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# Impact of Quick Commerce Applications on Consumers Buying Behaviour and Brand Perception

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**Abstract:** Q-commerce, or quick commerce, emphasizes rapid deliveries, usually within an hour. This article attempted to evaluate the impact of quick commerce apps on consumer buying behaviour and brand perception, considering demographic factors such as age, gender, occupation, educational qualification, and area of residence. A non-probability convenience sampling method was used to collect data from 100 users through a structured questionnaire. Statistical tools like ANOVA, regression, and correlation were applied for analysis. Findings indicate that demographic factors have no significant statistical correlation with brand perception towards quick commerce apps, with age, gender, qualification, and occupation negatively associated, while area of residence showed a positive association. Additionally, consumer awareness and acceptance of fintech were found to be statistically insignificant in relation to each other.

**Keywords:** Quick commerce, Brand Perception, Convenience sampling, Consumer Behaviour, E-commerce Adoption.

## 1 INTRODUCTION

Quick commerce (Q-commerce) has emerged as a transformative paradigm within the digital retail ecosystem, emphasizing ultra-fast delivery models typically ranging from 10 to 30 minutes. This rapid evolution is largely supported by technological advancements such as the Internet of Things (IoT), which enables real-time inventory tracking, efficient warehouse management, and enhanced consumer satisfaction through micro-fulfilment centers [1]. The integration of advanced technologies has significantly improved operational efficiency and service responsiveness in quick commerce platforms. The growing adoption of digital platforms has also reshaped consumer behavior, particularly in online shopping environments. Emerging technologies such as virtual reality (VR) and immersive digital interfaces are influencing consumer decision-making processes by enhancing product visualization and engagement, thereby strengthening purchase intentions [2].

In the context of Q-commerce, such technological interventions contribute to more personalized and interactive user experiences. Recent studies highlight that quick commerce is not only a logistics innovation but also a significant driver of customer loyalty and brand engagement. The increasing reliance on instant delivery services has led to evolving consumer expectations, where speed, reliability, and service quality play a critical role in shaping brand perception [3]. Additionally, sustainability-oriented initiatives within Q-commerce platforms have been found to positively influence customer engagement and brand trust, indicating the growing importance of environmentally responsible practices [4].

Pricing strategies and logistics models further influence consumer behavior and platform efficiency in Q-commerce. Behavior-based pricing mechanisms and the choice between self-logistics and platform-based logistics significantly impact service performance and customer satisfaction [5]. At the same time, artificial intelligence (AI)-driven marketing strategies are enabling companies to build stronger emotional connections with consumers, thereby fostering brand evangelism and long-term loyalty [6]. From an operational perspective, advanced computational techniques such as reinforcement learning are being utilized to optimize order scheduling and resource allocation in Q-commerce systems [7]. Similarly, integrated frameworks for delivery partner selection and demand optimization are enhancing service reliability under uncertain and dynamic market conditions [8]. These developments demonstrate the increasing role of intelligent systems in improving the efficiency and scalability of Q-commerce operations. Furthermore, the emergence of Q-commerce has led to significant changes in traditional retail supply chains, particularly through the adoption of dark stores and localized distribution networks, which enable faster deliveries in urban environments [9].

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Machine learning techniques are also being applied to product classification and pricing optimization, improving decision-making accuracy and operational effectiveness [10]. In addition, AI-driven solutions are contributing to performance enhancement and operational sustainability in Q-commerce retail systems [11]. Customer retention has become a key focus area for Q-commerce platforms, with AI-based systems enabling personalized recommendations and targeted engagement strategies. Comparative analyses of platforms such as Blinkit and BigBasket indicate that intelligent retention mechanisms play a crucial role in sustaining competitive advantage in the market [12]. Despite the rapid growth and technological advancements in Q-commerce, there remains a research gap in understanding its impact on consumer buying behaviour and brand perception, particularly in emerging markets like India [13][14].

While existing studies have extensively explored technological and operational aspects, limited attention has been given to how demographic factors, usage patterns, and awareness levels influence consumer perceptions and purchasing decisions. Therefore, this study aims to bridge this gap by examining the relationship between quick commerce applications, consumer behaviour, and brand perception using empirical analysis.

## 2 Literature Review

Quick commerce (Q-commerce) has significantly transformed modern retail and consumer purchasing patterns by enabling ultra-fast deliveries supported by advanced technological infrastructures. The role of Internet of Things (IoT) in optimizing operations through micro-fulfilment centers has been highlighted as a key enabler in improving delivery efficiency and customer satisfaction [1]. Alongside operational advancements, evolving digital environments such as virtual reality-based product exploration are reshaping consumer behaviour by enhancing engagement and influencing purchase decisions in online platforms [2]. The rapid growth of Q-commerce has attracted considerable research attention, particularly in understanding its impact on customer loyalty and brand perception.

Bhosekar and Gaurav [3] emphasized that service speed, reliability, and convenience are critical determinants of customer retention and brand loyalty in Q-commerce platforms. Furthermore, sustainable practices and green initiatives adopted by Q-commerce firms have been shown to positively influence customer engagement and strengthen brand relationships [4]. Pricing strategies and logistics frameworks also play a crucial role in shaping consumer behaviour and operational performance. Zhu and Xie [5] discussed behaviour-based pricing models and logistics structures, highlighting their influence on service efficiency and consumer satisfaction. In addition, AI-driven marketing strategies are increasingly being utilized to personalize customer interactions, thereby enhancing brand connection, engagement, and long-term loyalty [6].

From a technological perspective, the integration of advanced computational models has further strengthened Q-commerce systems. Reinforcement learning-based frameworks have been applied to optimize product scheduling and operational efficiency in multi-product environments [7]. Similarly, integrated decision-making models for delivery partner selection and demand optimization have improved system performance under uncertain and dynamic conditions [8]. These advancements demonstrate the growing importance of intelligent systems in ensuring service reliability and scalability. The emergence of Q-commerce has also led to structural changes in supply chains, particularly through the adoption of dark stores and localized distribution systems, which facilitate rapid delivery in urban areas [9]. Machine learning approaches for product classification and pricing optimization have further enhanced decision-making processes within Q-commerce platforms [10].

Additionally, artificial intelligence has been leveraged to improve operational performance, enabling better forecasting, inventory management, and customer service delivery [11]. Customer retention and engagement have become central to the success of Q-commerce platforms. AI-driven retention systems, including personalized recommendations and targeted marketing strategies, have proven effective in maintaining customer loyalty and improving user experience. Comparative studies on leading platforms such as Blinkit and BigBasket indicate that advanced AI-based retention mechanisms significantly contribute to sustaining competitive advantage in the Q-commerce sector [12].

Despite these advancements, there remains a significant research gap in understanding the behavioural dimensions of Q-commerce, particularly in emerging markets like India. While existing literature has extensively focused on technological, operational, and strategic aspects, limited studies have explored how demographic factors, awareness levels, and frequency of usage influence consumer buying behaviour and brand perception. Therefore, further empirical investigation is necessary to bridge this gap and provide deeper insights into consumer interactions with Q-commerce platforms.

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## 3 Preliminaries

This study focuses on evaluating consumer perception, adoption behaviour, and usage patterns associated with Quick Commerce (Q-commerce) applications. Given the rapid growth of instant delivery platforms, it is essential to understand how consumers interact with these services and how various factors influence their decision-making processes. The preliminary framework of the study establishes the foundation for systematic data collection, measurement, and analysis of consumer responses. The research primarily emphasizes behavioural constructs such as brand perception, level of awareness, frequency of usage, and purchasing behaviour, along with key demographic variables including age, gender, educational qualification, occupation, and area of residence. These variables are considered critical in examining variations in consumer adoption and perception towards Q-commerce applications.

### 3.1. Data Collection Framework

The data collection framework is designed to ensure systematic acquisition of relevant and reliable information from respondents. The study adopts a quantitative research approach, where primary data is collected directly from users of quick commerce applications. A structured methodology is employed to capture measurable insights into consumer attitudes, preferences, and behavioural patterns.

The data collection process involves identifying target respondents who have prior experience with Q-commerce platforms such as Blinkit, Zepto, and Swiggy Instamart. The framework ensures that responses are obtained from individuals who are familiar with the services, thereby enhancing the validity of the collected data. The study also incorporates multiple dimensions of analysis, including behavioural, perceptual, and demographic aspects, to provide a comprehensive understanding of consumer interaction with Q-commerce applications.

### 3.2. Data Collection Method

The study is based on primary data collected through a structured questionnaire, which serves as the main instrument for data gathering. The questionnaire is carefully designed to capture both qualitative and quantitative aspects of consumer behaviour. It consists of multiple sections, each addressing specific variables of the study.

The questionnaire includes:

- Multiple-choice questions to gather categorical data related to demographic characteristics and usage patterns.
- Likert scale statements to measure respondents' attitudes, perceptions, and satisfaction levels regarding Q-commerce services.
- Open-ended questions to obtain additional insights and subjective opinions from respondents.

The use of Likert scale items enables the quantification of abstract constructs such as brand perception, awareness, and user satisfaction, facilitating statistical analysis. The questionnaire is structured in a logical sequence to ensure clarity, ease of response, and minimization of respondent fatigue. Prior to distribution, the questionnaire is reviewed to ensure content validity and relevance to the research objectives.

### 3.3. Data Collection Tool

The primary tool used for data collection in this study is Google Forms, an online survey platform that allows efficient and scalable distribution of questionnaires. The use of digital survey tools offers several advantages, including ease of access, rapid data collection, automated response recording, and reduced chances of data entry errors. Google Forms enables the researcher to reach a diverse group of respondents across different geographic locations, particularly in urban and semi-urban areas where Q-commerce services are widely used.

The platform also ensures anonymity and confidentiality of responses, encouraging participants to provide honest and unbiased feedback. Additionally, the collected data is automatically compiled into structured datasets, which can be easily exported for further statistical analysis using tools such as Microsoft Excel or statistical software packages. This enhances the efficiency and accuracy of the data processing stage.

## 4 METHODOLOGY

This study examines the impact of quick commerce applications on consumer purchasing behaviour and brand perception. The research focuses on widely used platforms such as Blinkit, Zepto, and Swiggy Instamart, considering their increasing adoption and influence in the digital retail ecosystem.

### 4.1. Research Design

The study adopts a descriptive research design to systematically analyse consumer behaviour, preferences, and perceptions toward quick commerce services. This approach enables the identification of patterns such as frequency of usage, impulse buying behaviour, and satisfaction levels.

### 4.2. Sampling Method

A convenience sampling technique is employed to collect data from respondents who are accessible and actively use quick commerce applications. A total sample size of 100 respondents is considered adequate to identify behavioural trends and relationships among variables.

### 4.3. Variables of the Study

The key variables considered in this study are presented in Table 1, which categorizes demographic, independent, and dependent variables.

Table 1. Variables Considered in the Study

| Category | Variables |
|---|---|
| **Demographic Variables** | Age, Gender, Educational Qualification, Occupation, Area of Residence |
| **Independent Variables** | Usage of Q-commerce Apps, Level of Awareness, Frequency of Usage |
| **Dependent Variables** | Brand Perception, Consumer Purchasing Behaviour, Adoption |

### 4.4. Data Analysis Techniques

The collected data is analysed using statistical tools including regression analysis, ANOVA, and correlation analysis to examine relationships between variables and test the proposed hypotheses.

### 4.5. Scope of the Study

The study focuses on consumers using quick commerce applications in urban and semi-urban areas, analysing their buying behaviour, preferences, and brand perception.

### 4.6. Limitations of the Study

- Limited sample size
- Possible respondent bias
- Focus on selected platforms only
- Time constraints limiting deeper analysis

### 4.7. Summary of Key Findings

**H1**: Relationship between Demographic Factors and Brand Perception

The regression results presented in Table 2 indicate the overall model fitness and statistical significance.

Table 2. Regression Model Summary

| Model | R | R Square | Adjusted R Square | Std. Error | R Square Change | F Change | df1 | df2 | Sig. |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.179 | 0.032 | -0.019 | 1.435 | 0.032 | 0.625 | 5 | 94 | 0.681 |

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The coefficient values for individual variables are shown in Table 3.

Table 3. Regression Coefficients

| Variable | B | Std. Error | Beta | t | Sig. |
|---|---|---|---|---|---|
| **Constant** | 3.253 | 1.103 | — | 2.949 | 0.004 |
| **Age** | -0.011 | 0.232 | -0.005 | -0.048 | 0.962 |
| **Gender** | -0.079 | 0.298 | -0.028 | -0.264 | 0.792 |
| **Qualification** | -0.152 | 0.204 | -0.084 | -0.747 | 0.457 |
| **Occupation** | -0.060 | 0.138 | -0.050 | -0.435 | 0.664 |
| **Area of Residence** | 0.259 | 0.163 | 0.165 | 1.590 | 0.115 |

As observed from Table 2 and Table 3, demographic variables are statistically insignificant. Age, gender, qualification, and occupation show negative association, while area of residence shows a positive association with brand perception.

**H2:** Relationship between Usage and Brand Perception

The ANOVA results for usage-related variables are presented in Table 4.

Table 4. ANOVA Results for Usage of Quick Commerce Applications

| Usage Factor | Mean | Std. Dev. | F-Value | Significance |
|---|---|---|---|---|
| **Ordering groceries** | 3 | 1.421 | 2.998 | 0.220 |
| **Usage for urgent needs** | 3 | 1.421 | 3.269 | 0.075 |
| **Browsing without purchasing** | 3 | 1.421 | 3.705 | 0.008 |
| **Frequency of app usage** | 3 | 1.421 | 3.189 | 0.017 |
| **Reliance on apps for urgent needs** | 3 | 1.421 | 3.268 | 0.015 |

From Table 4, it is evident that browsing behaviour, frequency of usage, and urgent usage are statistically significant, whereas grocery ordering is not significant.

**H3:** Relationship between Awareness and Adoption

The correlation between awareness and adoption is shown in Table 5.

Table 5. Correlation between Awareness and Adoption

| Variable | Awareness | Adoption |
|---|---|---|
| **Awareness** | 1 | 0.192 |
| **Adoption** | 0.192 | 1 |
| **Significance (p-value)** | — | 0.055 |
| **Sample Size (N)** | 100 | 100 |

As indicated in Table 5, awareness and adoption are positively related but statistically insignificant.

**H4**: Relationship between Usage Frequency and Purchasing Behaviour

The correlation results are presented in Table 6.

Table 6. Correlation between Usage Frequency and Purchasing Behaviour

| Variable | Usage Frequency | Purchasing Behaviour |
|---|---|---|
| **Usage Frequency** | 1 | -0.016 |
| **Purchasing Behaviour** | -0.016 | 1 |
| **Significance (p-value)** | — | 0.874 |
| **Sample Size (N)** | 100 | 100 |

From Table 6, the relationship between usage frequency and purchasing behaviour is negative and statistically insignificant.

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## 5 Conclusion

The study also reveals that quick commerce apps are significantly impacting the thought process and behaviour of consumers. It has also been observed that demographic factors, such as age, income, and education, are important determinants in shaping the perception of the brands of these apps. On the other hand, the more a consumer uses quick commerce apps, the better they become acquainted with the brand, which in turn positively impacts the perception of the brands. Another important aspect of the study is that awareness also plays a significant role in shaping the behaviour of consumers in terms of quick commerce apps. The study reveals that consumers who are highly aware of quick commerce apps are likely to use these apps on a regular basis. Moreover, the frequent use of these apps also significantly impacts the behaviour of consumers in terms of making purchases.

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## Ethics Statement

This study did not involve human or animal subjects and, therefore, did not require ethical approval.

## Statement Of Conflict Of Interests

The authors declare that they have no conflicts of interest related to this study.

## Licensing



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