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Quick Commerce vs Traditional Logistics: A Comparative Study of Logistics Efficiency Awareness

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ABSTRACT

Quick Commerce (Q-commerce) is growing quickly in retail and logistics, with many services aiming to deliver products within 10–30 minutes. This study reviews research on dark stores, micro-fulfilment centres, last-mile delivery, route planning, warehouse networks and technology, and combines that review with a survey-style analysis of 130 Q-commerce users. Awareness was measured using eight multiple-choice questions, with one point for each correct answer. The average score was 6.92 out of 8 (median = 7.00; SD = 0.99), suggesting that respondents generally understood the main factors behind logistics efficiency. For every question, the response pattern differed significantly from an equal distribution across answer options ($p < 0.001$), and between 73.8% and 93.8% chose the correct answer. However, awareness was not significantly associated with how often respondents used Q-commerce, where they lived or how long they had used it ($p > 0.20$). Awareness scores also did not differ significantly by usage frequency, $F(4, 125) = 0.853$, $p = 0.494$. A regression model using usage frequency, duration, age and location was not significant ($R^2 = 0.013$, $F(4, 125) = 0.424$, $p = 0.791$). Overall, the results suggest that awareness was high across the groups included in the dataset. The literature also shows that Q-commerce must balance speed with operating costs and environmental impact. The dataset is synthetic and is used to demonstrate the research process, not to claim findings from real respondents.

Keywords: *Quick Commerce; Dark Stores; Micro-Fulfilment Centres; Last-Mile Delivery; Logistics Efficiency; Route Optimization; Chi-Square; ANOVA; Linear Regression.*

1. Introduction

The retail sector has changed considerably over the past decade. Smartphones, wider internet access and new technologies have changed what customers expect when they shop. Many people now value convenience and quick access to everyday products, which has helped new e-commerce models grow. One example is Quick Commerce (Q-commerce), which aims to deliver goods in minutes rather than over several days. It is especially popular in busy urban areas, where customers often want groceries, personal care items, medicines and household essentials without waiting long.

Q-commerce builds on traditional e-commerce but places greater emphasis on rapid order fulfilment and immediate customer needs. To meet these expectations, companies use dark stores, micro-fulfilment centres, local distribution hubs and technology-supported delivery systems. These facilities are placed close to residential and commercial areas so orders can travel shorter distances. This makes logistics a central part of the Q-commerce business model.

Logistics efficiency means moving, storing and delivering products reliably, on time and at a reasonable cost. For Q-commerce, it involves more than delivery speed: inventory availability, order accuracy, route planning, customer satisfaction, operating costs and environmental impact also matter. Customers may expect an order within 10–30 minutes, so delays in restocking, picking, packing or transport can affect service quality and customer loyalty.

Dark stores are a key part of this model. They are designed for online order fulfilment rather than for customers to browse in person. Staff can pick, pack and dispatch orders quickly. Micro-fulfilment centres serve a similar purpose by keeping stock closer to customers. When these facilities are located carefully, they can shorten processing times and delivery distances, improving last-mile performance.

Technology also helps Q-commerce companies manage logistics more effectively. Artificial intelligence (AI), machine learning (ML), big data analytics, the Internet of Things (IoT), cloud computing and large language models (LLMs) can support demand forecasting, inventory planning, customer-behaviour analysis, route selection and real-time monitoring. Using data to make decisions can improve resource use, control costs and make deliveries more reliable. Automation and algorithms can also help teams manage large numbers of orders while working within tight delivery windows.

Last-mile delivery—the journey from a fulfilment centre or dark store to the customer—is often one of the hardest and most expensive parts of logistics. Its performance has a direct effect on customer satisfaction. Companies use route-planning software, GPS tracking, delivery-management platforms and real-time communication to make this stage more reliable. These tools can reduce delivery time and fuel use while improving accuracy. Traffic, incorrect addresses, road restrictions and changes in demand can still cause delays.

Q-commerce is also changing the way companies organize warehouses and supply chains. Instead of relying only on a few large central warehouses, many businesses use smaller facilities closer to customers. This can make the network more responsive, but running several dark stores or micro-fulfilment centres also raises property, inventory and operating costs. Companies therefore need to find a workable balance between speed, cost and efficiency.

Despite its convenience, Q-commerce faces real business challenges. Operating costs can be high, profit margins may be narrow, and companies must manage labour, inventory and competition. Frequent deliveries, extra vehicle movements and packaging waste also raise environmental concerns. Electric vehicles, better route planning, sustainable packaging and energy-efficient fulfilment centres are possible ways to reduce the impact while maintaining service quality.

India's Q-commerce market has expanded with urbanization, digital adoption and changing customer habits. Platforms such as Blinkit, Zepto, Swiggy Instamart and BigBasket have invested in logistics facilities and technology to compete for customers. Their growth highlights why efficient logistics matters. As demand for rapid delivery increases, it becomes important to understand what supports strong logistics performance and what makes it difficult to achieve.

This study explores the link between Q-commerce and logistics efficiency through a review of research on dark stores, micro-fulfilment centres, route planning, last-mile delivery, supply-chain design and technology. It also examines a survey-style dataset to assess users' awareness of these logistics factors and whether their awareness differs by usage habits or demographic characteristics.

2. Review of Literature

Schorung (2024) explored how quick-commerce supply chains operate and how dark stores affect urban areas. The study describes a model built around dark stores, small local hubs, distributor partnerships, third-party logistics providers and last-mile delivery. Keeping inventory near customers can speed up deliveries, but it may also increase vehicle movements in cities. Q-commerce can therefore improve responsiveness while creating new urban-logistics pressures.

Kewalramani and Khadilkar (2023) looked at how companies can choose suitable locations for Q-commerce dark stores. Their approach considered factors such as delivery radius, travel time, traffic and warehouse capacity to serve as many customers as possible. Their work suggests that good location decisions can improve delivery performance and help companies meet short delivery promises.

Bhattacharya and Kumar (2025) examined route planning for Q-commerce deliveries. They noted that standard vehicle-routing methods may struggle with real-world problems such as incorrect addresses, incomplete maps, traffic and inaccurate distance estimates. They proposed using large language models to review and improve suggested routes. Better route choices may support more reliable deliveries and help control costs.

Anaswara and Rajeswari (2025) reviewed research on dark stores and Q-commerce published from 2021 to 2025. They grouped the main themes into operational efficiency, consumer behaviour and economic issues. Their review covered logistics, automation, last-mile delivery, convenience, customer satisfaction and pricing. It also noted that dark stores can support faster operations, while high costs and the ability to scale remain concerns.

Siwach (2026) reviewed the development of Q-commerce in India. The study highlights how dark stores and micro-fulfilment centres near customers can speed up order processing and last-mile delivery. It also discusses the use of AI, machine learning and data analytics for demand forecasting, inventory planning and route selection. Convenience and speed matter to Indian consumers, but operating costs and profitability continue to challenge businesses.

Deshpande (2025) studied Q-commerce's contribution to India's economy using secondary data. The study links the sector with greater consumer convenience, employment, investment and demand. It also describes how dark stores and local hubs can improve delivery speed, while AI and business analytics support demand prediction and cost control. This suggests that Q-commerce affects the wider economy as well as the customer experience.

Sarkar (2026) compared Q-commerce and traditional e-commerce using simulated scenarios involving emissions, operating costs and delivery efficiency. The study suggests that shorter delivery distances and electric vehicles may reduce costs and environmental impact. It also points to a trade-off between speed, cost and sustainability. Logistics performance should therefore be assessed using more than delivery time alone.

Boysen, Fedtke and Schwerdfeger (2021) reviewed last-mile delivery approaches from an operations-research perspective. They discussed the pressure that growing e-commerce volumes place on cities, including congestion, pollution, high delivery costs and tight delivery windows. Their work offers a broader basis for understanding why Q-commerce companies find it difficult to make last-mile delivery both fast and efficient.

Yang, Ostermeier and Hübner (2024) studied how Q-commerce businesses can design networks of micro-fulfilment centres. Their location-routing model considered the number, location, size and type of facilities, as well as transport, replenishment and processing costs. Their results suggest that several small centres may sometimes perform better than larger automated facilities in terms of lead time and cost. This highlights the importance of planning the whole network, not just individual warehouses.

Khare and Jaiswal (2026) examined changes in warehousing and supply-chain practices caused by Q-commerce. They describe a shift from large central fulfilment centres to smaller facilities placed closer to customers. This can shorten lead times and help companies respond to local demand. The study also stresses the role of technology, operating processes and location decisions in improving logistics efficiency.

3. Research Gap

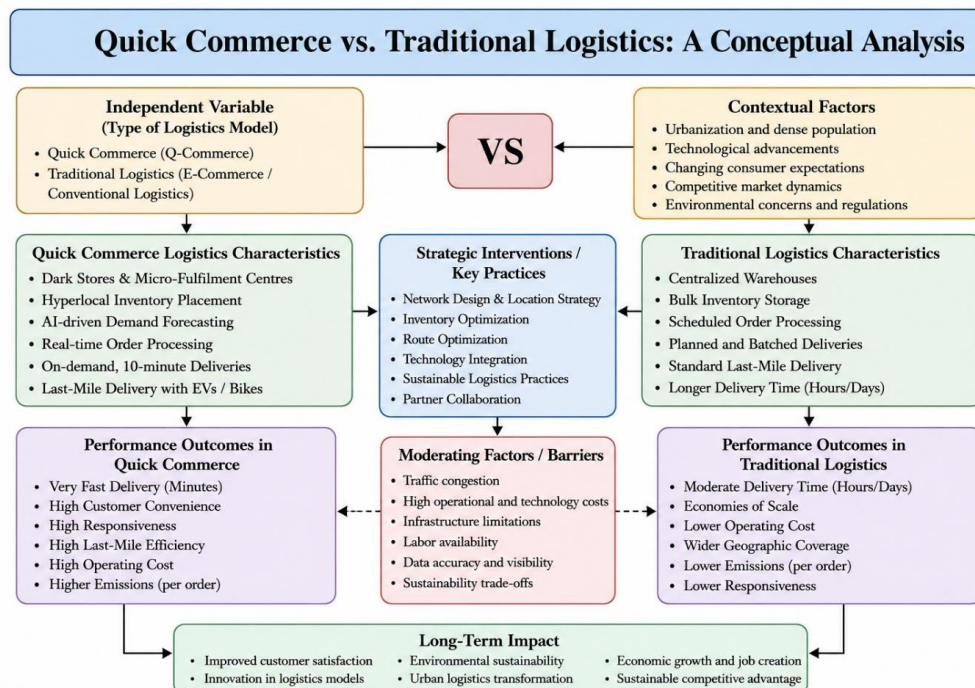
Most existing Q-commerce studies focus on one topic at a time, such as dark stores, last-mile delivery, route planning or technology. Fewer studies look at how these factors work together to affect logistics efficiency. There is also room for more research on the Indian market, especially on operating challenges, sustainability and profitability. The combined effect of dark stores, micro-fulfilment centres, inventory management and advanced technology is not yet fully understood. In addition, much of the existing work is conceptual, simulation-based or focused on operations, with less attention to how well customers understand the logistics behind rapid delivery. This study brings these themes together and adds a user-awareness analysis.

4. Objectives of the Study

1. To examine the role of dark stores and micro-fulfilment centres in improving logistics efficiency in quick commerce.
2. To analyse the impact of last-mile delivery systems on delivery speed and customer service performance in quick commerce.
3. To evaluate the influence of technology (Artificial Intelligence, Machine Learning, Data Analytics, and Route Optimization) on logistics operations in quick commerce.
4. To study the effect of warehouse location and network design on delivery performance and operational efficiency.
5. To identify the major logistics challenges faced by quick commerce companies, including high operational costs, traffic congestion, and sustainability issues.

5. Conceptual Framework of the Study

The framework compares two approaches to logistics. Q-commerce uses dark stores and micro-fulfilment centres, keeps inventory close to customers, forecasts demand with AI, processes orders in real time and arranges on-demand last-mile delivery. Traditional logistics generally uses centralized warehouses, bulk storage, scheduled processing and planned deliveries made in batches. Factors such as urban growth, new technology, customer expectations, competition and environmental rules affect both models. Location and network planning, inventory control, route optimization, technology, sustainable practices and partner coordination can improve performance. At the same time, traffic, high operating and technology costs, infrastructure limits, labour availability, data quality and sustainability trade-offs can hold it back. Q-commerce offers very fast and convenient service, but it can cost more to operate and may create higher emissions per order. Traditional logistics can benefit from scale and lower per-order costs and emissions, although delivery is usually slower. Both models can influence customer satisfaction, innovation, sustainability, urban logistics and economic growth over time. The empirical part of this study focuses on users' awareness of five Q-commerce logistics drivers.



6. Hypotheses of the Study

The study sets out null hypotheses (H0) and alternative hypotheses (H1). The first set, H01, is tested separately for the five objectives labelled (a) to (e).

H01(a–e): Respondents' answers on (a) dark stores and micro-fulfilment centres, (b) last-mile delivery, (c) technology, (d) warehouse location and network design and (e) operational challenges are spread equally across the answer options (no recognition of the logistics driver).

H11(a–e): Respondents' answers on each of these five logistics drivers are not spread equally across the answer options; they significantly favour the correct option.

H02: There is no significant association between high logistics awareness and (a) usage frequency, (b) location and (c) duration of Q-commerce use.

H12: There is a significant association between high logistics awareness and (a) usage frequency, (b) location and (c) duration of Q-commerce use.

H03: There is no significant difference in mean logistics awareness score across usage-frequency groups.

H13: There is a significant difference in mean logistics awareness score across usage-frequency groups.

H04: Usage frequency, duration of use, age group and location do not significantly predict the logistics awareness score (all regression coefficients = 0).

H14: At least one of usage frequency, duration of use, age group and location significantly predicts the logistics awareness score.

7. Research Methodology

This section explains how the study was planned and carried out, including its approach, design, target population, sample, sampling method, data source, measures, statistical tests and ethical considerations.

7.1 Research Approach

The empirical part uses a quantitative approach. Responses to the logistics questions are scored and analysed statistically, while the literature review provides the conceptual background for the study.

7.2 Research Design

A descriptive and analytical cross-sectional design is used. The descriptive analysis summarizes respondent profiles and awareness scores. The analytical part tests the hypotheses using chi-square tests, one-way ANOVA and linear regression.

7.3 Population of the Study

The target population is people in India who use quick-commerce platforms such as Blinkit, Zeto, Swiggy Instamart and Big Basket, including consumers in urban, semi-urban and rural areas.

7.4 Sample of the Study

The dataset contains 130 respondent records. This number is used for descriptive summaries, cross-tabulations, chi-square tests, one-way ANOVA and multiple regression with four predictors.

7.5 Sampling Technique

The study assumes non-probability convenience sampling. For a field study intended for publication, the researcher should clearly define the sampling frame and, where possible, use probability or stratified sampling to make the sample more representative.

7.6 Sources and Instrument of Data Collection

A structured questionnaire is used as the data-collection instrument. Part A covers demographic details and usage habits, including age, gender, occupation, monthly income, location, frequency of use, preferred platform, length of use and main reason for using Q-commerce. Part B asks multiple-choice questions about dark stores and micro-fulfilment centres, last-mile delivery, technology, warehouse location and network design, and operational challenges (see Appendix A). Eight items from Part B—items 1, 3, 6, 8, 9, 12, 13 and 17, labelled Q11–Q18 in the dataset—were included in the analysis. Each has one correct answer. The dataset is synthetic and was created to demonstrate the research process; it does not contain identities or responses collected from real participants.

7.7 Variables and Measurement

The main outcome is the Logistics Awareness Score, calculated by counting correct answers across eight questions, giving a score from 0 to 8. Five topic scores are also calculated: Dark Store and MFC (Q11–Q12; 0–2), Last-Mile Delivery (Q13–Q14; 0–2), Technology (Q15–Q16; 0–2), Warehouse Location (Q17; 0–1) and Operational Challenge (Q18; 0–1). A score of 7 or more, equal to the sample median threshold, is classified as high awareness. The explanatory variables are usage frequency (1 = rarely to 5 = daily), duration of use (1 = under 6 months to 5 = over 3 years), age group (1 = 18–25 to 4 = above 45) and location (1 = urban, 0 = semi-urban/rural). The correct answers are: Q11 faster order fulfilment; Q12 faster order processing; Q13 two-wheelers; Q14 fast and reliable delivery; Q15 artificial intelligence; Q16 all of the above; Q17 distance from customers; and Q18 high delivery and operating costs. Since awareness is measured with only a few single-answer questions, a real study should use validated multi-item scales and report their reliability.

7.8 Statistical Tools Used

The analysis uses percentages, means, medians, standard deviations, minimums and maximums, supported by bar charts. The chi-square goodness-of-fit test checks whether answers are distributed equally across options. The chi-square test of independence, with Cramér's V as an effect-size measure, checks relationships between categorical variables. One-way ANOVA compares average awareness scores across groups, with eta-squared, Levene's test and the Kruskal–Wallis test used as additional checks. Simple and multiple linear regression assess whether usage and demographic factors predict awareness; VIF and the Durbin–Watson statistic are used as diagnostics. The significance level is 5%. Calculations were performed in Microsoft Excel and checked with Python (SciPy and stats models), using procedures comparable to standard SPSS analyses.

8. Data Analysis and Interpretation

8.1 Profile of Respondents

Table 1. Demographic Profile of Respondents (N = 130)

Characteristic	Frequency	Percentage
Age Group		
18–25 years	81	62.3%
26–35 years	28	21.5%
36–45 years	12	9.2%
Above 45 years	9	6.9%
Gender		
Male	68	52.3%
Female	59	45.4%
Other	1	0.8%
Prefer not to say	2	1.5%
Occupation		
Student	47	36.2%
Private Employee	46	35.4%
Business / Self-employed	22	16.9%
Government Employee	9	6.9%

Characteristic	Frequency	Percentage
Other	6	4.6%
Monthly Income		
Below ₹15,000	42	32.3%
₹15,001–₹30,000	15	11.5%
₹30,001–₹50,000	29	22.3%
₹50,001–₹75,000	22	16.9%
Above ₹75,000	8	6.2%
Prefer not to say	14	10.8%
Current Location		
Urban area	78	60.0%
Semi-urban area	43	33.1%
Rural area	9	6.9%

Interpretation: The sample is relatively young and mainly urban. About 62.3% of respondents are aged 18–25, while 60.0% live in urban areas and 33.1% live in semi-urban areas. Male respondents make up 52.3% and female respondents 45.4%, so both groups are represented in similar proportions. Students (36.2%) and private employees (35.4%) together account for more than 70% of the sample. Around 32.3% report monthly income below ₹15,000. Overall, the profile reflects a group of digitally active consumers likely to use quick-commerce services.

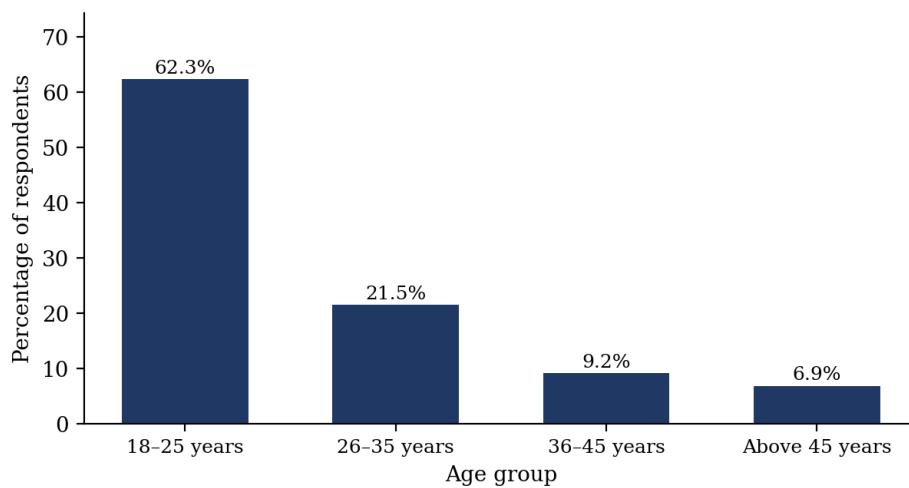
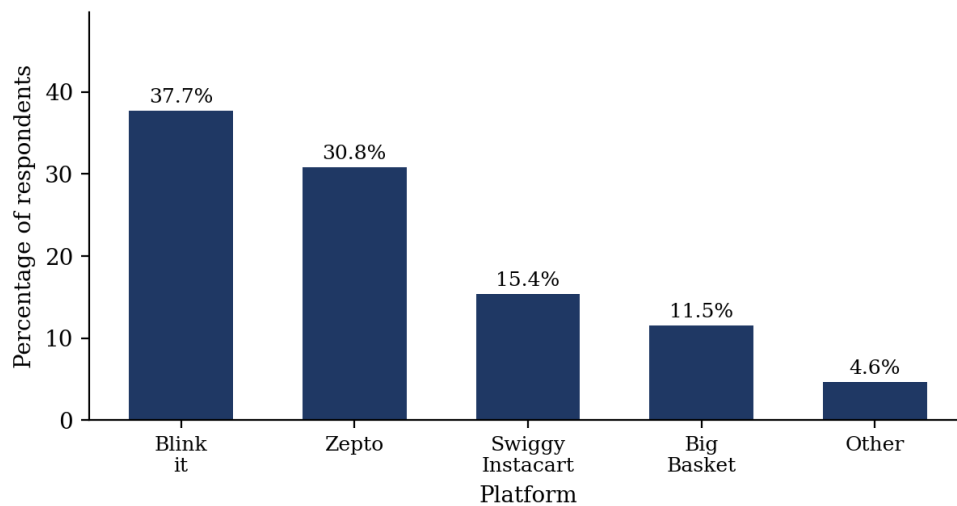
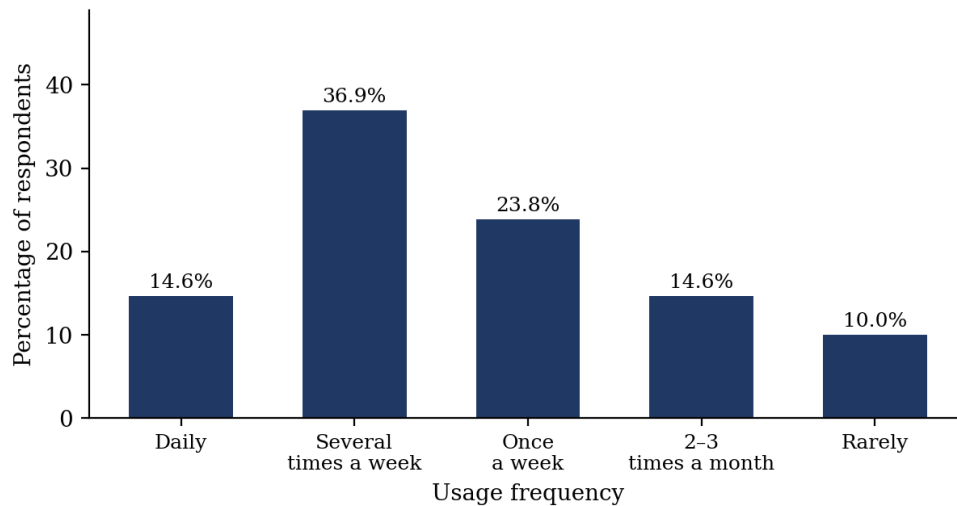


Table 2. Q-commerce Usage Profile of Respondents (N = 130)

Usage Characteristic	Frequency	Percentage
Usage Frequency		
Daily	19	14.6%
Several times a week	48	36.9%

Usage Characteristic	Frequency	Percentage
Once a week	31	23.8%
2–3 times a month	19	14.6%
Rarely	13	10.0%
Platform Used Most		
Blink it	49	37.7%
Zepto	40	30.8%
Swiggy Instacart	20	15.4%
Big Basket	15	11.5%
Other	6	4.6%
Duration of Use		
Less than 6 months	24	18.5%
6 months–1 year	27	20.8%
1–2 years	45	34.6%
2–3 years	23	17.7%
More than 3 years	11	8.5%
Main Reason for Use		
Convenience	34	26.2%
Fast delivery	30	23.1%
Discounts and offers	26	20.0%
Easy online ordering	21	16.2%
Wide product availability	19	14.6%

Interpretation: Most respondents use Q-commerce regularly: 36.9% place orders several times a week and 14.6% order daily, while 10.0% use it rarely. Blinkit (37.7%) and Zepto (30.8%) are the most commonly used platforms. Around 60.8% have used Q-commerce for at least a year. Convenience (26.2%), fast delivery (23.1%) and discounts or offers (20.0%) are the most common reasons for using these services, matching the literature's focus on speed and convenience.

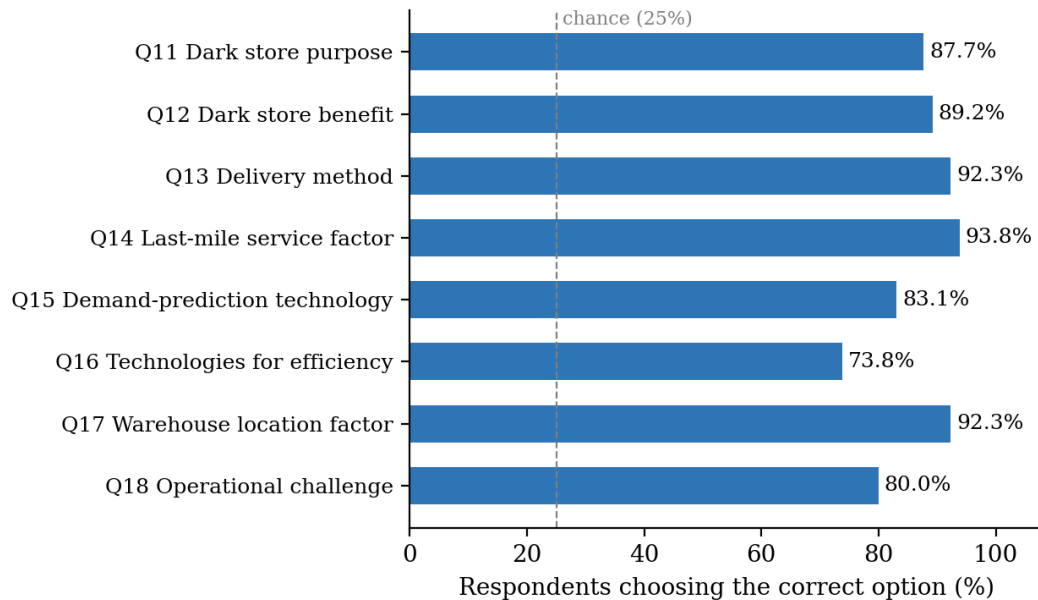


8.2 Item-wise Awareness of Logistics Drivers

Table 3. Correct Responses to Logistics Knowledge Items (N = 130)

Item (Logistics Driver)	Correct (n)	Correct (%)	Incorrect (n)
Q11 Dark store purpose	114	87.7%	16
Q12 Dark store benefit	116	89.2%	14
Q13 Delivery method	120	92.3%	10
Q14 Last-mile service factor	122	93.8%	8
Q15 Demand-prediction technology	108	83.1%	22
Q16 Technologies for efficiency	96	73.8%	34
Q17 Warehouse location factor	120	92.3%	10
Q18 Operational challenge	104	80.0%	26

Interpretation: Most respondents answered the logistics questions correctly. The strongest results were for the importance of reliable last-mile service (93.8%), the commonly used delivery method (92.3%) and warehouse location (92.3%). The lowest score was for the question about the combination of technologies that improve logistics efficiency (73.8%). This suggests that some respondents recognized individual technologies but did not identify how AI, machine learning, data analytics and route optimization can work together. Awareness of operating challenges (80.0%) and demand-prediction technology (83.1%) was also comparatively lower.



8.3 Descriptive Statistics of Awareness Scores

Table 4. Descriptive Statistics of Logistics Awareness Scores (N = 130)

Variable	Mean	Median	Std. Deviation	Minimum	Maximum
Dark Store & MFC (0–2)	1.769	2.000	0.491	0	2
Last-Mile Delivery (0–2)	1.862	2.000	0.368	0	2
Technology (0–2)	1.569	2.000	0.583	0	2
Warehouse Location (0–1)	0.923	1.000	0.268	0	1
Operational Challenge (0–1)	0.800	1.000	0.402	0	1
Total Awareness (0–8)	6.923	7.000	0.993	3	8

Interpretation: The average awareness score was 6.923 out of 8, and the median was 7.000, indicating generally strong awareness in this dataset. The standard deviation of 0.993 shows that scores were grouped closely around the average. Relative to each topic's maximum score, awareness was highest for last-mile delivery (93.1%), followed by warehouse location (92.3%), dark stores and MFCs (88.5%), operational challenges (80.0%) and technology (78.5%). Technology was therefore the weakest area, consistent with the individual question results.

Table 5. Distribution of Total Awareness Score and Awareness Classification

Total Score (out of 8)	Frequency	Percentage
3	1	0.8%
5	9	6.9%

Total Score (out of 8)	Frequency	Percentage
6	32	24.6%
7	44	33.8%
8	44	33.8%
High Awareness (score ≥ 7)	88	67.7%
Not High Awareness (score < 7)	42	32.3%

Interpretation: No respondent scored below 3, and 67.7% (88 people) scored either 7 or 8. About one-third of respondents (33.8%) answered all eight questions correctly. Scores were concentrated near the top of the scale, creating a ceiling effect. This limited variation may make it harder for the statistical tests to detect differences between groups.

8.4 Chi-Square Goodness-of-Fit Test (Hypothesis H01a–e)

Table 6. Chi-Square Goodness-of-Fit Test Results

Item (Hypothesis)	Options	χ^2	df	p-value	Decision (5%)
Q11 Dark store purpose (a)	4	272.646	3	< 0.001	Reject H01(a)
Q12 Dark store benefit (a)	4	286.615	3	< 0.001	Reject H01(a)
Q13 Delivery method (b)	4	314.246	3	< 0.001	Reject H01(b)
Q14 Last-mile service factor (b)	4	328.646	3	< 0.001	Reject H01(b)
Q15 Demand-prediction technology (c)	5	324.923	4	< 0.001	Reject H01(c)
Q16 Technologies for efficiency (c)	4	165.754	3	< 0.001	Reject H01(c)
Q17 Warehouse location factor (d)	4	314.185	3	< 0.001	Reject H01(d)
Q18 Operational challenge (e)	4	209.877	3	< 0.001	Reject H01(e)

Note: Expected frequency = equal across options.

Interpretation: All eight questions produced chi-square results with $p < 0.001$, so the relevant null hypotheses H01(a–e) were rejected. The answers were not evenly distributed across the options; respondents selected the correct answer much more often than would be expected under random choice. The pattern suggests that users recognized the roles of dark stores and micro-fulfilment centres in speeding up order fulfilment, the importance of reliable last-mile service, the contribution of AI and related tools, the value of locating warehouses close to customers, and the cost pressures faced by Q-commerce companies. These results support Objectives 1–5 in terms of user awareness. However, this test mainly shows that the response pattern was not random; it does not measure actual logistics performance.

8.5 Chi-Square Test of Independence (Hypothesis H02a–c)

Table 7. Cross-Tabulation of High Awareness with Usage Frequency, Location and Duration of Use

Group	Not High	High	Total	% High
Usage frequency				
Frequent (daily / several times a week)	25	42	67	62.7%
Occasional (weekly or less)	17	46	63	73.0%

Group	Not High	High	Total	% High
Location				
Urban	25	53	78	68.0%
Non-urban (semi-urban / rural)	17	35	52	67.3%
Duration of use				
One year or more	26	53	79	67.1%
Under one year	16	35	51	68.6%
Total	42	88	130	67.7%

Table 8. Chi-Square Test of Independence Results

Association Tested	χ^2	df	p-value	Cramér's V	Decision (5%)
Usage frequency $\times$ High awareness	1.584	1	0.208	0.110	Fail to reject H02(a)
Location $\times$ High awareness	0.006	1	0.939	0.007	Fail to reject H02(b)
Duration of use $\times$ High awareness	0.034	1	0.855	0.016	Fail to reject H02(c)

Note: Pearson Chi-square without continuity correction; all expected counts exceed 5 (minimum 16.5).

Interpretation: None of the three relationships was statistically significant at the 5% level ($p = 0.208, 0.939$ and 0.855), so the H02 null hypotheses were not rejected. High awareness was similar among urban respondents (68.0%) and non-urban respondents (67.3%), and among people who had used Q-commerce for under a year (68.6%) and for longer (67.1%). Occasional users had a somewhat higher high-awareness rate than frequent users (73.0% compared with 62.7%), but the difference was not statistically significant, and the effect size was small ($V = 0.110$). In this dataset, awareness did not show a meaningful relationship with how often, how long or where people used Q-commerce.

8.6 One-Way ANOVA (Hypothesis H03)

Table 9. Group Descriptives: Awareness Score by Usage Frequency

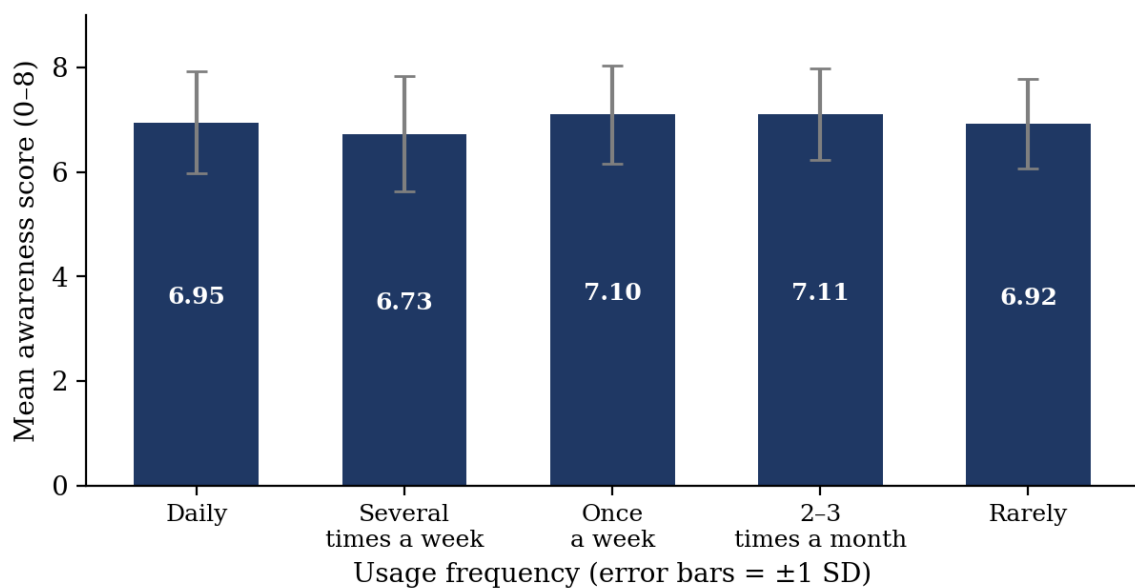
Usage Frequency	N	Mean Score	Std. Deviation
Daily	19	6.947	0.970
Several times a week	48	6.729	1.106
Once a week	31	7.097	0.944
2–3 times a month	19	7.105	0.875
Rarely	13	6.923	0.862
Total	130	6.923	0.993

Table 10. One-Way ANOVA: Awareness Score by Usage Frequency

Source	Sum of Squares	df	Mean Square	F	p-value
Between Groups	3.382	4	0.846	0.853	0.494
Within Groups	123.849	125	0.991	—	—
Total	127.231	129	—	—	—

Note: Levene's test $p = 0.873$ (equal variances); Kruskal–Wallis $H = 2.903$, $p = 0.574$; $\eta^2 = 0.027$.

Interpretation: The one-way ANOVA result was $F(4, 125) = 0.853$, $p = 0.494$. Since the p -value is above 0.05, the null hypothesis H_{03} was not rejected. Average awareness scores did not differ significantly across usage-frequency groups; the group means ranged from 6.73 to 7.11. Usage frequency accounted for only 2.7% of score variation ($\eta^2 = 0.027$). Levene's test supported the equal-variance assumption ($p = 0.873$), and the Kruskal–Walli's check reached the same conclusion ($p = 0.574$).

**Table 11. Supplementary One-Way ANOVAs on Total Awareness Score**

Grouping Variable	Groups	F	df	p-value	η^2	Kruskal–Wallis p
Age group	4	0.725	3, 126	0.539	0.017	0.400
Occupation	5	0.859	4, 125	0.491	0.027	0.450
Platform used most	5	0.057	4, 125	0.994	0.002	0.992
Location	3	0.464	2, 127	0.630	0.007	0.549
Duration of use	5	0.602	4, 125	0.662	0.019	0.825

Interpretation: The additional tests also found no significant differences in average awareness by age, occupation, platform, location or duration of use (all p -values were above 0.49). The small F and eta-squared values (0.002–0.027) indicate that scores were broadly similar across these groups in this dataset.

8.7 Linear Regression Analysis (Hypothesis H04)

Table 12. Multiple Linear Regression: Predictors of Logistics Awareness Score

Predictor	B	Std. Error	Beta	t	p-value	VIF
(Constant)	7.262	0.391	—	18.550	< 0.001	—
Usage frequency (1–5)	−0.053	0.076	−0.063	−0.693	0.490	1.053
Duration of use (1–5)	−0.060	0.074	−0.073	−0.813	0.418	1.010
Age group (1–4)	0.027	0.098	0.025	0.275	0.784	1.039
Urban (1 = yes)	−0.066	0.182	−0.033	−0.364	0.716	1.026

Model: $R = 0.116$, $R^2 = 0.013$, Adjusted $R^2 = -0.018$, $F(4, 125) = 0.424$, $p = 0.791$; Durbin–Watson = 1.978. Dependent variable: Total awareness score.

The main findings from the analysis are summarized below.

- The sample was young and mostly urban: 62.3% were aged 18–25 and 60.0% lived in urban areas. In total, 51.5% used Q-commerce daily or several times a week.
- Blinkit (37.7%) and Zepto (30.8%) were the most-used platforms. Convenience (26.2%) and fast delivery (23.1%) were the main reasons for using them.
- Awareness of logistics efficiency was high, with a mean of 6.923 and a median of 7.000 out of 8 (SD = 0.993). Overall, 67.7% of respondents met the study's high-awareness threshold.
- Respondents performed best on last-mile service (93.8%), delivery method (92.3%) and warehouse location (92.3%). The lowest accuracy was for the combined-technology question (73.8%), followed by operational challenges (80.0%).
- All eight-chi-square goodness-of-fit tests were significant ($p < 0.001$). This suggests that respondents recognized the roles of dark stores, last-mile delivery, technology, warehouse location and operating costs, supporting Objectives 1–5 at the awareness level.
- The chi-square independence tests found no significant relationship between high awareness and usage frequency ($p = 0.208$), location ($p = 0.939$) or duration of use ($p = 0.855$).
- The ANOVA found no significant difference in awareness scores across usage-frequency groups, $F(4, 125) = 0.853$, $p = 0.494$. Additional tests for age, occupation, platform, location and duration were also non-significant.
- The multiple regression model was not significant ($R^2 = 0.013$, $p = 0.791$), and none of the predictors was significant. In this dataset, usage behaviour and demographic factors did not explain awareness scores.
- Taken together, the results suggest that users in this dataset had a high and fairly consistent understanding of Q-commerce logistics. The literature, however, indicates that real operational performance still depends on facility location, technology, network planning and the balance between cost and sustainability.

10. Findings & Suggestions

1. Choose locations for dark stores and micro-fulfilment centres carefully. Respondents linked these facilities with faster order processing, and the reviewed studies suggest that good location planning and appropriately sized local facilities can improve delivery times and help manage costs.
2. Improve last-mile reliability through route planning, real-time tracking and sensible delivery scheduling. Reliable, fast delivery was the factor most closely linked to good last-mile service in the responses.
3. Explain how logistics technologies work together. The technology question had the lowest correct-response rate, so platforms could show how AI, machine learning, data analytics and route optimization jointly support stock availability and delivery performance.
4. Keep costs under control through better network design and demand forecasting. Companies should monitor inventory-holding costs and delivery costs, both of which put pressure on Q-commerce operations.

5. Reduce congestion and environmental impact by using electric vehicles, planning efficient routes and choosing more sustainable packaging. Companies can also work with local authorities when deciding where to place dark stores, helping limit unnecessary traffic and vehicle movements.
6. Since awareness scores were similar across age, location, occupation and usage groups, platforms may be able to use consistent logistics-awareness messages rather than designing separate campaigns for each segment.
7. Measure delivery time, order accuracy, cost per order and emissions together. This gives a more balanced view of logistics efficiency than focusing on speed alone.

11. Conclusion

This study explored the relationship between Q-commerce and logistics efficiency by reviewing previous research and analysing a synthetic dataset representing 130 users. The literature points to dark stores, micro-fulfilment centres, last-mile delivery, route optimization, warehouse network planning and technologies such as AI, machine learning and data analytics as important parts of the model. High operating costs, traffic and environmental concerns remain major challenges. In the dataset, users showed high awareness of these factors, with an average score of 6.92 out of 8, and answers to all eight questions differed significantly from an equal distribution across options. However, awareness did not differ significantly by usage frequency, location, duration of use or other respondent characteristics, and the regression model was not significant. The findings therefore suggest broad awareness among the people represented in the dataset, but they do not establish actual logistics performance because the data are synthetic. In practice, Q-commerce's long-term success will depend on balancing rapid service with cost control and sustainability.

12. Limitations and Scope for Future Research

The main limitation is that the dataset is synthetic, so the results cannot be treated as evidence about real consumers. The study measures knowledge of logistics concepts rather than actual delivery times, costs or emissions, and it does not collect direct data on traditional logistics. The comparison between Q-commerce and traditional logistics therefore remains conceptual. Awareness is measured using eight single-answer questions, scores show a ceiling effect, and the rural group is small ($n = 9$), which limits the strength of some comparisons. The sample is assumed to be a convenience sample and the design captures one point in time. Future research should collect original data from a clearly defined population, use validated multi-item measures, report reliability and validity, and adopt an appropriate sampling method. Researchers could also combine customer surveys with operating data from dark stores and delivery partners, compare Q-commerce directly with traditional e-commerce logistics, examine factors such as customer satisfaction and delivery reliability, and study profitability and environmental outcomes in India over time.

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