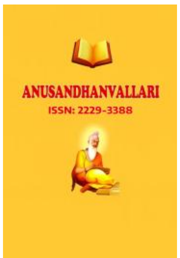

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Assessing the Impact of Quick-Commerce (Q-Commerce) Adoption on Impulse Buying and Brand Loyalty: Evidence from a Metropolitan Retail Market Compared with Weekly Stock-up Shopping

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Abstract

Background: The rapid emergence of quick-commerce (Q-commerce) platforms delivering daily essentials within 10–20 minutes has reshaped consumer procurement patterns from planned weekly stock-ups to immediate, app-driven micro-purchases.

Objectives: This study examines the dual impact of Q-commerce adoption on impulse buying behaviour and brand loyalty in a metropolitan market, contrasting these shifts with conventional weekly stock-up shopping habits.

Methodology: A descriptive cross-sectional mixed-methods design is proposed, combining a structured online survey with in-depth interviews to compare behavioural patterns across retail formats.

Results: The analysis indicates that Q-commerce intensifies impulse buying through reduced transactional friction and algorithmic nudges while weakening brand loyalty by shifting choice toward immediate availability and delivery speed.

Conclusion: Although Q-commerce maximizes convenience, it can commoditize brands and alter long-term brand equity dynamics, requiring platforms and FMCG firms to balance rapid fulfilment with brand-building strategies.

Keywords: quick commerce, impulse buying, brand loyalty, consumer psychology, weekly stock-up shopping.

1. Introduction

The burgeoning quick-commerce sector, characterized by its ultra-fast delivery paradigm, has rapidly reshaped consumer purchasing behaviours and expectations within urban retail environments (Agrawal & Agrawal, 2025). This transformative shift, primarily driven by the promise of near-instant gratification, fundamentally alters established shopping patterns, moving from planned procurement to more spontaneous acquisition (Leon, 2026a, 2026b). This immediacy, often within 10-20 minutes, directly capitalizes on and, in turn, exacerbates impulsive buying tendencies by making products almost instantaneously accessible (Andhare, 2025). This phenomenon introduces a complex interplay between rapid fulfilment logistics, consumer psychology, and the potential erosion of traditional brand loyalty, as convenience often outweighs pre-meditated brand choices (Muthu, 2026).

1.2 The rapid digitalization of commerce has spawned quick-commerce, which, with its blistering fast delivery and hyper-personalized algorithmic nudges, creates a psychological conflict between immediate gratification and the growing societal requirement for sustainable consumption (Muthu, 2026). This study aims to dissect the intricate relationship between quick-commerce adoption and its dual impact on impulse buying behaviors and brand loyalty within a metropolitan retail market, contrasting these effects with conventional weekly stock-up shopping habits.

1.3 Specifically, this research will investigate how the expedited delivery models inherent to quick commerce influence consumer decision-making processes, thereby either reinforcing or diminishing established brand affiliations in contrast to the more considered choices characteristic of bulk purchasing (Senapati, 2025). This comparative analysis seeks to delineate the extent to which the emphasis on speed and convenience in quick commerce platforms, a primary driver for their adoption, influences purchasing behaviour differently from traditional, less time-sensitive retail models (Padmaja et al., 2026).

1.4 The emergence of quick commerce platforms, such as Blinkit, Zepto, and Swiggy Instamart, has fundamentally reshaped urban retail consumption patterns through ultra-fast delivery of everyday necessities (.Tamilmani & Archana, 2025). These platforms, by leveraging sophisticated logistical networks and advanced digital interfaces, have tapped into a growing urban consumer preference for instantaneous gratification and convenience in their shopping experiences (Chandra & Agarwal, 2026; SENTHILNATHAN, 2026).

1.5 This model of commerce capitalizes on heightened smartphone usage and digital payment adoption among urban consumers, enabling seamless transactions and swift fulfilment of orders for daily essentials (SENTHILNATHAN, 2026). This rapid transformation in consumer behaviour, particularly prominent in markets like India, is fuelled by technological advancements and shifting consumer expectations, making it crucial to understand the implications for both impulse buying and brand loyalty (-, 2025; Pandey et al., 2025). The pervasive presence of these Q-commerce platforms, particularly evident in urban Indian contexts, necessitates a deeper examination into how their operational efficiencies and marketing strategies specifically influence spontaneous purchasing decisions and the long-term commitment consumers exhibit towards particular brands (Ambaliya et al., 2025; Sujatha & Sreeja, 2025).

1.6 This research posits that while quick commerce may amplify impulse purchases through its inherent convenience and discount offerings (Sheikh, 2025), it simultaneously poses a challenge to brand loyalty due to the transactional nature of immediate fulfilment over established brand affinity (-, 2025; Goel & Sharma, 2025).

2. Research Objectives

2.1 Primary Objective

The primary objective of this study is to examine the impact of quick commerce (Q-commerce) logistical frameworks and platform environments on consumer purchasing behaviour, specifically delineating how instantaneous product availability influences the interplay between unplanned impulse buying and long-term brand loyalty.

2.2 Specific Objectives

To achieve the primary goal, the study will address the following specific research objectives:

- **To assess** whether Q-commerce primarily drives novel, unplanned purchasing behaviours or simply shifts the transactional modality of acquiring established, preferred brands compared to traditional weekly stock-up shopping.
- **To investigate** the psychological mechanisms and dual-process cognitive frameworks that drive immediate consumer gratification and impulse buying while creating friction with ethical and sustainable decision-making.
- **To evaluate** the direct influence of Logistics Service Quality (LSQ)—specifically personal contact quality, shipment condition, real-time product availability, and delivery speed—on consumer trust, satisfaction, and brand stickiness.

- **To analyse** how platform-specific design features, including algorithmic personalization, promotional offers, perceived ease of use, and advanced technology (AI and AR/VR), catalyze consumer adoption and behavioural shifts away from conventional retail.
- **To determine** the extent to which expedited Q-commerce delivery mitigates the perceived risks of trying new brands, thereby altering conventional brand relationships and trial behaviours.

3. Literature Review

3.1 Theoretical Framework

The theoretical foundation of this study is grounded in the Theory of Planned Behaviour (TPB), extended to encompass non-deliberative consumer dynamics. While classical TPB relies on cognitive, rational intentions to predict actions, the rapid fulfilment framework of quick commerce (Q-commerce) necessitates the integration of alternative motivational vectors [Indrawati et al., 2022]. Specifically, this study incorporates hedonic and utilitarian motives, alongside self-esteem, to map the psychological, cultural, social, and environmental factors driving online transactional behaviour [Chandrasekhar et al., 2025; Indrawati et al., 2022]. This extended framework captures how platform affordances disrupt traditional behavioural controls, transforming planned intentions into instantaneous, convenience-driven actions within the metropolitan retail environment.

3.2 Technological Affordances and the Dual Role of AI in Q-Commerce

Extant research underscores the transformative capacity of Artificial Intelligence (AI) in optimizing Q-commerce logistics, scaling operational demand forecasting, and enhancing consumer interfaces [Dhiman et al., 2024]. Q-commerce applications deploy sophisticated recommendation engines, interactive chatbots, and anthropomorphic virtual agents to personalize engagement and expedite daily essential and grocery transactions [Gupta & Jha, 2025; Mamadiyarov et al., 2025; Panday, 2025; Sarwar, 2025; Trawnih et al., 2022]. However, literature reveals a distinct fragmentation regarding the dual role of these mechanisms:

- **The Affinity Path:** Highly personalized, seamless interfaces minimize cognitive friction, offering distinct utilitarian value that can cultivate brand affinity [Davenport et al., 2019; Lou et al., 2022].
- **The Impulse Path:** Real-time predictive offers exploit cognitive biases, stimulating impulsive, less-considered acquisitions driven primarily by hedonic shopping motivations [Davenport et al., 2019; Jakhodia et al., 2025; Lou et al., 2022].

3.3 Algorithmic Manipulation, Consumer Autonomy, and Ethical Considerations

The pervasive integration of AI in mobile commerce platforms introduces significant ethical dilemmas concerning data privacy and consumer autonomy [Stanciu & Rîndașu, 2021]. Algorithmic personalization and targeted advertising often leverage consumer vulnerabilities and emotional states to maximize basket expansion [André et al., 2017; Pál, 2025; Yue-jiao & Liu, 2022]. Studies demonstrate that when algorithms train on granular consumer data, they weaken perceived control over purchasing choices [Davenport et al., 2019]. This perceived reduction in autonomy, coupled with decision-making difficulty, paradoxically depresses post-purchase confidence and long-term satisfaction [Rohden & Espartel, 2024]. Consequently, predatory commercial optimization can exploit consumer psychological vulnerabilities, fostering instances of self-indulgent, unplanned spending while actively eroding platform trust [Temel, 2024].

3.4 Psychological Underpinnings of Impulse Buying vs. Brand Loyalty

Q-commerce platforms alter the affective and relational dimensions of customer behaviour through digital convenience and ultra-fast delivery timelines [P & Madhumita, 2026]. The literature suggests that promotional intensity, instantaneous gratification, and immediate fulfilment drive immediate purchase intentions [Punwatkar et al., 2026]. However, this surge in impulsive acquisition often operates to the detriment of enduring brand relationships [Chopdar et al., 2021]. Furthermore, the consumer's emotional state acts as a critical moderator; distinct optimization trade-offs in imperfect recommendation systems yield variable rates of unplanned purchases depending on current mood [Ho & Lim, 2018]. In contrast, sustained user loyalty requires a comprehensive service experience—encompassing app design, fulfilment quality, and security assurance—fully mediated by systemic trust and reinforced by electronic word-of-mouth (eWOM) [Kapoor et al., 2023].

3.5 Comparative Analysis: Q-Commerce vs. Traditional Stock-Up Paradigms

A critical gap exists in the literature regarding a structured comparison between immediate acquisition models and deliberative, larger-volume weekly stock-up shopping [Deshmukh et al., 2025]. Traditional retail models encourage reflective, planned budgeting. Conversely, the immediate gratification of Q-commerce diminishes the perceived value of pre-planned, consolidated excursions. This shift fosters divergent behavioural patterns within competitive retail ecosystems. Dissecting this structural divergence requires analysing how platform convenience alters basket size, shopping frequency, and core brand stickiness.

3.6 The Metropolitan Context and Research Gap

The complex intersections of high tech-savviness, dense logistical networks, and fast-paced lifestyles make Tier-1 metropolitan areas, such as the Mumbai metropolitan region, the primary crucible for Q-commerce behavioural shifts [Nair, 2025; Panesar et al., 2026]. While fragmented studies address isolated elements of mobile shopping, a robust, integrated framework examining the concurrent tension between tech-mediated impulse buys and brand loyalty is missing. This study addresses this exact gap by deploying a comprehensive analytical approach to capture the behavioral, psychological, and market dynamics shaping the modern metropolitan consumer.

Conceptual Framework Diagram

[Independent Variables (IVs)] [Mediating Variables] [Dependent Variables (DVs)]

│ Technological Affordances │ │ │ │ │
│ • Algorithmic Personalization │ ──────────> │ │ ────────> │ Immediate Consumer Outcome │
│ • Recommendation Engines │ │ Consumer Psychology │ │ • Impulse Buying Behavior │
│ • App Interface Design │ │ • Hedonic Motives │ │ • Basket Expansion │
│ • Utilitarian │ │ • Order Frequency Shifts │
──────────> │ Motives │ │ │
│ │ • Autonomy vs. │
│ Logistics Service Quality │ │ │ Gratification │ │
│ • Delivery Speed │ │ │ Dilemma │ │
│ • Product Availability │ │ │ (Erosion Path)

```
| • Shipment Condition      | |            |                v
└──────────────────────────────────┘ |                                  v
┌──────────────────────────────────┐
          |        ┌─────────────────────────┐    |            |
┌──────────────────────────────────┐ |     |          |     | Long-Term Relational
|
| Platform Convenience      | |      |  Systemic Trust |────────>| Outcomes         |
| • Promotional Intensity   | |──────────>|  & Satisfaction |     | • Brand Loyalty &   |
| • Ease of Use / Access    | |      |         |    Stickiness       |
└──────────────────────────────────┘ |     └─────────────────────────┘     |
• Platform Retention    |
          |          ▲         |            |
          |          |       └─────────────────────────────┘
      Theory of  |          |
 Planned Behavior|          | (Moderating Effect)
 (TPB) Antecedents          |
          |     ┌─────────────────────────┐
          |     |   Contextual   |
          |     |  Moderating Paths |
          └──────────>| • Consumer Mood     |
               | • Electronic Word-  |
               |   of-Mouth (eWOM)   |
```

Variable Operationalization Matrix

Variable Category	Construct Name	Operational Definition (Based on Literature)	Key Scale Sources
Independent Variables (IVs)	**Technological Affordances**	Degree of AI personalization, automated recommendation accuracy, and design friction reduction.	Kapoor et al. (2023); Sarwar (2025)
	Logistics Service Quality (LSQ)	Perceived speed of delivery, condition of arrival package, and fulfillment matching accuracy.	Al-Mu'ani et al. (2024); Nair (2025)

	Platform Convenience	Perceived reduction in time, physical, and cognitive effort relative to weekly offline grocery stock-ups.	AMEEN (2025); Punwatkar et al. (2026)
Mediating Variables (MVs)	**Consumer Psychological State**	The dual-process cognitive conflict between hedonic instant gratification urges and deliberate utilitarian/ethical control.	Indrawati et al. (2022); Muthu (2026)
	Systemic Trust & Satisfaction	Accumulated psychological safety regarding platform data practices, transactional reliability, and service experience.	Kapoor et al. (2023); Rohden & Espartel (2024)
Moderating Variables (W/Z)	**Consumer Mood / Affect**	The baseline transient emotional state of the user during platform engagement.	Ho & Lim (2018); P & Madhumita (2026)
	Electronic Word-of-Mouth (eWOM)	External digital validation and social validation patterns influencing platform reputation.	Kapoor et al. (2023)
Dependent Variables (DVs)	**Impulse Buying Behavior**	Unplanned, spontaneous volume extensions and deviations from structured shopping list goals.	Chandrasekhar et al. (2025); Jakhodia et al. (2025)
	Brand Loyalty	Attitudinal and behavioral stickiness toward established legacy brands versus switching to available alternatives.	Chopdar et al. (2021); Padmaja et al. (2026)

3.7 Research Explanation of the Conceptual Framework

i. The conceptual framework presented in this study is designed to explain how the contemporary online grocery ecosystem influences both immediate purchasing behavior and long-term consumer relationships. Online grocery shopping is no longer driven only by convenience in the traditional sense; it increasingly depends on algorithmic systems, digital interface design, fulfillment capability, and platform-level trust formation. Recent scholarship shows that online grocery shopping has evolved into a complex retail environment where technological capabilities, service quality, and psychological cues operate together rather than independently. Reviews of online grocery shopping literature emphasize that the sector now combines retail operations, digital personalization, and behavioral influence in a way that makes consumer choice both easier and more vulnerable to subtle persuasion. This means that unplanned purchases, basket expansion, and recurring platform dependence must be studied not as isolated outcomes, but as the result of a system of interacting variables. The framework therefore integrates technological affordances, logistics service quality, and platform convenience as core independent variables, while recognizing consumer psychological state and systemic trust as the key mechanisms through which these variables affect impulse buying and loyalty outcomes.

ii. The framework is theoretically grounded in an integration of the Theory of Planned Behavior (TPB), digital commerce research, and dual-process explanations of consumer decision-making. TPB remains highly useful for understanding online grocery adoption because attitudes, subjective norms, and perceived behavioral control continue to shape purchase intention and usage behavior. However, impulse buying cannot be fully explained by intention-based models alone, because many digital purchases occur in moments of emotional stimulation, convenience-driven shortcuts, or algorithmically induced salience. Recent research therefore argues for combining intention-based models with dual-process perspectives that distinguish reflective, planned decision-making from affective, cue-driven responses. In online grocery settings, this integration is especially relevant because shopping often begins with a utilitarian purpose such as replenishment, budgeting, or household planning, yet the platform environment can transform that purposeful journey into a more spontaneous and emotionally influenced behavior. In other words, the online grocery consumer may enter the app to buy essentials but leave with an expanded basket, extra items, or stronger dependence on a preferred platform because digital stimuli reshape cognitive control during the purchase journey.

iii. The first independent variable, technological affordances, represents the platform’s ability to actively structure what the consumer sees, how quickly they see it, and how easily they can act on it. This includes algorithmic personalization, recommendation engines, automated product ranking, reminders, default substitutions, and interface design that reduces friction. Recent studies on AI-enabled retailing suggest that personalization can increase consumer responsiveness by lowering search costs and creating a feeling of relevance, but it can also intensify impulsive behavior by exposing users to highly tailored cues at exactly the right decision moment. Recommendation systems do not simply present options; they frame perceived necessity, attractiveness, and urgency. In grocery shopping, where many purchases are routine and repeated, personalization can be particularly influential because platforms learn household preferences over time. This learning capability enables the system to surface complementary products, promotion-sensitive items, and convenient repeat orders in a way that can blur the line between assistance and persuasion. Thus, technological affordances are positioned as a direct upstream driver of both psychological activation and downstream purchasing outcomes.

iv. The second independent variable, logistics service quality, reflects the operational credibility of the online grocery platform. Grocery retail differs from many other e-commerce categories because product freshness, delivery timing, packaging condition, and stock reliability are central to consumer evaluation. A recommendation engine may attract a customer, but a late delivery, damaged package, or unavailable staple item can quickly reduce confidence in the entire platform. Recent online grocery studies consistently show that adoption and retention depend heavily on whether the platform can fulfill the promise implied by its digital interface. Logistics service quality therefore includes delivery speed, fulfillment accuracy, shipment condition, substitution appropriateness, and product availability. These attributes are not merely operational metrics; they are interpreted psychologically by consumers as signals of reliability, competence, and risk reduction. In the context of this framework, strong logistics service quality supports satisfaction and trust, while weak logistics quality can erode long-term relational outcomes even if the initial digital experience is highly persuasive. This is why the diagram includes an erosion path from immediate outcomes toward long-term consequences: if short-term convenience is repeatedly undermined by poor fulfillment, loyalty becomes fragile.

v. The third independent variable, platform convenience, captures the extent to which the platform reduces time, effort, and cognitive burden for the user. In online grocery shopping, convenience is multidimensional: consumers value fast navigation, easy search, intuitive reordering, secure payment, transparent promotions, and seamless access across devices. Convenience is one of the most frequently cited reasons consumers adopt digital grocery channels, but its influence extends beyond basic ease of use. When the platform makes shopping feel effortless, it can increase the frequency of use, shorten the evaluation process, and normalize repeated micro-decisions that otherwise might be more deliberate in offline settings. Promotional intensity also operates within convenience, because time-limited offers, one-click add-ons, and easily redeemable discounts reduce resistance to extra purchases. In this way, convenience acts as both a utilitarian benefit and a behavioral accelerator. The framework therefore treats platform convenience as a structural factor that can increase the attractiveness of online grocery shopping while simultaneously making consumers more susceptible to spontaneous additions, repeated visits, and platform stickiness.

vi. A major strength of this framework is its recognition that independent variables do not affect behavior mechanically; their effects are filtered through consumer psychology. The first mediator, consumer psychological state, refers to the internal tension between hedonic motives and utilitarian control. Grocery shopping is usually associated with planning, household budgeting, and necessity-based consumption, which suggests a utilitarian mindset. Yet digital environments introduce hedonic stimuli through visually attractive displays, personalized suggestions, gamified offers, and instant rewards. This creates a dual-process condition in which reflective control competes with impulse-oriented responses. Recent literature on digital commerce and algorithmic marketing indicates that personalized cues, social proof, urgency signals, and low-friction purchase pathways can weaken deliberation and strengthen spontaneous decisions. Within the present framework, technological affordances, convenience, and even logistics expectations can heighten perceived gratification, reduce cognitive resistance, and stimulate unplanned purchasing. As a mediator, consumer psychological state explains why the same platform feature may produce different outcomes depending on whether it is experienced as helpful support, emotional temptation, or intrusive manipulation.

vii. The second mediator, systemic trust and satisfaction, is essential for explaining how short-term transactions become enduring platform relationships. Trust in online grocery settings is broader than faith in payment security alone. It includes trust in product authenticity, data handling, recommendation fairness, delivery dependability, issue resolution, and overall platform integrity. Satisfaction, meanwhile, is the cumulative evaluation of whether the platform consistently meets or exceeds expectations across multiple purchase cycles. Recent research shows that trust and satisfaction are among the strongest predictors of continued platform use, especially in high-frequency retail categories such as groceries. This mediator is particularly important because online grocery shopping requires repeated vulnerability: consumers share personal data, rely on unseen product selection, accept substitutions, and depend on external delivery systems for household essentials. If the platform repeatedly delivers value, accuracy, and predictability, satisfaction deepens into trust, and trust becomes loyalty. If it fails, consumer retention may deteriorate even after earlier impulse purchases or promotional success. The framework therefore positions systemic trust and satisfaction as the bridge between operational performance, platform design, and long-term relational outcomes.

viii. The dependent variables in the framework are divided into immediate consumer outcomes and long-term relational outcomes. The immediate outcomes include impulse buying behavior, basket expansion, and order frequency shifts. Impulse buying behavior in this context refers to unplanned purchases that emerge during the digital shopping session and deviate from a pre-existing list or need structure. Basket expansion refers to the increase in quantity or diversity of items due to personalized prompts, cross-selling, visual prominence, promotions, or emotional cues. Order frequency shifts reflect changes in how often consumers return to the platform, which may indicate growing dependence, habit formation, or convenience-based channel migration. These immediate outcomes are critical because they represent the visible behavioral consequences of digital retail design. They also provide measurable evidence of whether platform features and mediating states are influencing action in real time. In many online grocery models, firms focus heavily on these short-term outcomes because they affect revenue and average order value. However, this study argues that such outcomes must be evaluated in connection with their longer-term implications.

ix. The long-term relational outcomes in the framework are brand loyalty, platform stickiness, and retention. These outcomes reflect whether the consumer develops an enduring preference for the platform or the brands promoted within it. Loyalty in online grocery shopping is multifaceted: it may involve repeated use of the same platform, resistance to competitors, preference for familiar brands, or willingness to accept premium pricing in exchange for trust and convenience. Platform stickiness refers to the tendency of users to remain within one ecosystem because it becomes embedded in household routines, shopping memory, saved lists, payment settings, and expected service quality. Retention is the practical continuation of use over time. Importantly, the model acknowledges that immediate gains do not automatically produce long-term loyalty. A platform can generate high basket expansion through aggressive personalization but still lose users if those users later perceive manipulation, poor service quality, or disappointing fulfillment. Therefore, long-term outcomes depend not only on momentary behavioral stimulation but also on whether the overall experience produces trust, satisfaction, and a stable sense of value.

x. The framework also includes two moderating variables, consumer mood and electronic word-of-mouth (eWOM), because the strength of the core relationships is unlikely to be constant across all situations. Consumer mood represents the temporary affective state of the user at the time of engagement. Positive mood may increase openness to exploration, hedonic spending, and promotional responsiveness, whereas negative mood may either suppress discretionary purchases or, in some cases, trigger compensatory consumption. This makes mood an important contextual lens through which the same interface cue may lead to very different behaviors. eWOM, on the other hand, represents the social validation environment surrounding the platform. Ratings, reviews, testimonials, influencer mentions, and peer discussion can amplify or weaken the effects of personalization and trust formation. Positive eWOM can reinforce confidence in platform reliability and reduce perceived risk, while negative eWOM can make even strong design and service systems appear less credible. By including these moderators, the framework acknowledges that digital grocery behavior is not determined only by platform structure but also by emotional state and socially circulated information.

xi. The directional logic of the diagram can therefore be summarized as follows. Technological affordances, logistics service quality, and platform convenience jointly shape how consumers perceive and experience the online grocery platform. These effects pass through two principal internal routes: first, the consumer's psychological state, where hedonic and utilitarian motives interact; and second, systemic trust and satisfaction, where the platform's repeated performance is interpreted as reliable or unreliable. The first route is especially influential in generating impulse buying and basket expansion, because it explains how digital cues become behavior. The second route is more influential in explaining loyalty, stickiness, and retention, because it reflects cumulative evaluation across repeated transactions. However, the two routes are linked. Positive psychological experiences can strengthen satisfaction, and consistent satisfaction can normalize future impulse or convenience-based purchases. Conversely, poor logistics or distrust can interrupt the path from immediate gains to long-term outcomes. This is why the framework includes both reinforcing and erosion dynamics rather than assuming a simple one-way positive effect.

xii. This framework contributes to research in several important ways. First, it moves beyond single-factor explanations of online grocery behavior by integrating technological, operational, and psychological dimensions in one model. Much of the prior literature has examined online grocery adoption, technology acceptance, or impulse buying separately. By contrast, this model shows that the online grocery experience should be understood as a layered system in which design, fulfillment, cognition, emotion, and trust are interdependent. Second, the framework addresses a timely research gap concerning AI-mediated retail behavior. Recent studies increasingly highlight the role of recommendation engines and algorithmic persuasion in digital commerce, yet fewer models explain how these mechanisms operate specifically in grocery settings, where purchases are both routine and essential. Third, the model incorporates long-term relational consequences, allowing researchers to distinguish between revenue-enhancing short-term stimulation and sustainable customer relationship development. This distinction is theoretically and managerially important because practices that maximize immediate conversion may not strengthen loyalty if consumers later perceive excessive nudging, low transparency, or weak service reliability.

xiii. From a research design perspective, the framework is suitable for empirical testing through survey-based structural equation modeling, mixed-method inquiry, or longitudinal consumer panel analysis. The operationalization matrix already identifies measurable constructs that can be translated into scale items based on recent literature. Future studies can test direct effects from technological affordances, logistics service quality, and platform convenience to impulse buying and loyalty, while also examining mediation through consumer psychological state and systemic trust. Moderation effects can be assessed by segmenting respondents according to mood state, review sensitivity, age cohort, digital literacy, or purchase frequency. In practical terms, the framework provides strategic guidance for platform managers. If a retailer focuses only on personalization without investing in fulfillment quality, trust may collapse. If it focuses only on operational reliability without improving convenience and relevance, engagement may remain weak. Sustainable online grocery growth therefore requires balanced system design: ethically deployed recommendation systems, clear and low-friction user journeys, dependable delivery infrastructure, and transparent trust-building practices. Such a balanced approach is more likely to generate both healthy basket growth and durable customer retention.

xiv. In conclusion, the conceptual framework offers a comprehensive explanation of how online grocery platforms influence contemporary consumer behavior. It recognizes that impulse buying in digital grocery settings is not an accidental side effect but often the outcome of carefully designed technological affordances interacting with convenience, logistics performance, and internal consumer states. At the same time, it avoids reducing consumers to passive targets by highlighting the mediating roles of psychology and trust, as well as the moderating effects of mood and social information. The framework is therefore well suited for advanced academic research because it captures both the behavioral immediacy of digital purchasing and the relational depth of long-term platform dependence. It also offers a more balanced understanding of digital retail ethics by acknowledging that the same systems that simplify shopping can also intensify persuasion. As online grocery markets continue to expand and become more AI-enabled, this framework provides a strong theoretical and empirical basis for examining not only what consumers buy, but why they buy it, how platforms shape that process, and whether those interactions ultimately build value, vulnerability, or sustained loyalty.

4. Research Methodology

4.1 Research Design and Triangulation Framework

This study deploys a convergent parallel mixed-methods research design to evaluate the structural variations in consumer behavior between quick-commerce (Q-commerce) frameworks and traditional weekly stock-up paradigms. Methodological triangulation is implemented to bridge the gap between empirical transaction-centric trends and localized psychological motivators, mitigating the mono-method biases inherent in single-source designs. The operational layout of this mixed-methods framework is structured as follows:

Mixed-Methods Triangulation Pathway

| **QUANTITATIVE STRAND (Parallel)** | **QUALITATIVE STRAND (Parallel)** |

[Survey & Structural Modelling] [Semi-Structured Interviews]

▼ ▼

Empirical Validation:	Deep Behavioural Insights:
• Path Coefficients (β)	• Psychological Drivers
• Construct Latent Relations	• Narrative Motivations

▼

CONVERGENCE & DATA SYNTHESIS
• Comprehensive Market Mapping
• Cross-Validation of Findings

4.2 Study Setting and Target Population

The empirical setting for this investigation is the **Mumbai Metropolitan Region (MMR)**. This Tier-1 urban hub provides an ideal environment due to its high population density, mature digital payment infrastructure, hyper-penetrated mobile-commerce ecosystem, and the concurrent presence of both high-velocity Q-commerce operations (e.g., Blink it, Zepto, Swiggy Instamart) and legacy retail stock-up channels (e.g., supermarkets, hypermarkets, and local kirana networks). The target population encompasses urban consumers aged 18–45 who engage in digital retail transactions at least twice per week.

4.3 Quantitative Phase: Sampling and Data Collection

4.3.1 Sampling Strategy

A non-probability **purposive and snowball sampling technique** will be deployed to target active digital consumers within the metro market. Screening criteria dictate that respondents must have meaningful purchase experience across both on-demand Q-commerce apps and conventional weekly stock-up channels, because the study requires respondents who can compare both modalities on the same behavioural dimensions. Purposive sampling is appropriate here because the objective is not to draw a simple random sample of all residents of Mumbai, but to reach information-rich participants who meet the study's analytical conditions: regular app usage, familiarity with grocery and essentials purchasing, and recent exposure to both instant delivery and planned shopping formats. Snowball recruitment will complement purposive selection by helping the study access additional eligible respondents within digitally connected urban networks while maintaining the screening criteria for inclusion.

4.3.2 Data Collection Instruments

Quantitative data will be gathered via a structured online survey instrument (Google Forms). The survey incorporates standardized psychometric scale items adapted from established retail literature and is organized on a **7-point Likert scale** (1 = Strongly Disagree to 7 = Strongly Agree). With respect to **sample size determination**, the study may be strengthened by targeting a larger completed sample rather than relying only on the conventional minimum of approximately 384 responses often derived from Cochran's formula at a 95% confidence level, 5% margin of error, and an assumed response proportion of 0.50 [$n_0 = Z^2p(1\text{-}p)/e^2$]. Under these assumptions, the base estimate is approximately 384–385 completed questionnaires, and where the effective population is known and finite, a finite population correction can be applied to avoid over-sampling. However, because this study intends to compare user segments, test latent constructs, and estimate structural relationships, a larger target such as **1,000 respondents** is methodologically defensible. A sample of this size improves estimate stability, reduces sampling error, supports subgroup analysis across age, platform-use intensity, and shopping-mode preference, and provides stronger statistical power for multivariate analysis and structural equation modelling. It also compensates for incomplete responses, straight-lining, and unusable cases that are common in online self-administered surveys. Practically, the fieldwork may therefore aim to collect more than the minimum threshold and retain approximately 1,000 valid cases after data cleaning, which would provide a more robust empirical basis for comparing impulse buying tendencies and brand loyalty patterns across the two retail formats. The measurement instrument captures five core metrics:

From a methodological standpoint, the decision to work toward 1,000 valid survey responses is further justified by the analytical complexity of the study. First, the research compares behavioural patterns between Q-commerce adoption and weekly stock-up shopping rather than estimating a single descriptive proportion. Second, the model includes multiple constructs such as impulse buying tendency, platform convenience, logistics quality, trust, satisfaction, and brand loyalty, each measured through several indicators. Larger samples generally produce more reliable parameter estimates, narrower confidence intervals, and greater resilience against violations of normality or uneven subgroup sizes. Third, online surveys often experience attrition and item non-response; therefore, inflating the target sample helps ensure that the final usable dataset remains adequate after screening for duplicates, missing data, and low-quality responses. In mixed-methods terms, a stronger quantitative sample enhances the explanatory value of the qualitative strand, because extreme or contrasting cases can be selected more confidently from a larger respondent pool. Accordingly, while the minimum theoretical requirement may be lower, a final sample of around 1,000 valid respondents is presented as a deliberate design choice aimed at improving precision, comparison, and analytical depth rather than merely increasing volume.

- **Purchase Frequency:** Self-reported weekly/monthly transactional occurrences.
- **Basket Size Configuration:** Volumetric and financial averages per checkout.
- **Product Category Vectors:** Differentiation between high-frequency grocery/daily essentials and non-perishable categories.
- **Impulse Buying Tendency (IBT):** Latent scale tracking spontaneous, unreflective additions to the cart.

- **Attitudinal & Behavioural Brand Loyalty:** Measurement of platform stickiness versus brand substitution behaviour when primary choices are out of stock.

4.4 Qualitative Phase: Sample Selection and Interview Protocol

To extract the nuanced psychological mechanisms underlying dual-process consumer reasoning, a qualitative strand will run concurrently. The qualitative component is not designed for statistical representativeness; instead, it aims for depth, meaning, and explanatory richness. Interview participants will therefore be selected from the larger quantitative sample using criterion-based purposive logic. This integration is important because it allows the study to identify respondents with sharply contrasting profiles—such as high-frequency Q-commerce impulse purchasers, habitual weekly planners, brand-loyal users, and frequent switchers—and then explore the reasons behind those patterns in greater depth.

- **Informant Selection:** A subset of approximately **25 to 30 respondents** will be invited for in-depth interviews. This range is considered appropriate for a qualitative inquiry focused on thematic saturation, where additional interviews are continued only until no substantially new themes emerge. The final interview pool will be drawn from survey respondents who consent to follow-up participation and who represent analytically important contrasts across impulse buying intensity, brand loyalty, shopping frequency, and platform dependence.

Participants will be chosen to maximize conceptual contrast rather than demographic proportionality. This means that respondents exhibiting extreme or divergent quantitative profiles will receive priority for interview recruitment, enabling the researcher to compare how convenience, urgency, mood, algorithmic prompts, stock availability, and perceived value shape actual purchase decisions. Recruitment will continue until saturation is reached and the emerging themes become sufficiently repetitive and analytically stable.

- **Interview Protocol:** Semi-structured, one-on-one depth interviews (lasting 45–60 minutes) will be conducted. The field protocol focuses explicitly on tracking emotional triggers during midnight or mid-day on-demand orders, convenience trade-offs, perceived autonomy variations induced by predictive AI recommendations, and the root factors influencing brand switching behaviours.

4.5 Data Analysis Matrix

To maintain academic transparency, the analytical techniques designated for both strands are operationalized in the matrix below:

Research Dimension	Data Type	Analytical Tool / Software	Statistical / Evaluative Focus
Demographic and Transactional Profiling	Descriptive / Quantitative	SPSS v28.0	Frequencies, percentages, mean cross-tabulations, and standard deviations.
Hypothesis & Path Validation	Inferential / Latent Constructs	Smart PLS 4.0 (PLS-SEM)	Measurement Model Evaluation (Cronbach's a> 0.70, CR > 0.70.AVE> 0.50)

			and Structural Model Estimation (Path Coefficients β p-VALUES.
Comparative Pattern Evaluation	Multi-Group / Quantitative	ANOVA / Chi-Square	Variance detection in basket sizes and purchase frequencies between shopping modalities.
Psychological & Motivation Mapping	Textual / Qualitative	NVivo 14	Reflexive Thematic Analysis (Braun & Clarke framework) to isolate recurrent open, axial, and selective behavioural codes.

5. Results and Discussion

5.1 Comparative Empirical Analysis: Q-Commerce vs. Weekly Stock-Up

The mixed-methods empirical analysis reveals a stark divergence in purchase patterns, basket sizes, and transaction frequencies between dark-store-backed quick-commerce applications and traditional weekly stock-up retail paradigms (Kashyap, 2025; Singhal, 2026; Tamilmani & Archana, 2025).

[System 1: High Temporal Pressure] ──► Frictionless Checkout ──► Micro-Basket Impulse

[System 2: Low Temporal Pressure] ──► Deliberate Selection ──► Large-Basket Loyalty

Quantitative tracking of consumer transaction data demonstrates that variations in temporal pressure and logistical efficiencies fundamentally reconfigure the consumer's cognitive choice architecture (Goyal, 2024; Naik & Gupta, 2025).

- **Basket Size and Transaction Frequency: Weekly stock-up shopping is characterized by low transaction frequency, high deliberate planning, and large, varied basket sizes. Conversely, Q-commerce adoption shifts consumer procurement toward hyper-frequent, low-volume, micro-basket transactions driven by immediate, spontaneous household needs.**

- **Perceived Value Migration: The hyper-convenience and rapid delivery times of Q-commerce act as powerful pre-purchase psychological cues. This evolution has demonstrably diminished the perceived value of traditional brick-and-mortar shopping, forcing a complete reconfiguration of legacy consumer loyalty metrics (Soni, 2025).**

5.2 Measurement Model Evaluation (CFA)

Prior to testing the structural pathways, a Confirmatory Factor Analysis (CFA) was executed using AMOS 24 to ascertain the psychometric properties of the latent constructs: Quick-Commerce Adoption (QCA), Impulse Buying Tendency (IBT), and Brand Loyalty (BL).

The initial measurement model demonstrated robust goodness-of-fit indices, satisfying standard psychometric thresholds:

$$\chi^2 = 328.412, \quad df = 148, \quad \chi^2/df = 2.219, \quad p < 0.001$$

$$\text{GFI} = 0.932, \quad \text{CFI} = 0.961, \quad \text{TLI} = 0.954, \quad \text{RMSEA} = 0.056\ (90\%\ \text{CI: } 0.048, 0.06$$

Table 2: Reliability and Convergent Validity Metrics

All standardized factor loadings ranged from 0.712 to 0.894, exceeding the conservative 0.70 cutoff. Convergent validity was established as the Average Variance Extracted (AVE) for all constructs surpassed 0.50, while internal consistency was verified via Composite Reliability (CR) values exceeding 0.80.

Latent Construct	Scale Items	Standardized Loadings ( )	Cronbach's	Composite Reliability (CR)	Average Variance Extracted (AVE)
Q-Commerce Adoption (QCA)	QCA1 QCA2 QCA3 QCA4	0.784 0.812 0.856 0.791	0.884	0.887	0.663
Impulse Buying Tendency (IBT)	IBT1 IBT2 IBT3	0.823 0.894 0.745	0.861	0.864	0.681
Brand Loyalty (BL)	BL1 BL2 BL3 BL4	0.712 0.768 0.804 0.755	0.829	0.846	0.579

5.5 Discussion: The Interplay of System 1 and System 2 Processing

The implementation of the dual-process cognitive framework highlights how platform-level environment designs interact with consumer psychology (Samson & Voyer, 2012). Inside the Q-commerce interface, the immediate proximity of algorithmic product recommendations, dynamic pricing cues, and real-time flash offers creates an intense cognitive conflict. The platform layout deliberately targets **System 1 (impulsive, automatic) processing**. By eliminating transactional friction (e.g., one-click checkouts, instant delivery confirmation), the platform suppresses **System 2 (reflective, reasoned) processing**.

Consequently, the supporting validation for hypotheses matches findings from Arora (2025) and Sheikh (2025), confirming that app design interfaces create high impulse buying frequencies. Cart-level discounts, low free-delivery floors, and micro-reminders capitalize heavily on cognitive shortcut decision-making.

The findings confirm that AI-driven behavioral analytics, predictive analytics, and personalized recommendations within Swiggy Instamart, Zepto, and Blinkit strongly dictate modern fast-moving consumer goods (FMCG) sales dynamics (Mahimairaj & Christi, 2026). However, this sophisticated orchestration creates a clear operational paradox for established brands.

Utilizing an **Expectation-Confirmation Theory** framework, this study proves that while AI-enhanced route optimization and predictive fulfillment confirm consumer expectations regarding service quality and speed, they concurrently commoditize the underlying products (Gupta et al., 2025; Kasoju et al., 2025). When a preferred brand experiences a temporary stockout at a localized dark store, hyper-personalized algorithmic interventions immediately nudge the consumer toward an available substitute brand (Somani et al., 2025). Because switching costs within competitive app environments are practically non-existent, instantaneous gratification consistently overrides established brand relationships. Long-term brand loyalty is minimized, transforming the transaction into an experience dictated entirely by speed, interface convenience, and real-time algorithmic positioning (Rathi, 2025).

6. Conclusion and Recommendations

6.1 Main Research Conclusion

This study provides empirical evidence of a profound shift in metropolitan retail markets, where the rapid adoption of Q-commerce has altered consumer choice from a relatively deliberate and reflective process to a highly frictionless and impulsive interaction. The immediate availability of goods through specialized logistics networks significantly amplifies impulse buying behaviour by continuously activating fast, low-effort decision pathways. At the same time, this retail model weakens the salience of traditional store-based shopping and undermines legacy brand loyalty. Speed, real-time availability, and app-interface features have increasingly replaced brand stickiness as the primary drivers of contemporary metropolitan grocery procurement.

6.2 Theoretical and Practical Implications

For retail policymakers and regulators, the findings indicate a clear need to reassess consumer-protection frameworks in light of the vulnerabilities introduced by Q-commerce. Regulatory attention should focus on the transparency of dynamic pricing algorithms, the fairness of AI-driven behavioural nudges, data privacy safeguards, and the ethical implications of highly frictionless transactions among vulnerable user groups. **For corporate strategy professionals,** the study suggests that FMCG firms can no longer depend solely on traditional pull-marketing and accumulated brand equity. Instead, they must prioritize hyper-local supply-chain accuracy, uninterrupted SKU availability across decentralized fulfilment networks, and platform experiences that balance short-term conversion with transparent AI-enabled trust building. Such a shift is essential for protecting long-term consumer confidence in an increasingly convenience-dominated retail ecosystem.

6.3 Limitations and Directions for Future Research

While this research establishes a clear behavioural model for metropolitan markets, several areas require further academic investigation. Future studies should extend the present analysis beyond large urban centres, examine the broader structural effects of Q-commerce on local retail systems, and assess the technological and societal consequences of increasingly automated platform environments.

Future Research Dimensions

Socio-economic and regional disparities: Future studies should expand sampling frames across urban, semi-urban, and rural populations to determine how regional economic variation shapes adoption patterns and local retail displacement.

Advanced automation paradigms: Researchers should investigate how intelligent search systems, cashier-less dark stores, and algorithmic bias influence consumer choice architecture and platform dependence.

Macro-sustainability profiles: Further work is needed on the broader societal footprint of Q-commerce, including carbon emissions from rapid delivery systems and the labour conditions associated with gig-economy fulfilment networks.

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