

CONSUMER BEHAVIOUR IN QUICK COMMERCE: FACTORS INFLUENCING ADOPTION AND LOYALTY

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INTERNATIONAL TRANSPORTATION AND LOGISTICS MANAGEMENT

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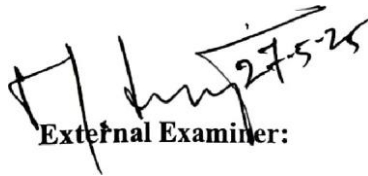


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ABSTRACT

This research examined the primary behavioural factors for consumers' adoption and loyalties in Q-commerce platforms (e.g., Blinkit, Swiggy Instamart, Zepto). The emergence of Q-commerce has exploded in growth due to ultra-fast delivery, digital interface accelerators, and hyperlocal fulfillment, completely disrupting consumer expectations and retailing logistics. In order to examine the relationships that influence user engagement in an emerging sector, we employed PCA analysis using the R studio with survey responses from 128 active Q-commerce users.

The survey contained 20 behaviour based Likert-scale items detailing measurements on trust, convenience, speed of delivery, promoter sensitivity and platform loyalty. PCA analysis revealed two key components explaining over 50% of the variance in consumers' behaviour. The first component loaded on trust and adoption behaviours, looking at user satisfaction, ease of use, metrics on frequency of use and perceived reliability of service. The second component loaded on loyalty and expectations of service, that is to say, promotional effect and sympathy/emotional component, as well as customer service.

Supporting analysis such as the KMO test ($KMO = .899$) confirmed adequate sampling, while scree plots and parallel analysis produced similar responses and confirmed we only kept two principal components. Correlation plots, biplots and loadings explained contributions of each behaviour and campaign strategy into the first and second components. The PCA summary gave some strategic implications.

Overall, the study provides a data-driven understanding of behavioural drivers in Q-commerce, helping platforms refine customer experience, enhance loyalty mechanisms, and maintain competitive advantage in a rapidly evolving retail space.

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LIST OF ABBREVIATIONS

Abbreviation	Full form
Q-Commerce	Quick Commerce
PCA	Principal Component Analysis
KMO	Kaiser-Meyer-Olkin Test
R	R Programming Language
UI	User Interface
UX	User Experience
FMCG	Fast-Moving Consumer Goods
B2C	Business-to-Consumer
CSV	Comma-Separated Values
SEM	Structural Equation Modelling
OTP	One-Time Password
SD	Standard Deviation

I. INTRODUCTION

A new retail business model known as "Q-commerce" has begun to develop rapidly as a result of the irreversible shaping of consumers' immediate desires by the rapid development of Internet technology. It's extremely fast delivery times and "minute-level" experience from order placement to reception have completely changed the expectations and purchasing habits of customers. For example, providers on Q-commerce platforms (like Blinkit and swiggy instamart) can deliver goods to customers in less than 30 minutes as opposed to traditional e-platforms (like Amazon and Flipkart).

Research on this area by Luna Sanchez (2024), perceived ease of use, interface quality, and data quality have the biggest effects on consumer purchasing behaviour in fast commerce platforms. High interface quality, that is responsiveness, organization, and visual appeal brings trust and the platform is more entirely easy to use and efficient will drive higher engagement among the users. Accurate product information including availability and price influence the purchase decision. One hundred twenty survey responses were analysed through Partial Least Squares-based Structural Equation Modelling (PLS-SEM) in relation to Technology Acceptance Model and Mobile Service Quality Model. Improved user-friendly interfaces, well-defined product information, seamless transactions all depend on the success of rapid commerce systems based on research that users adapt and stay loyal with these key points.(Luna Sanchez, 2024a)

The emergence of Quick Commerce (Q-commerce) has significantly transformed the e-commerce landscape, driven by changing consumer behaviour and technological advancements. Compared to existing forms of e-commerce, Q-commerce systems leverage data-based demand forecasts, micro-fulfilment facilities, and hyperlocal distribution networks that allow delivery within minutes where applicable, if not hours. The emergence of companies like Blinkit, Swiggy, Instamart and Zepto relates largely to their demand for rapid delivery, particularly groceries or essentials. The objective of this study is to understand the key factors influencing user acceptance and loyalty, for Q-commerce centred on fast delivery, convenience, and virtual delivery. To examine consumer preferences, this mixed-method study will collect quantitative data through surveys to measure accepted ideas and qualitative measures through expert interviews in order to deduct their operational challenges.

The task of automatically assigning the appropriate class labels to images is referred to as image annotation. Image annotations are primarily for classification for image databases and search engines. In the case of image retrieval, the task of retrieval is to find images which share certain semantic dimensions with the query image. Q-commerce is commerce that digitally closes in a few minutes after an order has been placed. Companies such as Blinkit, Swiggy, Instamart, and Zepto are capitalizing on the demand to have almost anything delivered as quickly as possible, particularly groceries and other essential goods. Furthermore, this research investigates the key dimensions of customer acceptance and loyalty in Q-commerce: speed, convenience, and digitization. The study uses a mixed-methods approach; it reports exploratory quantitative surveys, of consumers, and deeper dive qualitative expert interviews aiming to understand the operational issues.(Ranjekar & Roy, 2023)

The evolution of Quick Commerce (Q-commerce) has not only redefined consumer expectations but has also introduced significant operational challenges and business model uncertainties. Companies are adjusting to hyperlocal delivery, dark stores, and express logistics networks as they seek to capture their share of the market. Unfortunately, the financial performance of most Q-commerce companies, the rising costs of operation, and regulated scrutiny make it difficult to sustain that growth. All too many players have actually left their acquisitions of market share, or in terms of other players, merged into each other after their initial rounds of investment venture capital. There was so much early-stage hype that allowed Q-commerce to become, potentially, a niche in urban retail. Now sustainability is a reference point. The key to surviving lies with improved logistics efficiencies, strategic partnerships/alliances and sustainability issues.(*Quick Commerce Will the Disruption of the Food Retail Industry Happen*, 2023)

Q-commerce continues to reshape the retail industry, optimizing logistics infrastructure and operational efficiency has become a primary focus. The Multinomial Logit (MNL) Choice Models and Integer Programming Models to model consumer preferences, reliability in services, and assortment of products are vital to advance applications. Data-driven logistics optimization is essential to optimizing last-mile delivery, working under the constraints of limited resources. But the sustainability of Q-commerce remains a major concern due to excessive operational costs, regulatory hurdles and environmental impacts. Additionally, fair wages, job safety, and labour rights are impacted by reliance on gig workers. While Q-commerce is a disruptive force of nature in new retail, these issues require the right workforce management, logistical, and regulatory compliance concerns addressed for a sustainable future.

This research aims to explore key determinants of acceptance and sustainability relative to Q-commerce, to understand how optimization tools and business models will shape the future of this new sector. (Chen et al., 2024)

Recent developments in Quick Commerce (Q-commerce) have reshaped the food retail industry, driving innovation in business models and logistics strategies. The rise of research is driving the move from conventional e-commerce to instant delivery, which greatly relies on third-party logistics providers, hyper-local fulfillment centers, and the use of data to sophisticatedly forecast demand. Instant delivery is what has raised the quality and comfort of the Q-commerce platforms such as Blinkit and Swiggy Instamart. Developing a high service quality comes at an operational cost, however, which I also believe carries labour sustainability issues for the workforce, and government oversight regarding labour standards and urban infrastructures has posed challenges as a result of rapid development. Now, more than ever, it is crucial to examine how the multiple business models and sustainability of the industry have changed due to the emergence of Q-commerce. The approach described will examine the extraordinary paradigm shift food retail has undertaken due to Q-commerce, in terms of digital platform integration, last-mile logistics optimization, and the economic viability of on-demand delivery service. We will track the consequences of dark stores, measure consumer adoption trends, and examine ways to enhance profitability and scalability using quantitative and qualitative mixed-method approaches. It is expected that results will help one gain further insights into the impact of Q-commerce towards changing retail dynamics while focusing on operational and legal issues that need to be solved for the long-term success of Q-commerce.

The transformation is discussed by many researches, bringing in perspectives from the traditional e-commerce shopping to instant delivery services by third-party logistics providers, hyperlocal fulfilment centre, and data-driven demand forecasting. The likes of Blinkit or Swiggy Instamart have enhanced their convenience of customer facing services. However, this has posed several challenges high operating costs, sustainability of labour workforce, and the issues in service delivery such as, government scrutiny of standards of labour and urban infrastructure. Therefore, it is highly relevant to track the new business models evolving in this sector for their sustainability taking into account the disruptive new growths of Quick commerce. Areas of investigation include real time digital platform service delivery, last mile logistics improved efficiencies, financial viability with the re-structuring of food retail influenced by Q-commerce. Analogous areas of investigation include efficiency involving dark stores; trends involving consumer adoption of last mile service; evaluation of strategies

which provide financial viability to sustain delivery growth and assessment of profitability and scale will be examined using qualitative-quantitative mixed-methods approach. The impetus for areas of investigation is to gain a better understanding of how Q-commerce is re-writing the retail landscape, and to refocus attention on the operational and legal matters that need to be resolved for sustainable financially viable long-term operations.

Research is increasing on this transition from old-fashioned e-commerce to instant delivery service dependent on third-party logistics providers, hyperlocal fulfilment centres, and demand forecasting through data. Naturally, these Q-commerce players, such as Blinkit and Swiggy Instamart, quickly gained traction and raised the ante on customer convenience measurement, thanks to their fast delivery times. New challenges to this improvement include high operational expenses, retention of the workforce sustainability, and city government intervention of labour standards and urban infrastructure. It is critical to now examine the trajectory of various business models in these industries and their sustainability, with Q-commerce growth occurring. The proposed method examines disruption as an effect of Q-commerce in food retail by focusing on the adoption of digital platforms, optimization of last-mile logistics, and the market feasibility of on demand delivery services. The use of dark stores as an effective business case will be studied, consumer adoption patterns will be assessed, and strategies for improving profitability and scale will be investigated by integrative mixed methods (qualitative-quantitative approaches). It is anticipated that such an outcome will provide greater depth in our knowledge of how Q-commerce transforms the retail landscape, along with the implementation of operational and regulatory challenges that may need to be considered to successfully operate in the long run.(Schorung,2024)

The rapid expansion of Quick Commerce (Q-commerce) has raised significant concerns regarding its environmental impact, particularly in terms of urban air pollution and packaging waste. An increased Q-commerce delivery has been causing an increase in carbon emissions, thanks in large part to frequent motorized vehicles that are used for last-mile deliveries. Packaging materials have begun to contribute to waste management troubles by being capable of making product handling and safety easy; however, with overuse, they have caused more concern on the waste front than Q-commerce itself. As cities strive towards developing sustainable urban transport systems, addressing the environmental impact of Q-commerce will be among their main points of discussion. The work will address the environmental impacts of Q-commerce that link waste generation, frequent delivery, and urban air quality. This study will evaluate the efficacy of sustainable practices on integrated green delivery fleets, eco-

packaging alternatives, and enhanced last-mile logistics by employing a mixed-methods approach. The outcome is expected to provide vital intelligence to policymakers and industry stakeholders in formulating regulatory frameworks and sustainable business models that balance ecological imperatives with efficiency. (Son & Kwon, 2024a)

1.1 OBJECTIVE OF THE STUDY

The main objective of this research is:

- To identify the key behavioural factors influencing consumer adoption and loyalty in Quick Commerce platforms through the application of Principal Component Analysis (PCA).
- To evaluate and interpret the underlying dimensions of these identified factors based on their contribution to consumer behaviour patterns.

The objective of this research paper is to study and understand the various psychological and service-related factors affecting consumer engagement with Q-commerce services like Blinkit, Zepto, and Swiggy Instamart. In order to identify these factors, a cross-sectional primary survey was carried out using a structured Likert-scale questionnaire covering aspects such as convenience, trust, pricing, delivery speed, and experience of the platform. After the collection of the data, its dimensionality followed by an extraction of latent variables that best explained customer behaviour was carried out using Principal Component Analysis in R Studio. This analytical approach helps truly pullout important variables and cluster related constructs to provide recommendations to Q-commerce platforms by which they can increase retention, loyalty, and long-term satisfaction of their customers.

2.0 LITERATURE REVIEW

A growing body of literature has investigated the key factors influencing consumer behaviour in Q-commerce, with several studies emphasizing speed, convenience, and technology-driven engagement as the primary drivers. Platforms that offer digital experiences devoid of friction, with great user interface design and efficient order fulfilment processes, stand a better chance of attracting and retaining customers, as confirmed by several studies (Master Luna Sanchez Pedro, 2024). Prompt delivery plays quite a huge role in customer acceptance, especially when

it comes to ultra-fast deliveries for groceries, home supplies, and medicines, as seen from many studies focusing on what immediacy does to consumer expectations (Master Luna Sanchez Pedro, 2024).(Luna Sanchez, 2024b).

Previous research highlights that consumer retention in Q-commerce is a major challenge due to intense competition and low switching costs Key loyalty drivers include service reliability, personalized interactions, and attractive promotions (Master Luna Sanchez-Pedro, 2024). Evidence suggests that time-limited discounts, AI-generated suggestions, and engagement strategies drive repeat purchase, and longer-term consumer fidelity (Ranjekar & Roy, no date). Moreover, platforms that offer low rates, fast last-mile delivery, and high customer trust mechanisms also have a higher customer penetration (Rise of Quick Commerce in India: Business Models and Infrastructure Requirements). Nevertheless, despite these efforts, several Q-commerce players find difficulties realizing sustainable scale. Opportunities based on operations challenges such as delivery costs, urban traffic congestion, and poorly developed supply chains are instead very serious issues (Quick Commerce and the Evolving Business Models of the Food Retail Industry). These challenges must be successfully addressed for any true growth potential and lasting customer trust in the Q-commerce space.(Ranjekar & Roy, 2023).

A number of studies have considered the impact of logistics and business models on the sustainability of Q-commerce. The role of dark stores and micro-fulfilment centres has been extensively examined to show their utility for fast deliveries, and there have been negative comments regarding their contribution to zoning issues and urban congestion (Quick Commerce and the Evolving Business Models of the Food Retail Industry) (Schorung, 2024). Moreover, a plethora of discussions have been generated surrounding gig workers used in Q-commerce, with research arguing that lawmakers are still paying attention to issues related to workable compensation, job security, and labour laws (Quick Commerce: Will the Disruption of the Food Retail Industry Happen?). An extensive examination of Q-commerce inventory management has proved that MNL models and integer programming can maximize assortment, enhance productivity, and finally improve profitability (An Integer Programming Approach for Q-Commerce Assortment Planning). It has been shown that these models achieve coherence between inventory management strategies and customer demand, ensuring that companies meet expectations while minimizing wastage.

Much research has been conducted to investigate consumer behaviour, logistics, and sustainability in relation to quick commerce. Multiple studies have highlighted both innovative business models and strategic partnerships that keep the fast commerce platforms competitive (Strategic Business Models: Analysing Vertically Integrated Fast Commerce Business). Furthermore, there are many academics who addressed several sustainability challenges in the fast commerce sector through their studies on packaging waste and initial carbon emissions. The studies generally focused on incorporating green packaging solutions and optimizing delivery routes that could mitigate the negative consequences of fast reputable commerce (Sustainable Spatial Strategies for Mitigating Air Pollution in Quick Commerce). (Son & Kwon, 2024a)

A growing body of literature has investigated the factors influencing consumer purchasing decisions in quick commerce. A plethora of studies highlight the ease of use, perceived usefulness, and personalized experiences as core determinants of consumer adoption and loyalty (The Impact of Quick Commerce that Influence Consumers' Purchase Decisions on E-Grocery). Studies abound on the impact of Quick Commerce variables on consumer decision-making mechanisms, focusing more towards the adoption and loyalty drivers. This study sets out to investigate the extent to which speed, convenience, and online interaction influence consumers' buying decisions on Q-commerce platforms (A Study on Impact of Quick Commerce on Consumer Decision-Making Process). The methodology is mixed, including qualitative and quantitative analysis in the fields of behavioural analytics and consumer surveys to derive insights for purchase trends. Findings indicate that while speedy delivery increases customer satisfaction, it promotes impulse buying, thus breaking down the traditional modes of client-engagement frameworks. However, a significant gap in this research is the ambiguity being created concerning how the demographics such as income levels, geographic location, and alike affect consumers' Q-commerce service reaction. Even though Q-commerce from this study bears several fruitful advantages in speed and accessibility, companies should focus on logistical enhancements and personalized tactics for ensuring loyal customers. Q-commerce sustains future investigations regarding issues such as sustainability, impacts on the environment, and scalability of the operating model. (Goswami & Kumari, 2024)

The multi-objective instant logistics optimization in recent years has been wide-ranging, as it appeared to have a stake in the coupling of truck and drone technologies as a way to enhance delivery efficiency in recent Q-commerce developments. (Integration of Trucks and Drones Supporting Multi-Objective Logistics of Time-sensitive Orders) The work presents an

evaluation of the integrated delivery system which supports improved route planning and reduced delivery timing and product quality degradation for perishable goods. A multi-objective memetic algorithm allowed for significant efficiency gains for the reasons of minimizing drone sub-route computations in addition to overcoming time-window constraints while optimizing. Results concluded that, by implementing this hybrid approach, effectiveness can be assured and one could reasonably expect an overall satisfaction rate of 97% in large scale operations with a vastly improved delivery timing, product quality retained and customer satisfaction level high. Several areas formed a comprehensive research gap analysis focussing on the limiting concepts around drone delivery sources of battery lifecycle, cargo capacity and airspace restrictions. The models used show that while truck-drone hybrid models could change the face of Q-commerce logistics services they will need more comprehensive work on the concepts of scale, environmental impacts and consideration of regulatory changes in order to promote long-term viability and greater acceptance if only because from a practical perspective they retain the advantages of truck delivery to remain flexible and viable in reality.(Ma et al., 2025)

Much of the current literature on Quick Commerce (Q-commerce) and E-commerce pays particular attention to their comparative environmental impacts, especially concerning greenhouse gas (GHG) emissions from last-mile logistics. The purpose of this study is to analyse the differences in emissions, logistics efficiency, and sustainability strategies between Q-Commerce and E-Commerce retail models. A structured, state-of-the-art comparison of greenhouse gas emissions alongside last-mile logistics. Following Kitchenham's (2004) funnelling method to allow for a systematic literature review process, 140 relevant papers were evaluated against defined selection criteria. It was determined that on the whole there are benefits to e-commerce because of bundling and increased efficiencies in logistics, whereas Q-commerce appears to produce significantly higher emissions per confirmed order for same-day deliveries. One of the significant research gaps identified was the lack of adequate life-cycle assessment for both models that account for packaging waste, energy consumption in warehousing and reverse logistics. In conclusion, the research argues that any sustainable measures for last-mile logistics, including electric vehicles, urban consolidation centres, and enforcement measures are crucial in reducing the environmental harm related to Q-commerce while upholding operational efficiencies.(Gund & Daniel, 2024)

The significance of behaviour-based pricing (BBP) techniques in rapid commerce (Q-commerce) logistics models has received more attention lately. The effect of these strategies

on platform profitability, consumer buying behaviour and the dynamics of competition is explored. The essence of this research is to explore platform-led (PL) services' and self-led (SL) logistics pricing strategies; and the connection between supplier profitability and service efficiency; (Q-commerce Service with Behaviour-based Pricing). For developing a two-period competitive pricing model, it has adopted both game theoretical approach and Hotelling model, which collectively illustrate price differentiation and consumer switching behaviour. The take away, concluded is that Q-commerce merchants benefit the most from SL logistics, primarily in their client acquisition and retention efforts, while conventional e-commerce merchants prefer PL logistics. The latter is considered price discrimination that is based on behaviour-based pricing: attracting new customers with lower prices, to drive customer adoption; while eventually prices would increase for existing customers. However, it needs empirical validation; in particular, assessing consumer behaviour towards price strategies in real involving markets. To conclude, a report on, the long term impact on customer retention, trust, and market sustainability, Q-commerce companies are encouraged to invest in dynamic pricing based on customer behaviour. Future research should address the ethical issues raised by discrimination in prices on Q-commerce platforms and the effect of regulatory laws on pricing strategies.(Zhu & Xie, 2024)

The emphasis in most works that seek to analyse the behaviour-based pricing (BBP) system in Q-commerce has been mainly in the areas of market competition, consumer behaviour, and profitability of the platform. This paper seeks to differentiate between platform logistics (PL) and self-logistics (SL) approaches in a two-period price-setting game theory framework with Hotelling neighbour. Along the results we have seen, we can see that SL is a great way to reach consumers in Q-commerce, which is an important way to capture and retain customers, but PL does a fine job with traditional e-commerce. The BBP scheme of price discrimination allows for tiered payment levels for loyal consumers while getting new customers discounts. There is a considerable gap because there appears to be no empirical evidence of consumer reactions to BBP. Our key contributions is we offer adaptive pricing mechanisms that balance the trade-off between long-term loyalty and trust versus profitability.(Reif & Morschett, 2022)

In order to increase sustainability, efficiency, and resilience, recent research looked at the way Q-commerce fresh and short food supply chains (FSFSCs) might incorporate the ideas of the circular economy (CE). The aim of this research was to develop and validate a CE framework (Redesigning Quick Commerce Fresh and Short Supply Chain) to enhance last-mile delivery, resource allocation, and reduce wastes. This research study consisted of multiple phases of a

literature review, survey-based data collection, PLS-SEM model and k-means clustering. Results showed that reduced waste, sustainable procurement and route optimization were high impact strategies, while energy efficiency, re-sale and composting were low-moderate strategies. In summary, the major barriers to the adoption of CE practices by Q-Commerce were the lack of a standard evaluation model, and under-funding. Overall, based on the research findings, CE-based supply chains could increase sustainability and resilience, but further investigation must be conducted about how they behave scalable, cost-competitive and acceptable to consumers.(Chavhan & Dutta, 2024)

The quick development or booming of quick commerce empire has led to commensurate environmental degradation, such as air pollution as a result of frequent deliveries using fossil fuels and packaging waste. In fact, studies show that non-recyclable packing materials add into the burden of waste systems (Duan et al., 2019; Fan et al., 2017), and last-mile logistics dramatically increase greenhouse gas emissions as well as urban congestion (Allen et al., 2021; Gund & Daniel, 2023). While companies are adopting green practices, much more comprehensive sustainable solutions need to be identified in balancing convenience with environmental accountability. Such include nurturing local business and home-borne solutions.(Son & Kwon, 2024b)

It has become more important than ever to understand how rapid commerce, or q-commerce, impacts client loyalty. Research shows that while service assistance has little impact on loyalty, three key elements of the service experience—app design, security assurance, and fulfilment—have a major impact (Kapoor et al., 2023). The connection between these factors and loyalty is strengthened by trust, showing up as a crucial mediator, especially when e-WOM (positive electronic word-of-mouth) is present (Shankar & Behl, 2021). Based on hybrid analyses that integrate SEM and fsQCA, customer retention is determined by intricate connections among quality of service, trust, and electronic word of mouth rather than by a single component (Abbasi et al., 2022). The findings highlight how crucial it is to improve q-commerce experiences holistically, striking the right balance between technological advances efficiency and consumer confidence and social validation.(Kapoor et al., 2023)

According to this investigation, rapid commerce (Q-commerce) profoundly reconfigures consumer behaviour, logistics, and business models, concentrating on adoption and loyalty. Research indicates trust, service reliability, availability and price are essential for customer retention while speed, convenience and a personal touch are the primary drivers for uptake.

Other research highlights economic feasibility, ecological issues and logistical challenges pertaining to Q-commerce with some very promising avenues of improvement. However, one of the significant areas missing research is comprehensive studies on the demographic factors of consumer behaviour and sustainability of rapid delivery models in the long term. In order to enhance consumer happiness and make the market more appealing, the report concludes with recommendations for companies to construct their operating models around sustainability frameworks, dynamic pricing frameworks and technology applications. This investigation aims to pave the way for a sustainable, consumer-centric retail model by examining aspects of consumer priorities, trust mechanisms and strategic considerations affecting the uptake and engagement of Q-commerce.

3.0 METHADODOLOGY

3.1 Research Design

The study investigates how people behave on quick commerce platforms and what motivates them to begin and continue using them. To examine this, developed a comprehensive analytical framework, and decided to use Principal component analysis (PCA) to understand the user behaviour patterns. In order to get a full picture with PCA, have designed a complete questionnaire with 20 Likert-scale items, where each question represents factors like delivery speed, trust of the platforms, usability of the app, attractiveness of loyalty rewards, pricing strategies etc. By examining these 20 factors, the study aims to expose not only what drives people to Q-Commerce, but also what drives them to return.

3.1.1 Data collection

Data was collected with a questionnaire on March 2025 via Google Forms, targeting individuals are consumers who are active users in the field of quick commerce-like Blinkit, Swiggy Instamart, and Zomato for food delivery services. In fact, the study surveyed 128 respondents. All respondents provided adequate responses to all questions concerning consumption patterns and rationale regarding quick commerce services, thus representing a balanced view on the importance of such services in their lives. The responses were also revealed insights into consumer preferences and perspectives in the dynamically evolving world of Q-commerce.

3.1.2 Questionnaire Structure

The text has been developed into two sections, with twenty separate questions in a questionnaire intended to light upon the factors that comprise convenience or price sensitivity, delivery speed, trust/service quality, app usability behaviour, and loyalty behaviour. These questions were extracted considering the various writings bearing relevance to consumer behaviour and loyalty in Quick Commerce (Q-commerce). 5-point Likert scale scoring was used. A 20-item questionnaire was developed that focuses in on the factors like convenience vs. price sensitivity, delivery speed, trust vs. service quality, app usability, and loyalty behaviour. These have been extracted from the insights drawn from literature related to

consumer behaviour and loyalty in Quick Commerce (Q-commerce). Each item was scored by the respondents through a 5-point Likert scale:

- 1 = Strongly Disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

This format was chosen to allow quantifying the level of agreement on each behavioural statement, as well as allowing for statistical analysis wherein Principal Component Analysis (PCA) was used to arrive at identifying the underlying dimensions affecting consumer adoption and loyalty in the Q-commerce sector.

3.1.3 Sampling technique

The study employed systematic purposive sampling to collect study participants. Purposive sampling is that form of non-probability selection in which respondents are deliberately selected in relation to the phenomenon under study. Hence, consumers who have tasted using or availing of Q-commerce platforms such as Blinkit, Zepto, Swiggy Instamart, and Zomato were purposively selected for this study to create contextual depth and meaningfully speak to the varying factors that could affect such adoption and loyalty toward such services.

Table 1: Factors effecting in Quick commerce

Factors	Description	Abbreviations
Convenience & Adoption	Represents consumers' preference for the Q-commerce platform as compared to traditional retail due to being easy and simple to use.	TRD
Convenience & Accessibility	Assess how consumers perceive Q-commerce services to be highly accessible and convenient to attend to their simple needs	DLY

App Usability	Assesses consumers' adoption decisions from easy navigation, simpler ordering, and user-friendliness of the platform	PUR
Delivery Speed Importance	Refers to fast delivery times that play an essential role in consumer choice and Q-commerce preference.	TME
Pricing & Promotions	Denotes how much discounts, deals, and promotions usually affect consumers' decision-making in Q-commerce	D&P
Customer Service Trust	Measures consumers' trust in Q-commerce platforms based on customer support quality and problem resolution.	COS
Product Quality Trust	Refers to the level of trust consumers bestow upon Q-commerce platforms to deliver products in good, reliable condition.	GDC
Willingness to Pay for Speed	Looks at whether consumers are willing to bear extra costs for faster deliveries to satisfy urgent needs.	FAS
Shift in Shopping Behaviour	Explores how the convenience of Q-commerce has led to behavioural change from physical store visit to the online shopping of Q-commerce.	PHY
Habitual Convenience	Refers to habitual choice by consumers to use Q-commerce products even when they do not need to use them in a hurry.	CON
Loyalty Behaviour	This dimension measures the tendency of consumers to stick loyally to one favourite Q-commerce platform rather than switching brands.	SME
Brand Loyalty Over Price	Assesses the strength of consumer loyalty even when other platforms offer marginally better prices.	COM
Emotional Brand Connection	The emotional bonding that a consumer develops with a platform creates more loyalty.	EMO

Influence of loyalty programs	This examines how loyalty incentives, mainly rewards and cashback, contribute to consumer retention and repeat purchases.	L&R
Satisfaction with the Platform Overall	Consumer satisfaction with the Q-commerce platform's service quality as well as experience and features were checked in this study.	EXP
Loyalty Despite Price Change	Established loyalty of consumers to the platform even if it increases slightly the price of delivery or product.	DLC
Urgency-based Usage	Measures the reliance on Q-commerce services for immediate or last-minute shopping needs.	LMS
Delivery Reliability	Assesses how the consistency and reliability of deliveries contribute to building loyalty toward a Q-commerce platform.	Q&R
Word-of-Mouth Advocacy	Measures the consumer's likelihood of recommending the Q-commerce platform to friends, family, and peers	FRQ
Platform Commitment	Captures the degree to which consumers are committed to staying with a particular platform once trust and reliability are established.	SWT

3.2 Data Analysis Procedures

Data collected through the questionnaire was analysed in R Studio. The following steps were taken:

3.2.1 Data Cleaning and Preparation:

The survey responses were first saved as .xlsx files and imported into R Studio. Data was then checked for inconsistency, missing values, and outliers. Only completed responses were retained for the analysis to ensure reliability and accuracy.

3.2.2 Descriptive Statistics (mean scores, frequency distributions):

Likert-scale data (1-5) can be standardized, and while all of the responses options are flat, standardization was used through the `scale()` function in R Studio to create a level of equality contribution of the variables in Principal Component Analysis (PCA). PCA, or Principal Component Analysis was chosen as a method of dimensionality reduction and retained important dimensional information. R studio for Principal Component Analysis of the collected data. Principal Component Analysis is a multivariate statistical tool for transformation of dense datasets into lower components, while allowing users to interpret the real structure governing the related behaviour factors which were included in the core component. This improved the interpretation of consumer behaviour in terms of adoption of Quick Commerce and loyalty.

3.2.3 Kaiser-Meyer-Olkin (KMO) Test for Sampling Adequacy:

Before running PCA, Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity were run to ensure the data would be suitable for factor analysis. Retain factors having eigenvalues greater than 1, and apply varimax rotation for better interpretability of the extracted component.

KMO Value 0.895.: therefore, acceptable adequacy for factor analysis.

Based on the PCA results, different behavioural drivers could be described under different central themes (e.g., Convenience, Trust & Reliability, Pricing & Promotions, and Platform Loyalty), which contributed further to identifying the significant factors that underpin consumer behaviour in the Quick-commerce industry. Determining number of Components: To decide how many Components to retain in interpreting the final components, a Scree Plot and Parallel Analysis were used, as there may be an optimal number of components to retain in the PC and final evaluation. Components with eigenvalues greater than 1 thus formed the final selection for interpretation.

3.2.4 Visualization and Interpretation

The visuals were created for the purpose of interpreting the PCA results:

Scree Plot: To see the proportion of variance each of the components represents, also to decide the number of significant components. Variable Contribution Plot: To check how each questionnaire item relates to the principal components.

Correlation Plot: For understanding the relationships and patterns of clustering between behavioural variables. Component scores were finally extracted and saved for likely further

analysis or subsequent regression modelling if required for deepening the understanding of the dimensions driving consumer adoption

4.0 RESULT AND DISCUSSION

4.1 Introduction

This chapter discusses the results of data analytics for identifying significant factors affecting consumer adoption and loyalty in Quick Commerce (Q-Commerce). The analysis was conducted based on PCA, where the attempt was made to reduce the dimensionality of the dataset and examine latent variables having explanatory power with respect to consumer behavior. Analysis in this study was conducted using R Studio, and here results have been presented systematically, in order to include descriptive statistics, scree plots, biplots, correlation matrices and interpretation of components.

4.2 Data Preparation

The preprocessing steps were the ones taken before carrying out Principal Component Analysis. The raw data obtained from the questionnaire were cleaned, filtered, and formatted for analysis in R Studio.

The present research study utilized a developed questionnaire as an instrument and was constructed using the Google Forms platform. The overall survey examined consumer behaviour in the Quick Commerce industry with specific focus on some influencing factors of use and loyalty. The respondents' ratings of 20 behavioural statements were solicited via a 5-point Likert scale (whether the respondent Strongly Disagreed or Strongly Agreed with a respective statement). Two hundred and eighty complete responses were received, and all partial or questionable records can be purged from the dataset, to maintain the integrity of the data. Demographic variables were excluded so that pure behaviour could be measured through PCA analysis. The 20 survey items were organized by behavioural types: Convenience and Speed, Trust and Service Quality, Loyalty and Emotional Attachment, Promotions and Price Sensitivity. This grouped set (20 items) was kept in the Excel dataset from column six to column twenty-five in the data sheet. This data block was extracted for further analysis and processing in R Studio.

4.3 Descriptive Statistics and Distribution

Then, we applied the basic statistical methods that include plotting histograms, Q-Q plots, and conducting the Shapiro-Wilk normality test before performing PCA with respect to all twenty behavioural variables. This method evaluates how reasonably data are good for PCA as well as tests assumptions, such as linearity and, to a lesser extent, normality. But before applying PCA,

such basic statistical techniques as plotting histograms, Q-Q plots, and conducting Shapiro-Wilk normality tests were first conducted to check for behaviour among the 20 behaviours being analysed. This methodology tests how well the data fit for use in PCA and whether key assumptions such as linearity and approximate normality have been reasonably fulfilled.

4.3.1 Histogram of Area

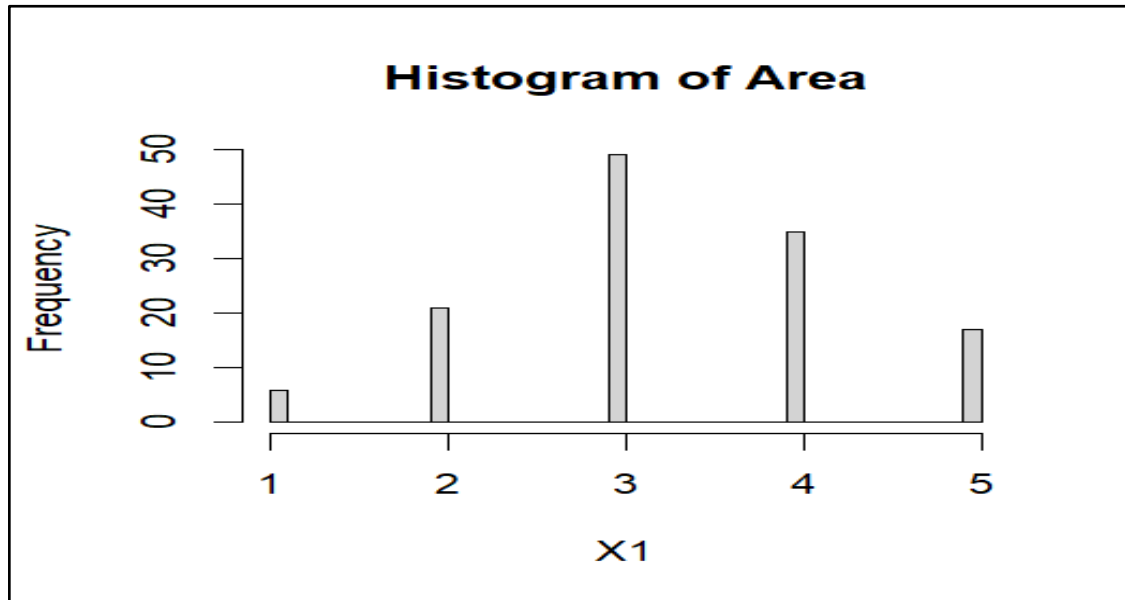


Figure 1: Histogram of Area

Histograms were produced to visualize the data distribution of the responses for each Likert scale question. Figure 4.1 shows the frequency distribution for one of the variables (X1). X1 stands for consumer preference in using Quick Commerce platforms. The histogram shows a very centralized distribution with responses clustered around value 3 (Neutral) and value 4 (Agree). This suggests a slight agreement to an agreement with the statement. Histograms are also important to assess whether the distribution is skewed or symmetrical and trends in customer behaviours before undertaking more detailed multivariate analyses of the data, such as PCA.

4.3.2 Q-Q Plot

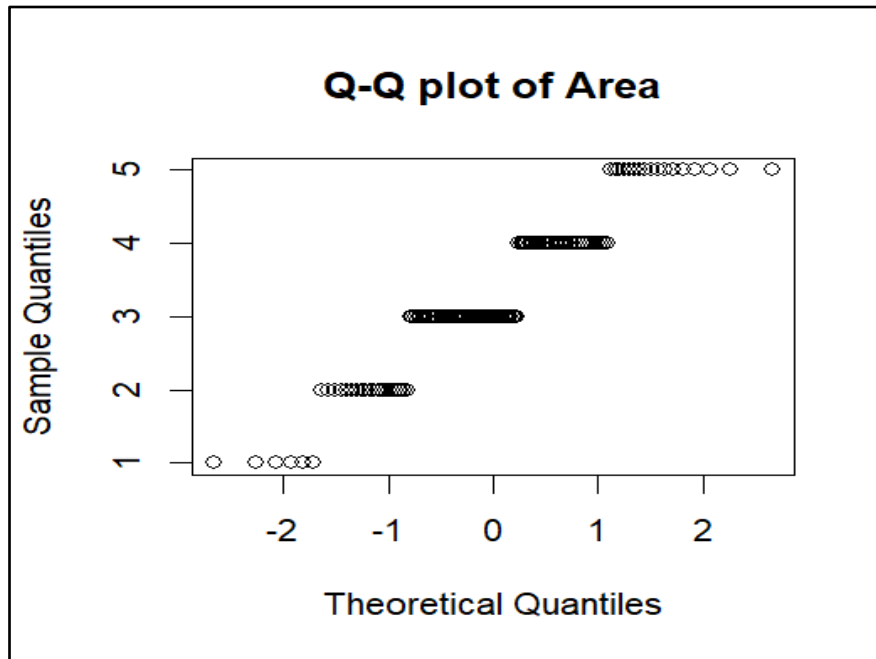


Figure 2: Q-Q Plot

A Quantile-Quantile (Q-Q) plot was created in order to further assess normality for the same variable (X1). Figure 4.2 shows the scatter of sample quantiles against theoretical quantiles derived from a normal distribution. The plot does indicate some dislocation of the data points away from the reference line, particularly at both ends of the scale. In other words, the distribution of X1 is showing some evidence of metrics peaking away from normality, justified by the nature of the limited applicability of Likert-type data. The distribution is certainly not strictly normal, but there is some corroborative visual evidence illustrated in the Q-Q plot that was corroborated by other statistical assessments. On a more positive note, minor separation from normality does not preclude the data being assessed with PCA based on the strength of PFA/PA with n admitted above 100.

4.4 Sampling adequacy

The suitability of the dataset for deriving factor could be shown through the Kaiser-Meyer-Olkin test of sampling adequacy which was done prior to double principal component conversion. A high KMO value indicates that the variables share common variance enough to be able to enter into PCA. Beneath the application of factor extraction, the adequacy of a dataset has to be checked out. This was done by using the Kaiser-Meyer-Olkin (KMO) test, which measures sampling adequacy, where a high value of KMO implies that the variables have common variance sufficient for PCA.

4.4.1 KMO Test

KMO Values by Variable

Table 2: KMO Values

Variable Code	KMO Value	Factor
1. TRD	0.897	Convenience & Adoption
2. DLY	0.919	Convenience& Accessibility
3. PUR.	0.919	App Usability
4. TME	0.827	Delivery Speed Importance
5. D&P	0.921	Pricing & Promotions
6. COS	0.878	Customer Service Trust
7. GDC	0.861	Product Quality Trust
8. FAS	0.901	Willingness to Pay for Speed
9. PHY	0.9	Shift in Shopping Behaviour
10. CON	0.894	Habitual Convenience
11. SME	0.897	Loyalty Behaviour
12. COM	0.872	Brand Loyalty Over Price
13. EMO	0.938	Emotional Brand Connection
14. L&R	0.928	Influence of loyalty programs
15. EXP	0.921	Satisfaction with the Platform Overall
16. DLC	0.851	Loyalty Despite Price Change
17. LMS	0.902	Urgency-based Usage
18. Q&R	0.914	Delivery Reliability
19. FRQ	0.927	Word-of-Mouth Advocacy
20. SWT	0.872	Platform Commitment

The overall KMO score was 0.899, which falls into the "meritorious" category. This indicates a fair amount of shared variance between the different variables and strong factorability for the whole data set. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was calculated to determine the appropriateness of the dataset for Principal Component Analysis. In addition, the KMO individual values for all the 20 variables exceeded the acceptable threshold of 0.70,

further confirming the appropriateness of the data set for PCA. Hence, the data is suitable for dimension reduction and extraction of underlying factors.

4.5 principal component analysis (initial run)

Principal Component Analysis (PCA) will be used to discover the structure of the 20 behavioural parameters. The data set was standardized and ran through the PcaClassic() function in R Studio for the first PCA run, producing eigenvalues and proportion of variance accounted for for every component. This allows the researcher to determine the appropriate number of principal components to keep for further interpretation.

4.5.1 Standardization

All 20 behavioural variables were standardized using the scale () function in R Studio to ensure comparability and equal contribution to the analysis. Standardization transforms the data into a common scale with a mean of 0 and standard deviation of 1. This step is essential for PCA, especially when variables are measured using Likert scales with the same response format but different interpretations. The standardized dataset was then used to perform the initial PCA.

4.5.2 PCA Execution

Table 3: PCA Execution

Component	Standard Deviation	Proportion of Variance	Cumulative Proportion
PC1	2.8744	0.4131	0.4131
PC2	1.35747	0.09214	0.50524
PC3	1.04068	0.05415	0.5594
PC4	0.9913	0.04913	0.60853
PC5	0.91704	0.04205	0.65058
PC6	0.87828	0.03857	0.68915
PC7	0.84823	0.03597	0.72512
PC8	0.82438	0.03398	0.7591
PC9	0.8111	0.03289	0.792
PC10	0.78004	0.03042	0.82242
PC11	0.76693	0.02941	0.85183
PC12	0.68155	0.02323	0.87505
PC13	0.66721	0.02226	0.89731
PC14	0.61829	0.01911	0.91643

PC15	0.60415	0.01825	0.93468
PC16	0.55835	0.01559	0.95026
PC17	0.52594	0.01383	0.96409
PC18	0.52482	0.01377	0.97787
PC19	0.49898	0.01245	0.99031
PC20	0.44012	0.00969	1

The PCA was completed on the standardized data set using the `PcaClassic()` function in R Studio. The output showed that the first component (PC1) captured 41.31% of the total variance, the first component's standard deviation was 2.8744, while the second component (PC2) had a standard deviation of 1.3575 and accounted for an additional 9.21%. Together, these two components accounted for 50.52% of the total variance and by far, were the most powerful components to interpret the behaviour patterns of consumptions. Cumulative variances of the other components gradually increased, but the additional components did not add much value after PC2. Therefore, only the first two components were analysed and interpreted, as they provided a solid balance between simplicity (of the model) and explained variance.

4.6 Screen plot analysis

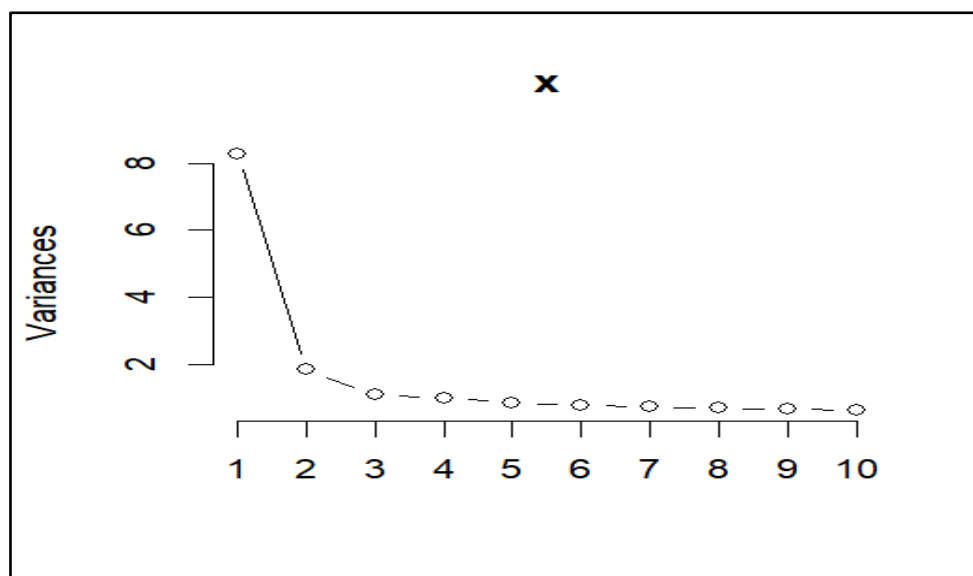


Figure 3: Screen plot analysis

The Screen Plot, a visual means of determining the appropriate number of principal components to keep in the context of a principal component analysis, displays the eigenvalues for all components so as to illustrate the point at which taking more components adds little

explanatory value—known as the elbow criterion. As can be seen in Figure 4.3, a clear elbow is observed after PC2, where the line representing the eigenvalues had a steep decrease in slope. The conclusion we can draw is that the first two components explain most of the variance and that there will be very little explained variance by other components. Therefore, with respect to the observations we made and 50.52% of cumulative variance, retaining two components to continue with our further analyses is statistically and interpretively meaningful.

4.7 Component Retention and Justification

The number of components to retain for analysis was determined by the following three well-established criteria: eigenvalue-greater-than-weighting rule, scree plot elbow method, and parallel analysis. The eigenvalue summary from PCA showed that the first two components had eigenvalues well above 1, and thus together accounted for a total of 50.52% variance. Besides, above these two components, scree plot showed a marked "elbow" on further such components with respect to variance explained (Figure 4.3).

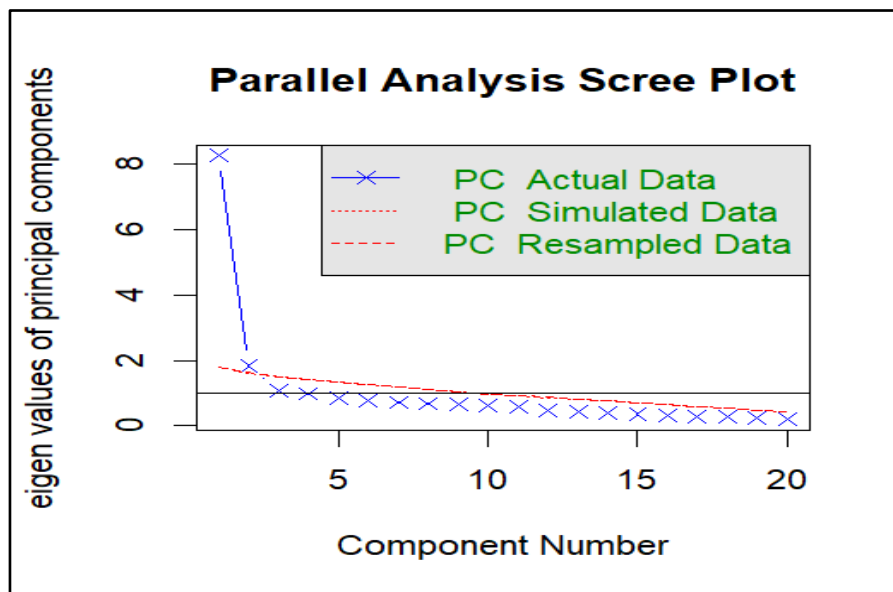


Figure 4: Parallel Analysis Screen plot

This decision was further supported by reference to the parallel analysis carried out (Figure 4.4), in which the actual eigenvalues were plotted against the eigenvalues of the random simulated data: Only the first two components had eigenvalues greater than the simulated dataset, confirming their relevance and statistical significance for interpretation. Therefore, on the basis of triangulation through methods, only two components were retained for further interpretation. The combination of these two components resulted in an ideal situation for

parsimonious and explanatory purposes while also being interpretable with meaningful structure regarding consumer behaviour.

4.8 Final PCA Results.

In this section we will present the results of PCA with retention of two components based on the Scree Plot and Random data parallel analysis criteria. The loadings of the variables on the two components were examined in a way to provide some insights into the underlying dimensions of consumer behaviour. These components best represent the truncation of the data set into the largest number of discrete patterns to reduce complexity and retain the interpretability of the factors. The subsections below discuss the discussion regarding comments on each principal component.

4.8.1 Summary Table

It would construct an overview table that represents the loading values for both PC1 and PC2 to interpret the influence of each of the behavioural variables on the main components. Higher positive or negative loading values indicate greater association with that component.

Table 4: Summary Table

Variable	PC1 Loading	PC2 Loading
1. TRD	0.2150376	-0.236199053
2. DLY	0.2422828	-0.23190258
3. PUR	0.2077367	-0.242538076
4. TME	0.1908138	-0.267278902
5. D&P	0.2116208	-0.30036419
6. COS	0.1927705	0.25601471
7. GDC	0.213918	0.279493183
8. FAS	0.2202527	-0.000491316
9. PHY	0.2304489	0.246519797
10. CON	0.2116079	0.332363064
11. SME	0.2063574	0.15690394
12. COM	0.2161516	0.277250104
13. EMO	0.2385924	0.120533293
14. L&R	0.238514	-0.093092157
15. EXP	0.2575163	-0.097776744

16. DLC	0.1907526	0.37411151
17. LMS	0.2108622	-0.151951387
18. Q&R	0.2557009	-0.235446658
19. FRQ	0.2486053	-0.036550906
20. SWT	0.2528263	-0.031487603

Table 4.3 clearly depicts that most of the variables are loading strongly on the first principal component PC1 which portrays the common behavioural dimension concerning consumer trust, loyalty, and continued usage of the service. Meanwhile, the second principal component, PC2, captures differences in experience-related and service efficiency factors with delivery logistics, app usability, and time-saving contrastingly loading on the variables. This table is a basis for determining which components would be influential in consumer adoption behaviour and loyalty in the Quick Commerce field.

4.8.2 Interpretation of Components

- Principal Component 1 is more broadly characterized by trust, convenience, customer satisfaction, app usability, and continued use. Most variables show high positive loadings which suggest that PC1 represents the common behavioural engagement dimension, with users often assigning similar preference, satisfaction, and comfort levels to Q-commerce platforms. This component brings together the central underpinnings of initial adoption and sustained use.
- Principal Component 2 is articulated by discount sensitivity, loyalty programs, and emotion charge. The mix of positive and negative loading refers to a scenario in which users develop functional loyalty (reward-driven behaviour alongside emotional loyalty (brand affinity). Accordingly, PC2 can be said to capture consumer loyalty behaviour and promotional responsiveness.

4.9 Correlation Plots and Loadings

To show the relationships between the original behavioural variables and the extracted principal components, correlation plots were created. In this way, insights arise on how strongly and in what direction each variable influences the underlying components. This plot facilitates the understanding of component loadings and demonstrates clusters of related behaviours.

4.9.1 Full Loading Matrix

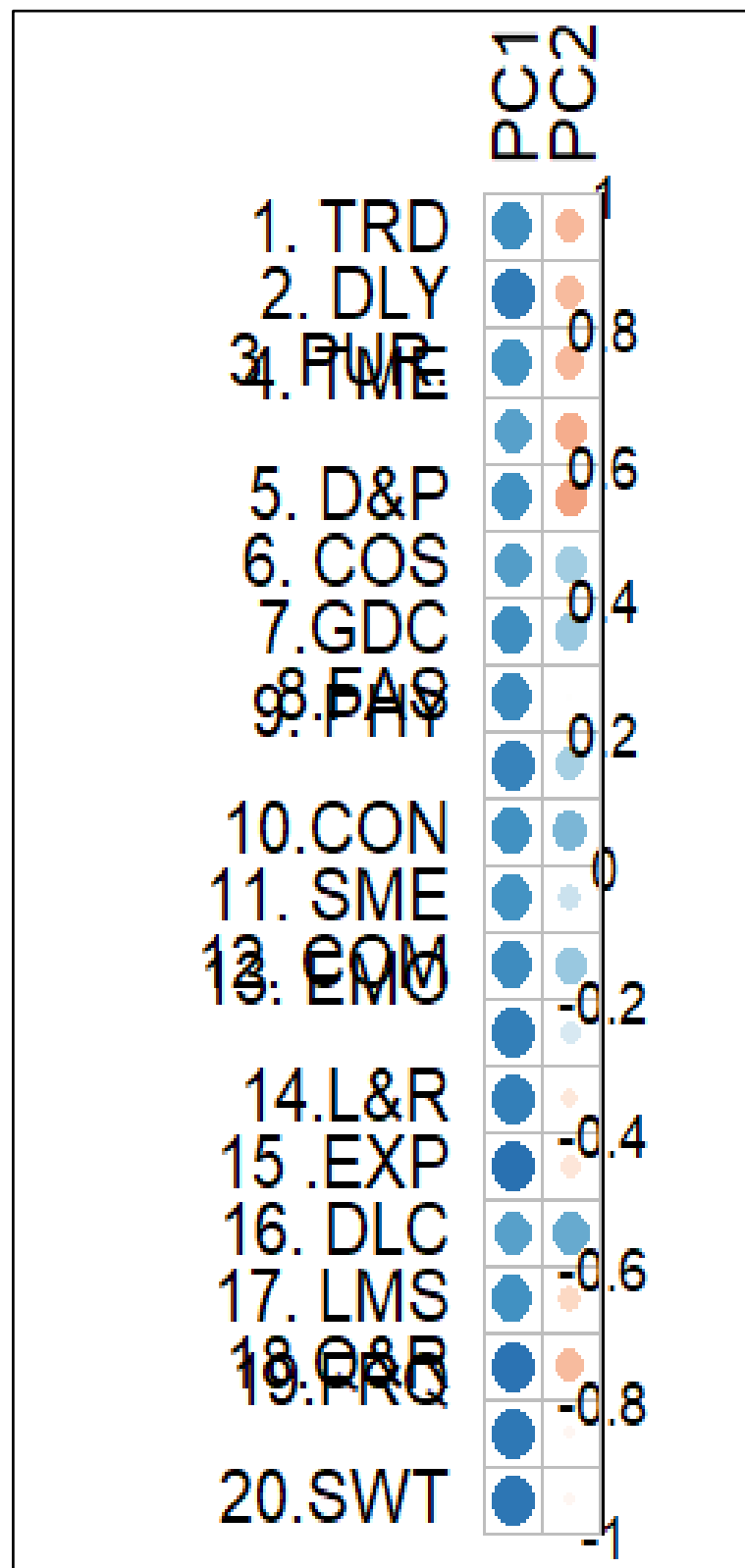


Figure 5: Full Loading Matrix

This was also presented in a full loading matrix to illustrate the strength and direction of behavioural variables in relation to each other and the extracted principal components. As depicted in the upcoming figure (Figure 4.6), the matrix shows what is in PC1 and PC2, with colour intensity and size indicating how strong the variable was related. Clearly PC1 has the most common variance across all variables with highly and consistently positive correlation to, trust, satisfaction, app usability, and habitual usage behaviour; whereas PC2 definitely has less consistent distribution characteristics with less consistent influences from variables related to loyalty, promotions and emotional engagement. So, this was a matrix representing a constructed structure of principal components, which was also strong evidence that there are two dimensions relevant to consumer adoption and loyalty behaviour towards Quick Commerce.

4.9.2 Final Component Loadings

The last correlation plot (Figure 4.6) depicts how each of the behavioural variables correlates with the two retained principal components describing user satisfaction. The size and colour of the circles plotted in the graph describe the strength and direction of those associations. PC1 correlates very well with most of the variables, particularly those pertaining to trust (TRD) and frequency of recommendation behaviour (FRQ), on-time delivery and scalability of reliability (Q&R), loyalty/ rewards (L&R), and customer satisfaction with the platform (SWT). Thus, PC1 indicates a broad dimension of engagement and trust associated with user satisfaction and motivation to continue using the platform. In very stark contrast, the second component, PC2, relates to a much narrower range of variables. Strong positive loading exist in the delivery logistics (DLC) and customer service (CON), while moderate negative associations emerge in time-saving (TME) and discount-related sensitivity (D&P) variables. Thus, this component appears to be indicative of the trade-off between functional performance and emotional engagement, where users assess operational performance and personalized brand connection in quite different terms. The table below summarizes the key contributing variables of each of the components:

Table 5: PC1 and PC2

Component	Key Contributing Variables	Description
PC1	TRD, FRQ, SWT, Q&R, EXP, L&R	Convenience & Adoption, Platform Commitment, Word-of-Mouth Advocacy, Delivery Reliability, Satisfaction with the Platform Overall, Influence of loyalty programs
PC2	DLC, CON, COM, SME, D&P (NEGATIVE), TME (NEG)	Loyalty Despite Price Change, Habitual Convenience, Brand Loyalty Over Price, Loyalty Behaviour, Pricing & Promotions (neg), Delivery Speed Importance (neg)

This interpretation bolsters previous findings linking PC1 to generalized user satisfaction and loyalty and PC2 to mutualized expectations related to service experience and promotional factors. Together, these insights provide the groundwork for understanding clusters of consumer behaviour in Quick Commerce environments.

4.10 Biplot and Factor Visualization

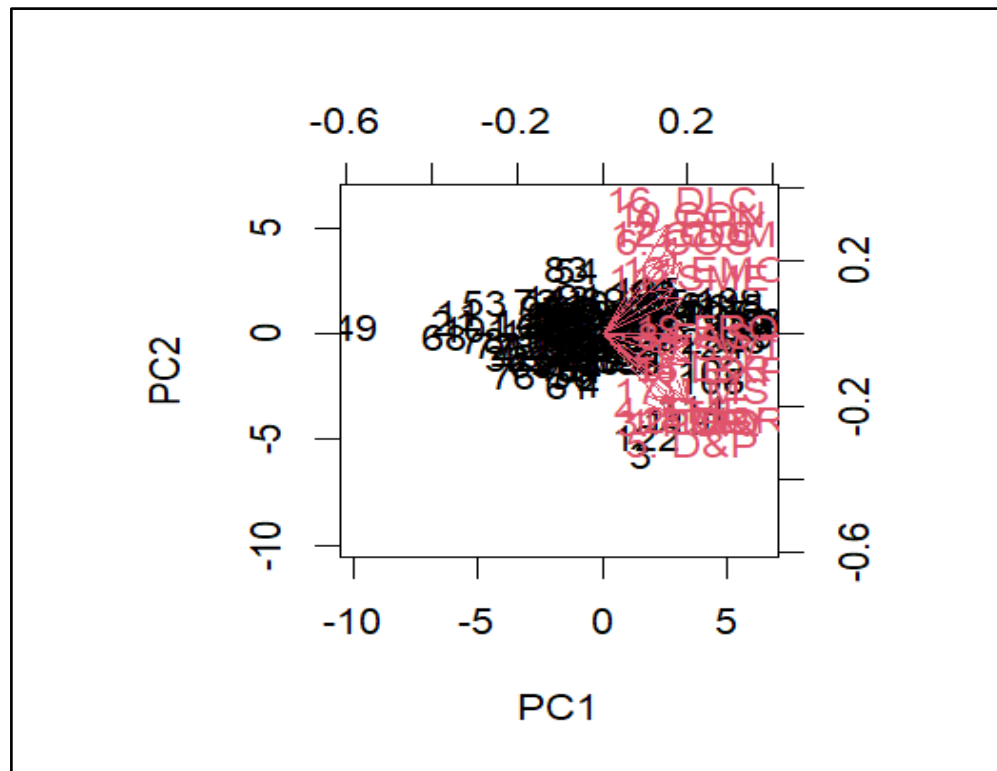


Figure 6: Biplot and Factor visualization

It combines a visual representation of the variables and this respondent along the first two principal components. The black dots represent the individual surveys in this chart (Figure 4.8), with the red vectors dictating the direction and magnitude of each behavioural variable with respect to PC1 and PC2. Looking from the biplot, nearly all the variables cluster towards the positive end of PC1, reaffirming this general dimension is contributing to the understanding of engagement, including trust, satisfaction, loyalty, and platform usability. Other variable presentations, such as Q&R (Quality & Reliability), SWT (Switching Tendency), and EXP (Platform Experience), have longer vectors which suggests they were stronger principal contributors. There are some other variables with shorter arrows or more centrally located suggesting at least some tendency of lesser influence or a at least a inter-matching contribution over components. Moving onto PC2, this was further characterized through dispersing directions of variable indicative of change in behaviour resulting from delivery experience, emotional attachments, and customer services. The respondents for whom a not much massive variation exists seem to make up the glue grouped around the centre. Overall, the biplot enhances the interpretation by, confirming the variables that each component is structured upon, and illustrating the proportionate variance captured.

4.11 Component Naming and Final Interpretation

The Principal Component Analysis (PCA) kept only two components which jointly accounted for about 50.52% of the total variance in consumer behaviour data. These components were clearly interpretable, and they were distinct in terms of the type of behaviour they measured:

- Component 1 has high positive factor loadings on mostly all of the variables, especially trust in platform reliability (TRD), customer experience (EXP), recommendation intent (FRQ), and satisfaction with the platform (SWT). Given its strong convergence on high usage frequency, good perception, and easy adoption, PC1 has been named "Trust and Adoption Behaviour."
- Component 2 shows characteristic profiles being driven by delivery logistics (DLC), customer service experience (CON), and emotional bonding (EMO), with promotional engagement responses being another driving factor. These variables capture loyalty patterns on a micro-level and reward-based engagement, hence endeavouring to name PC2 "Loyalty and Service Expectations."

The interpretation of these components lends credence to the real drivers of consumer behaviour in Q-commerce. PC1 predominantly describes the basic trust and ease of use, while PC2 concerns emotional and service factors that provide continued loyalty toward the platform. Therefore, these results have implications in formulating strategies to enhance customer retention, satisfaction, and platform differentiation in a highly competitive quick commerce market.

5.0 FINDINGS AND CONCLUSION

5.1 Key Findings

In-depth understanding of the behavioural dimensions influencing consumer adoption and loyalty in Quick Commerce platforms was the basis of this study, which applied Principal Component Analysis (PCA). The study distilled behaviour factors into two components from primary data collected through a structured questionnaire and analysed using R Studio. The components reflect basic motivations and expectations from users in Q-commerce, offering actionable strategies for such platforms. Findings, In Principle

The PCA identified two broad components that were responsible for the behavioural dimension of Q-commerce users:

Trust and Adoption Behaviour.

It is the perceived user confidence, satisfaction, and choices with regard to quick commerce. It elucidates strong contributions from:

- Platform trust (TRD)
- Delivery satisfaction (DLY)
- App experience (EXP)
- Frequency of use and recommendations (FRQ)
- Overall satisfaction (SWT)

Insights: Q-commerce users trust service as possessing value offerings, and ease of use makes them more inclined to adopt and continue using a Q-commerce platform.

Loyalty and Service Expectations/PC2

This is reflection of emotional drivers and expectations for quality of service over time. The key variables presented include:

- Loyalty rewards (L&R)
- Emotional attachment (EMO)
- Customer service and response (CON)
- Discounts and delivery charges (D&P, DLC)

Insight: Loyalty in Q-commerce embraces emotional elements and responds to the rewards.

5.2 Conclusion

This is the quest through which one can understand the behavioural factor towards quick commerce adoption and loyalty. It derives two distinct behavioural dimensions of Trust and Adoption Behaviour and Loyalty and Service Expectations through applying Principal Component Analysis (PCA) on data collected through a structured Likert scale questionnaire. Initial adoption of Q-commerce by consumers is mainly due to convenience and speed. In contrast, acceptance of Q-commerce for long-term loyalty is found to be due to trust and reliability, emotional connection, and other service-related factors. Thus, the implications of the study suggest a dual perspective—both operations and consumer experience need to be optimized. The other findings include the demonstration of PCA as an appropriate tool for bringing practical patterns in consumer decision-making. The entire analyses constitute a valuable foundation for future Q-commerce businesses to recalibrate their customer engagement techniques, improve platform usability, and develop personalization-based loyalty programs. This study serves toward better understanding the consumers' mind in a quickly instigated scope of Q-commerce with much relevance for practice in building future-proof and competitive digital retailing solutions.

5.3 Limitation of the study

- **Limited Sample Size and Geographic Scope:** Response data were collected from a limited sample of respondents, mainly within a particular region, which may limit generalization to a broader population.
- **Self-Reported Responses:** The study relied mostly on self-report data gathered via a structured questionnaire and there may have been response bias or social desirability with respect to the answers given by the participants.
- **Emphasis on Quantitative Analysis Only:** The research employed PCA for dimensionality reduction yet lacked qualitative insights that would have contributed to a richer insight into consumer motivation and experiences.

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