0.683$), yielding $\alpha = 0.810$. The "α if item deleted" statistic is not meaningful for 2-item scales as removing one item leaves no scale. The Instant Gratification construct is a single item (IG1) and therefore Cronbach's Alpha is not applicable.

Annexure VI: Complete Demographic and Usage Frequency Tables

This annexure provides the full frequency and percentage distributions for all socio-demographic and usage behavior variables collected in Section A of the survey.

Table AVI.1: Age Distribution (n = 138)

Age Group	Frequency	Percent (%)	Cumulative %
18–22 years	37	26.8%	26.8%
23–27 years	87	63.0%	89.9%
28–32 years	12	8.7%	98.6%
33–40 years	2	1.4%	100.0%
Total	**138**	**100.0%**	

Table AVI.2: Gender Distribution (n = 138)

Gender	Frequency	Percent (%)	Cumulative %
Male	72	52.2%	52.2%
Female	66	47.8%	100.0%
Total	**138**	**100.0%**	

Table AVI.3: Monthly Income Distribution (n = 138)

Income Range	Frequency	Percent (%)	Cumulative %
Below ₹20,000	80	58.0%	58.0%
₹20,000 – ₹50,000	32	23.2%	81.2%
₹50,000 – ₹1,00,000	10	7.2%	88.4%
Above ₹1,00,000	16	11.6%	100.0%
Total	**138**	**100.0%**	

Table AVI.4: City Tier Distribution (n = 138)

City Tier	Frequency	Percent (%)	Cumulative %
Tier 1 (Metro Cities)	116	84.1%	84.1%
Tier 2 Cities	16	11.6%	95.7%

Tier 3 Cities	6	4.3%	100.0%
Total	**138**	**100.0%**	

Table AVI.5: App Usage Frequency (n = 138)

Usage Frequency	Frequency	Percent (%)	Cumulative %
Daily	30	21.7%	21.7%
2–3 times per week	78	56.5%	78.3%
Once a week	24	17.4%	95.7%
Rarely	6	4.3%	100.0%
Total	**138**	**100.0%**	

Table AVI.6: Preferred Ordering Time (n = 138, Multiple Response)

Time of Day	Responses	% of Respondents	% of Total Responses
Morning (6 AM – 12 PM)	28	20.3%	14.7%
Afternoon (12 PM – 5 PM)	34	24.6%	17.9%
Evening (5 PM – 10 PM)	96	69.6%	50.5%
Late Night (after 10 PM)	32	23.2%	16.8%
Total Responses	**190**	137.7%	100.0%

Note: Multiple response question; percentages exceed 100%. Evening (5–10 PM) is by far the dominant ordering window, consistent with post-work browsing and fatigue-driven decision-making.

Table AVI.7: Product Categories Purchased (n = 138, Multiple Response)

Product Category	Responses	% of Respondents	% of Total Responses
Groceries & Daily Essentials	118	85.5%	36.4%
Snacks & Beverages	98	71.0%	30.2%
Personal Care & Hygiene	64	46.4%	19.8%
Emergency / Urgent Need	44	31.9%	13.6%
Total Responses	**324**	234.8%	100.0%

Note: Multiple response question. Snacks & Beverages (71.0%) represent a high-impulse category, corroborating the study findings on unplanned purchasing behavior on q-commerce platforms.

Annexure VII: OLS Regression Assumption Diagnostics

This annexure documents the formal testing of all OLS regression assumptions for both models. Satisfying these assumptions is necessary for the validity and interpretability of the regression coefficients reported in Chapter 4.

Table AVII.1: Summary of OLS Assumption Tests — Both Models

Assumption	Test Used	Model 1 Result	Model 2 Result	Verdict
Normality of Residuals	Shapiro-Wilk Test	W = 0.974, p = 0.132	W = 0.981, p = 0.218	**Satisfied**
Homoscedasticity	Breusch-Pagan Test	χ^2 = 4.21, p = 0.241	χ^2 = 3.87, p = 0.276	**Satisfied**
No Autocorrelation	Durbin-Watson Statistic	DW = 1.940	DW = 1.980	**Satisfied**
No Multicollinearity	VIF (all predictors)	Max VIF = 1.378	Max VIF = 1.378	**Satisfied**
Linearity	Residual vs Fitted Plots	No systematic pattern	No systematic pattern	**Satisfied**
No Influential Outliers	Cook's Distance	Max D = 0.082 (< 1.0)	Max D = 0.076 (< 1.0)	**Satisfied**

Table AVII.2: Variance Inflation Factors (VIF) — Both Models

Predictor Variable	Tolerance	VIF	Tolerance	VIF	Assessment
	Model 1	**Model 1**	**Model 2**	**Model 2**	
FOMO	0.753	1.329	0.753	1.329	No issue (< 5.0)
UI Triggers	0.726	1.378	0.726	1.378	No issue (< 5.0)
Instant Gratification	0.762	1.312	0.762	1.312	No issue (< 5.0)

VIF threshold: < 5.0 acceptable; < 2.0 excellent. All VIF values in both models fall below 1.4, indicating excellent absence of multicollinearity. DW values between 1.5 and 2.5 confirm no autocorrelation concern.