European Journal of Management Studies

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Received 22 June 2025
Revised 26 October 2025
Accepted 3 December 2025

Understanding Q-commerce adoption: the role of technological, social, marketing stimuli, and service quality on usage intention

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Abstract

Purpose – Q-commerce has revolutionised the entire shopping landscape with its ultra-fast deliveries. There is a lack of studies that provide a comprehensive understanding of the factors affecting Q-commerce adoption. This study aims to identify the various antecedents that affect perceived value, trust and usage intention in the context of Q-commerce.
Design/methodology/approach – The study employed a causal research design to examine consumers' intentions to use Q-commerce platforms. A 5-point Likert scale was administered in the questionnaire. A purposive sampling method was used, and 795 valid responses were retained for analysis. The analysis was done using Partial Least Squares Structural Equation Modelling (PLS-SEM).
Findings – A study confirms that technological advancements, effective marketing, strong social influence, and high service quality significantly enhance perceived value and trust, ultimately driving usage intention in the q-commerce sector.
Practical implications – The study provides actionable insights for Q-commerce managers to reinforce technological, service, marketing, and social factors that strengthen consumers' perceived value and trust. By effectively integrating these dimensions, platforms can enhance user engagement, stimulate stronger usage intentions, and build long-term loyalty. Furthermore, developing personalised incentives and structured loyalty programs can encourage repeat purchases, foster enduring trust, and improve overall competitiveness in the fast-paced digital marketplace.
Originality/value – This study makes theoretical contributions to consumer behaviour research and provides practical insights for Q-commerce platforms to enhance user engagement and trust.

Keywords Q-commerce, SOR model, PLS-SEM, Trust, Perceived value, Social stimuli, Technological stimuli, Marketing stimuli, Service quality

Paper type Research article

1. Introduction

In March 2020, the entire world came to a standstill due to the COVID-19 outbreak. Some countries witnessed a complete lockdown for months, making it difficult for people to survive. E-commerce came to the rescue of the population by delivering goods to their doorsteps in 2–3 days, challenging the might of traditional distribution provision channels. The last five years have seen unprecedented growth in the sector, with the entry of ready-to-eat companies like Zomato and Swiggy, which have helped deliver food to households. These companies sought to expand their market presence due to high transportation costs and idle time. They discovered a

European Journal of Management Studies
Vol. 31 No. 2, 2026
pp. 67-86
Emerald Publishing Limited
e-ISSN: 2635-2648
p-ISSN: 2183-4172
DOI 10.1108/EJMS-06-2025-0079

concept called Q-commerce, which has rapidly emerged as a transformative force in retail and e-commerce, driven by consumers' increasing demand for speed, convenience, and accessibility. Q-commerce has revolutionised the Indian e-commerce landscape by offering ultra-fast delivery (10–30 min) for high-demand items, such as groceries and personal care products. This sector is poised for massive growth, as is expected to clock sales of US $5 billion by 2025 and US$9.94 billion by 2029 (Red-Seer report) owing to changing consumer preferences, digitalisation, high disposable income, increased e-commerce adoption, and demand for better convenience among millennials and Gen Z. Quick commerce, also known as "Q-commerce," sets the standard for this new level of convenience. This business model prioritises speed and efficiency in retail operations by optimising processes in the so-called "last mile", where a significant portion of the economic parameters is determined by the speed of order execution (Stojanov, 2022), thereby providing customers with a seamless shopping experience. Presently, India's Q-commerce market is witnessing intense competition with the entry of players like Zepto, Zomato's Blinkit, and Swiggy's Instamart. Traditional e-commerce platforms typically offer delivery windows spanning several days, focusing on extensive product catalogues and competitive pricing strategies. However, the growing consumer expectation for immediacy has propelled the transition to Q-commerce. Studies indicate that two-thirds of consumers prioritise speed over other marketing elements when selecting an online delivery platform that supports local vendors and utilises real-time inventory management systems.

The Stimulus-Organism-Response (S-O-R) model provides a strong, fundamental framework for investigating consumer behaviour in the context of Q-commerce. The SOR model also provides insight into how external stimuli drive internal processes, subsequently influencing consumers' behavioural responses. In this study of Q-commerce, the SOR model encompasses:

(1) The stimulus consists of factors such as social, marketing, technological, and service elements, each of which has components that consumers consider when selecting a platform.

(2) The organism represents the consumer's internal states, including perceptions, emotions, and attitudes.

(3) Finally, the response concerns consumers' actions, such as engagement, purchase intention, and loyalty.

Despite the burgeoning interest in Q-commerce, existing literature reveals several research gaps. Many studies have focused on logistical and operational challenges, with limited attention to understanding the psychological and behavioural aspects that drive customer engagement and satisfaction. Furthermore, fewer than 30% of existing e-commerce studies examine consumer behaviour using integrated theoretical models, leaving a significant gap in applying frameworks such as the S-O-R model to Q-commerce. This study aims to address two key questions: (1) to identify the various antecedents affecting perceived value and trust in the context of Q-commerce. (2) Which factor influences building consumer purchase intention more, perceived value or consumer trust? The research will contribute to the existing dimensions of Q-commerce in the following ways. Firstly, we add technological, service quality, marketing, and social stimuli dimensions. The existing literature has widely acknowledged the various constructs of the stimuli mentioned above that impede perceived value and trust. Our research contributes to the examination of multiple forms of stimuli, including technology, service quality, marketing, and social media, as well as the nature and interaction of these with perceived value and trust. Secondly, perceived value and trust are crucial in forming customers' purchase intentions. However, there is limited empirical evidence on whether perceived value or trust is more dominant in shaping purchase intention in the Q-commerce context. Moreover, as Q-commerce platforms expand rapidly, consumer expectations are evolving. It is essential to assess whether value-driven factors (e.g.

convenience, efficiency, and personalisation) outweigh trust-related factors (e.g. security, reliability, and transparency) in influencing purchase decisions. The lack of consensus in the literature regarding the relative impact of these constructs creates an opportunity for further investigation. Moreover, by leveraging the S-O-R framework, we seek to uncover the key drivers of Q-commerce customer engagement, satisfaction, and purchase intentions. This research is particularly relevant in the current scenario, as the Q-commerce sector continues to expand and redefine consumer expectations.

2. Theoretical background and conceptual foundation of Q-commerce

2.1 Technological stimuli with perceived value and trust in Q-commerce

Technological factors, such as user experience, convenience, and service reliability, are crucial in shaping consumers' perception of the value of Q-commerce platforms. Consumers evaluate these platforms based on transaction efficiency, feature-driven convenience, and security measures to safeguard their personal and financial information. A well-designed, easy-to-use application enhances their perceived value by reducing resistance in the buying process.

Kapoor *et al.* (2023) emphasised that by prioritising intuitive navigation, negligible loading times, and smooth transaction flows, Q-commerce apps can create a seamless experience for consumers, which is better associated. Platforms with engaging, functional features also help reduce the consumer's transition time from browsing a product to adding it to their cart and purchasing it without technical difficulties, thereby strengthening their perceived value. Lately, Q-commerce platforms have become the preferred choice for consumers, offering personalised recommendations based on their browsing history, real-time order tracking, and one-click checkout options (Jeong *et al*., 2022). Q-commerce offers AI-based customer support, personalised usage insights, and loyalty programs to enhance consumer satisfaction. Q-commerce app features and immediate delivery services add a sense of instant gratification, justifying their skimming pricing models (Astini *et al*., 2024). Consumers' trust in secured transactions further enhances their willingness to engage with a platform and create value. Features such as robust encryption, fraud prevention mechanisms, and secure payment processing make consumers perceive them as more valuable (George, 2024). Service reliability encompasses timely deliveries, accurate stock levels, and precise order fulfilment, all of which contribute to the perceived value. Consumers expect Q-commerce platforms to deliver goods as promised, with minimal delays and discrepancies (Harter *et al*., 2024). Their ability to maintain seamless operations and resolve potential issues efficiently enhances customer satisfaction and strengthens brand credibility.

Trust is a fundamental factor influencing consumer adoption and long-term retention in Q-commerce. As all transactions are conducted digitally, users primarily rely on the platform's technological infrastructure to ensure security, reliability, and transparency. App usability helps to build trust, as users feel more confident and engaged with those platforms that offer intuitive interfaces and transparent transactional processes. Rahma *et al*. (2022) argued that users are more likely to trust platforms that provide seamless navigation, well-structured interfaces, and smooth logout processes. Advanced platform features that enhance transparency and customer engagement further reinforce trust. Vindytia and Balqiah (2024) highlighted that real-time order updates, AI-powered chat support, and clear return policies reduce consumers' ambiguity and make them feel more confident about the platform's dependability. Research by Luna Sanchez (2024) suggests that platforms with integrated interactive features, such as dynamic customer feedback systems, generate greater user satisfaction. Perceived security is another strong determinant of consumer trust in digital commerce. Features such as multi-factor authentication, encrypted transactions, and fraud detection mechanisms help create a sense of safety and assurance; otherwise, users will hesitate to engage with platforms lacking stringent cybersecurity measures (Hewei and Youngsook, 2022). Reliability in service execution, such as accurate and timely order fulfilment, also plays a key role in building a loyal user base (Astini *et al*., 2024).

Trust in Q-commerce platforms is distinctive in how efficiently service failures are handled, even when goods are not delivered on time (Haneefa, 2025). Despite occasional service disruptions, platforms that offer proactive issue resolution, transparent refund policies, and consistent communication help retain and build consumer trust. By optimising these technological dimensions, Q-commerce providers can build long-term engagement, encourage repeat transactions, and establish themselves as credible market leaders. Based on the above discussion, we propose the hypothesis as follows:

H1. Technological stimuli influence the user's perceived value of the Q-commerce platforms.

H2. Technological stimuli influence the user's trust in the Q-commerce platforms.

2.2 Service quality stimuli relationship with perceived value and trust in Q-commerce

The recent boom in Q-commerce has made service quality a key indicator of speed, product availability, reliability, and seamless customer support, influencing consumer behaviour and building trust. Perceived value in Q-commerce is influenced by how efficiently a platform meets consumer needs, balancing convenience, affordability, and service excellence to deliver a time-saving, hassle-free shopping experience. Speed is the defining characteristic of Q-commerce, as quick deliveries create a sense of immediate gratification, reinforcing the perception that Q-commerce is more convenient (Harter *et al.*, 2024). The Expectation-Confirmation theory (Oliver, 1980) posits that perceived value increases when delivery performance exceeds pre-purchase expectations. Furthermore, Kapoor *et al.* (2023) emphasised that consistent product availability enhances consumer involvement and makes the platform more dependable. Real-time product information on platforms helps enhance consumer-perceived value. Customer service involves promptly resolving complaints and addressing concerns such as refunds, order modifications, or delivery issues to enhance the customer's perceived value. Astini *et al.* (2024) found that platforms offering 24/7 customer support, clear policies, and easy returns provide a better user experience. An adaptable and responsive support system reinforces the perception that the platform is reliable and consumer-centric.

Trust extends beyond a one-time experience and is built over the long term through Q-commerce's reliability, security, and consistent service. Trust develops over time, shaping consumers' willingness to repeatedly rely on the platform. Consistency in delivery time is a key factor in building trust. Jeong *et al.* (2022) observed that consumers trust those platforms that consistently meet delivery commitments, as it reinforces reliability. Occasional delays may be tolerated, but frequent and recurring disruptions erode user trust, leading them to switch to competitors. George (2024) notes that inconsistent stock levels deplete trust, as consumers expect transparency in inventory management. Maintaining real-time stock accuracy builds trust by demonstrating operational efficiency and transparency. Consumers are more likely to stay loyal to platforms that consistently deliver value, rather than those that frequently cancel or delay their orders. Moreover, Vindytia and Balqiah (2024) found that trust is built through the experience of smooth transactions and the ability to handle problems effectively. Platforms that offer clear refund policies, proactive communication, and empathetic customer service gain consumer confidence. The discussion helps us to frame the hypothesis as:

H3. Service quality influences the user's perceived value of the Q-commerce platforms.

H4. Service quality influences the user's trust in the Q-commerce platforms.

2.3 Marketing stimuli relationship with perceived value and trust in Q-commerce

Marketing stimuli play a distinct role in shaping consumers' perceived value in Q-commerce by enhancing their assessment of benefits relative to costs. Promotional offers, such as discounts and limited-time deals, create an immediate desire to save, thereby increasing product attractiveness and enhancing perceptions of a better bargain (Jeong *et al*., 2022). Personalised recommendations based on consumers' past purchases simplify decision-making and highlight relevant choices, thereby building satisfaction (Goswami and Kumari, 2024). Bundled price offerings, which combine complementary products at a discounted rate, further enhance perceived customer value by providing them with a cost-effective purchasing experience (Astini *et al*., 2024). The way consumers perceive value varies drastically across demographic and geographic factors. Younger consumers tend to respond more positively to flash sales and personalised recommendations, valuing instant gratification and affordability, whereas older consumers often prioritise product quality and reliability over deep discounts (Kapoor *et al*., 2023). Urban consumers frequently emphasised convenience, speed, and premium service, while rural markets respond more to incentive-driven pricing, such as bundled pricing. In developed markets with high disposable income, perceived value might stem from seamless digital experiences and high-quality service. In contrast, in emerging economies, price sensitivity drives a stronger response to aggressive discounts and bulk pricing strategies (Luna Sanchez, 2024).

Marketing stimuli also play a crucial role in building consumer trust and influencing purchase decisions. Consistent promotional offers contribute to a brand's credibility by demonstrating a commitment to customer benefits (Ariker, 2021). Personalised recommendations based on past behaviour and customer reviews help reinforce trust by reducing dilemmas and enabling consumers to make informed choices (Hewei and Youngsook, 2022). Bundled price offerings, intensely promoted with no hidden costs, instil consumers' confidence in the platform's pricing integrity, but it varies owing to diverse demography and geography. Younger consumers tend to trust AI-driven recommendations and digital interfaces more, while older consumers tend to rely on brand reputation and peer recommendations (George, 2024). Strong regulatory frameworks and consumer protection laws further instil trust among geographically diverse consumers in Q-commerce platforms (Haneefa, 2025). Additionally, cultural norms influence trust dynamics; some consumers respond well to influencer endorsements and community-driven recommendations. In contrast, others react to strict adherence to data privacy and transparency policies (Kapoor *et al*., 2023). Based on the above discussion, we propose the hypothesis as follows:

H5. Marketing stimuli influence the user's perceived value of the Q-commerce platforms.

H6. Marketing stimuli influence the user's trust in the Q-commerce platforms.

2.4 Social stimuli relationship with perceived value and trust in Q-commerce

Social stimuli in Q-commerce encompass reviews and ratings, community engagement, and social influence (Gass and Seiter, 2022), which play a crucial role in shaping consumers' perceived value. Studies have found that people consult online consumer reviews on various e-commerce websites before making a purchase (Cheung *et al*., 2012; Román *et al*., 2023). It is clearly established that higher ratings by the reviewers instil trust among other users and also enhance the perceived value of the platform or products under discussion (Tabar *et al*., 2025). Consumers also rely heavily on peer-generated content, such as product ratings and customer testimonials, to assess the credibility of offerings (Heriyanto, 2024), providing reassurance about product quality and seller reliability (Jeong *et al*., 2022). The shift in consumer purchasing decisions, in which ratings and reviews increasingly influence choices, has prompted companies to reassess their promotional strategies. A sense of belonging, along with shared customer experiences, leads to higher perceived value through social validation (Goswami and Kumari, 2024). Social influence, encompassing brand advocacy and influencer endorsements, shapes product desirability by leveraging peer approval as a proxy for value (Chavadi *et al*., 2024).

Consumer trust in Q-commerce is significantly shaped by social stimuli, mainly through reviews and ratings, community engagement, and social influence (Kapoor *et al.*, 2023). Studies have shown that transparent, verified customer reviews enhance trust by reducing uncertainty and mitigating perceived risk in online transactions (George, 2024; Racherla *et al.*, 2012). Consumers' active participation in trust-based commerce models, such as discussions within brand communities, leads to higher trust levels and repeat purchases (Kapoor *et al.*, 2023). Engaging consumers through live Q&A sessions and social media-driven commerce helps build authenticity, reinforcing trust in both products and platforms (Rahma *et al.*, 2022). Recommendations from peers, family, and influencers act as a more credible source of trust-building than direct brand promotions (Haneefa, 2025). However, a significant difference lies in the regulation of standardised product ratings in developed and developing nations, which is a key driver of consumer trust (Astini *et al.*, 2024). Based on the above discussion, we postulate the following hypothesis:

H7. Social stimuli influence the user's perceived value of the Q-commerce platforms.

H8. Social stimuli influence the user's trust in the Q-commerce platforms.

2.5 Perceived value and trust in Q-commerce

Perceived value and trust are essential components that shape consumer behaviour in Q-commerce, where the expectation of speed, convenience, and affordability drives purchase decisions. Perceived value is influenced by pricing structures, delivery efficiency, product reliability, and ease of transaction, which collectively enhance the consumer's evaluation of a platform's offerings (Jeong *et al.*, 2022). The appeal of discount-based promotions, bundled pricing, and seamless digital payment systems often enhances the perceived value, making Q-commerce a more attractive alternative to traditional retail (Astini *et al.*, 2024). However, high perceived value alone does not ensure customer retention unless it is reinforced by trust. Consumers are more likely to repeat purchases when they feel confident in the platform's commitment to product authenticity, transaction security, and service consistency (Kapoor *et al.*, 2023). A significant trust-building factor in Q-commerce is social validation, including customer reviews, peer ratings, and third-party endorsements, which provide credibility and mitigate risk perceptions (George, 2024). Companies like Swiggy Instamart, Zepto, and Blinkit implement proactive consumer feedback mechanisms and transparency in their fulfilment policies to enhance value perception and trust, ensuring a reliable shopping experience (Haneefa, 2025). Demographic and geographic factors also influence the relationship between perceived value and trust, as purchasing priorities differ across consumer segments. Younger consumers, including Millennials and Gen Z, are more inclined to use personalised recommendations and influencer marketing. At the same time, older individuals emphasise brand credibility and return policies as indicators of trust (Goswami and Kumari, 2024). The above discussion helps us to propose the hypothesis as:

H9. Perceived value of the Q-commerce platforms influences the users' trust in the Q-commerce platforms.

2.6 Perceived value and consumer trust on adoption intention

Perceived value strongly influences the decision to adopt Q-commerce services and the trust consumers place in these platforms. Perceived value, defined as the balance between costs and benefits, is crucial in shaping adoption intention, as consumers evaluate whether speed, convenience, pricing, and product availability justify their purchase decisions (Jeong *et al.*, 2022). Studies have shown that when consumers perceive economic benefits, such as cost savings from discounts and promotional offers, alongside time-saving advantages from instant delivery, they are more likely to adopt Q-commerce platforms (Astini *et al.*, 2024).

Additionally, service-related factors such as seamless user interfaces, efficient refund policies, and personalised product recommendations enhance perceived value, reinforcing positive adoption behaviour (Kapoor *et al.*, 2023). Additionally, optimised customer engagement strategies that create a sense of exclusivity and urgency, such as limited-time offers and loyalty-based incentives, enhance value (Luna Sanchez, 2024).

Trust is a fundamental element in influencing consumer adoption, particularly in a digitalised marketplace where risks related to product authenticity, transaction security, and service consistency are prevalent (George, 2024). Studies also indicate that verified reviews, transparent pricing, and secure payment options instil confidence in Q-commerce platforms (Rahma *et al.*, 2022). Moreover, strong customer support systems and efficient issue resolution mechanisms help users engage in repeat transactions and recommend the service to others (Haneefa, 2025). In regions with weaker consumer protection laws, trust becomes an even more critical determinant of adoption, as buyers seek additional reassurance through peer recommendations, influencer endorsements, and visible quality certifications (Astini *et al.*, 2024). It is also established that perceived enjoyment of speech recognition systems enhances trust in them, which, in turn, enhances the experience of individuals and encourages their use (Arachchi and Samarasinghe, 2024). While urban consumers may exhibit higher adoption rates due to greater exposure to digital transactions, rural consumers tend to rely more on interpersonal trust factors, such as community-driven credibility and word-of-mouth recommendations (Luna Sanchez, 2024). Thus, for Q-commerce platforms to maximise adoption rates, they must align value-driven incentives with trust-enhancing strategies, ensuring that customers perceive not only the benefits of the service but also the assurance of security and consistency in their purchasing experience. The above discussion helps us to frame the hypothesis as:

H10. The perceived value of the Q-commerce platforms influences the users' intention to use the Q-commerce platforms.

H11. Trust in Q-commerce platforms influences users' intentions to use these platforms.

Figure 1 shows the conceptual model.

3. Research methodology

3.1 Sample and data collection

The study employed a quantitative research design to examine consumers' intentions to use Q-commerce platforms. According to reports, the major Indian cities—Mumbai, Delhi,

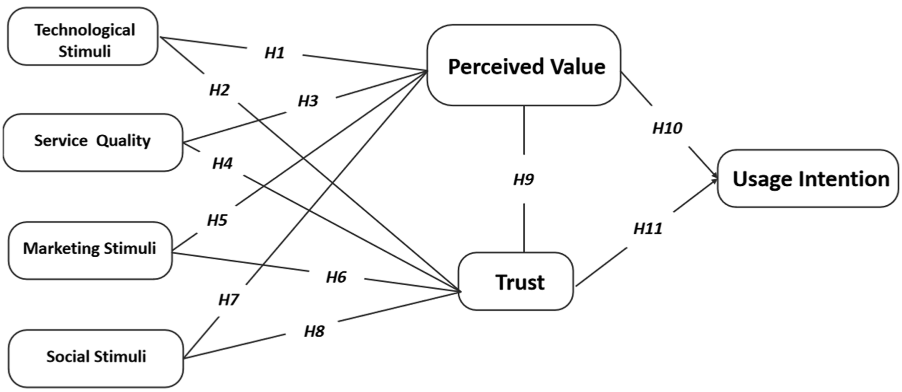

Figure 1. Proposed conceptual model. Source: Authors' own work

Bengaluru, Chennai, Ahmedabad, and others—account for 70% of Q-commerce usage in the country. Additionally, companies are expanding their presence in tier 2 and tier 3 cities, as Gen Z are increasingly willing to experiment with ordering groceries based on their needs. Hence, for this study, Delhi and Gurugram were chosen as ideal locations to investigate consumer intent to use Q-commerce platforms due to their diverse consumer base, rapid urbanisation, and the presence of Gen-Z, who are a major inhabitant of these cities, as well as the growing emphasis on convenience and a fast-paced lifestyle. As the tech cities in India spend significant time on different online platforms, a questionnaire was distributed via social media platforms such as Facebook, LinkedIn, and WhatsApp to gather data from a diverse user base. Participants were asked if they had ever placed an order on a Q-commerce platform as the screening question. A purposive sampling method targeted individuals directly exposed to Q-commerce platforms. A structured questionnaire was conducted through an online survey to collect consumer responses. A total of 950 respondents participated, out of which 795 valid responses were retained for analysis."

3.2 Scale development

Each construct, excluding demographic variables, was assessed using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The scale items were refined to align with the study's specific focus. Measurement items for technological stimuli were adapted from Acosta and Reinhardt (2025), Adesiji *et al*. (2024), and Zaheer *et al*. (2024). Items evaluating service quality were drawn from Tripathi *et al*. (2024). The measurement of marketing stimuli was based on the studies by Hu *et al*. (2024), Nguyen-Viet *et al*. (2024), and Zhou (2024). Constructs related to social influence were adapted from Busalim *et al*. (2024), Vazquez *et al*. (2023), and Wang and Huang (2023). Statements assessing perceived value were derived from Vij and Kaur (2024), while trust was measured using items from Abbas *et al.* (2025). Lastly, usage intention was evaluated using adapted statements from Chong *et al.* (2025).

3.3 Statistical method

The study utilised the nonparametric variance-based partial least squares structural equation method (PLS-SEM) using SmartPLS 4.0 (Ringle and Sarstedt, 2016). In social and behavioural sciences, PLS-SEM is recognised as a suitable technique for prediction-based research within theoretical frameworks (Hair *et al*., 2022). Due to its ability to handle complex models, it is an effective method for multivariate data analysis (Hair *et al*., 2019, 2022). PLS-SEM has gained significant academic interest across various disciplines and has been widely applied in numerous research studies (Hair *et al*., 2022). The PLS-SEM algorithm was used to assess the measurement model's reliability and validity. Additionally, path analysis was conducted using bootstrapping procedures to test the research hypothesis.

4. Data analysis

4.1 Analysis of demographic profile

Table 1 presents the demographic profile of the study's respondents. The offline survey of 795 consumers shows a gender distribution in which males constitute 40.88% (325 respondents) and females 59.12% (470 respondents). This indicates higher female participation, suggesting a greater interest among women in purchasing grocery items through Q-commerce platforms. In terms of age distribution, 20.13% (160 respondents) fall within the 18–30 age group, 39.62% (315 respondents) are aged 31–40, 30.19% (240 respondents) belong to the 41–50 age category, and 7.55% (60 respondents) are between 51 and 60 years old. The remaining 2.52% (20 respondents) are over 60 years old. This pattern suggests that consumers aged 31–40 purchase the majority of products using Q-commerce platforms. Regarding educational background, most respondents hold a postgraduate degree or higher (43.40%, 345

Table 1. Demographic profile of respondents

Variable	Category	Actual numbers	Percentage
Gender	Male	325	40.88%
	Female	470	59.12%
Age (yrs)	18–30	160	20.13%
	31–40	315	39.62%
	41–50	240	30.19%
	51–60	60	7.55%
	More than 60 years	20	2.52%
Education	High School	110	13.84%
	Graduate	340	42.77%
	Postgraduate or above	345	43.40%
Income (monthly) (Rs.)	Less than 30 K	140	17.61%
	30 –50 K	285	35.85%
	50 –70 K	160	20.13%
	70 –90 K	130	16.35%
	Above 90,000	80	10.06%
Occupation	Student	120	15.09%
	Govt Employee	140	17.61%
	Private Employee	305	38.36%
	Professional	140	17.61%
	Self-Employed	90	11.32%
Marital Status	Single	405	50.94%
	Married	350	44.03%
	Others	40	5.03%

Source(s): Authors’ own work

respondents), followed by those with a graduate degree (42.77%, 340 respondents). The remaining respondents have completed high school (13.84%, 110 respondents), indicating that higher education levels may positively influence Q-commerce platform usage behaviour. When analysing income levels, the largest segment falls within the 30–50 K range (35.85%, 285 respondents), suggesting that middle-income consumers represent a key segment to utilise the Q-commerce platform. Other income levels also represent equitable representation in using Q-commerce platforms, with 50–70 K income levels accounting for 20.13% (160) and 70–90 K income levels accounting for 16.35% (130). Other income levels, such as less than 30 K (17.61%, 140) and more than 90 K (10%, 80), also significantly represent the use of Q-commerce platforms. For occupation, private employees have the highest level of Q-commerce usage (38.36%, 305), followed by govt employees and professionals, with equal representation at 17.61% (140 each). The remaining respondents are represented by students (15.09%, 120) and the self-employed (11.32%, 90). Regarding marital status, a significant portion of respondents are single (50.94%, 405 respondents), followed by married respondents (44.03%, 350), and the remaining respondents are in the other category (5.03%, 40).

4.2 Assessment of measurement model

To ensure the accuracy and precision of the measurement model, common method bias (CMB) was assessed (Bozionelos and Simmering, 2022) to detect multicollinearity among the constructs. The analysis showed an explained variance of 40.294%, which was below the acceptable threshold of 50%. This indicated that common bias was not an issue in the dataset. VIF is another method for assessing the absence of multicollinearity among constructs. According to Hair *et al*. (2017), multicollinearity among the constructs is deemed absent if the VIF for each item is less than 3.3. Table 2 indicates that there is no multicollinearity among the constructs, as the VIF values in this study are all less than 3.3. Further validation of the

Table 2. Internal consistency reliabilities and convergent validities

Factors	Items	INT_USE	Cronbach's alpha	Composite reliability (rho_a)	Average variance extracted (AVE)	VIF per item
Usage Intention	INT_USE1	0.824	0.866	0.866	0.713	1.955
	INT_USE2	0.869				2.383
	INT_USE3	0.847				2.206
	INT_USE4	0.838				2.031
Marketing Stimuli	MKTG_ST1	0.813	0.85	0.856	0.691	1.924
	MKTG_ST2	0.861				2.11
	MKTG_ST3	0.866				2.286
	MKTG_ST4	0.782				1.632
Perceived Value	PERVAL1	0.794	0.824	0.826	0.656	1.74
	PERVAL2	0.856				2.112
	PERVAL3	0.823				1.824
	PERVAL4	0.762				1.519
Service Quality	SERV_Q1	0.742	0.803	0.804	0.629	1.359
	SERV_Q2	0.841				2.104
	SERV_Q3	0.793				1.663
	SERV_Q4	0.793				1.942
Social Stimuli	SOC_ST1	0.719	0.718	0.717	0.541	1.523
	SOC_ST2	0.79				1.708
	SOC_ST3	0.728				1.281
	SOC_ST4	0.702				1.211
Technology Stimuli	TEC_ST1	0.842	0.83	0.84	0.663	1.957
	TEC_ST2	0.861				2.177
	TEC_ST3	0.756				1.61
	TEC_ST4	0.794				1.686
Trust	TRST1	0.837	0.801	0.805	0.715	1.892
	TRST2	0.874				2.02
	TRST3	0.824				1.503

Source(s): Authors' own work

conceptual framework was conducted by assessing convergent and internal validity through confirmatory factor analysis within partial least squares structural modelling (Hair *et al.*, 2019, 2022). Convergent validity was measured using the average variance extracted (AVE) method, which requires a minimum threshold of 0.50 (Hair *et al.*, 2019). Table 2 shows that all constructs exceeded the 0.50 benchmark, confirming their convergent validity.

Indicator reliability was also evaluated using item factor loadings, all of which exceeded the critical threshold of 0.708 (Hair *et al.*, 2019). Construct-level reliability was also examined using Henseler's rho_a and Composite Reliability (CR), requiring a minimum threshold of 0.70 (Hair *et al.*, 2019). As detailed in Table 2, all constructs demonstrated strong internal reliability, as evidenced by rho_a and Cronbach's alpha (CR) values exceeding 0.70.

The study assessed discriminant validity using both the heterotrait-monotrait (HTMT) ratio (Table 3) and the Fornell-Larcker criterion (Table 4). The HTMT matrix values remained below the 0.85 threshold, confirming discriminant validity (Henseler *et al.*, 2015). Additionally, the researchers validated the constructs' discriminant validity using the Fornell-Larcker criterion, as shown in Table 4. In each construct, the square roots of the AVE were higher than their correlation with any other construct (Fornell and Larcker, 1981). This indicates that each construct exhibits greater convergence with itself than with others, further supporting discriminant validity. The constructs are reflective in the present study.

Table 3. Discriminant validity (HTMT criteria)

	INT_USE	MKTG_ST	PER_VAL	SERV_Q	SOC_ST	TEC_ST	TRST
INT_USE							
MKTG_ST	0.806						
PER_VAL	0.673	0.717					
SERV_Q	0.458	0.502	0.646				
SOC_ST	0.752	0.846	0.651	0.51			
TEC_ST	0.771	0.785	0.677	0.505	0.671		
TRST	0.827	0.71	0.663	0.639	0.647	0.751	

Source(s): Authors' own work

Table 4. Discriminant validity (Fornell-Larcker criteria)

	INT_USE	MKTG_ST	PER_VAL	SERV_Q	SOC_ST	TEC_ST	TRST
INT_USE	*0.844*						
MKTG_ST	0.692	*0.831*					
PER_VAL	0.57	0.602	*0.81*				
SERV_Q	0.39	0.419	0.528	*0.793*			
SOC_ST	0.595	0.659	0.512	0.399	*0.735*		
TEC_ST	0.659	0.661	0.565	0.421	0.526	*0.814*	
TRST	0.695	0.593	0.54	0.52	0.504	0.62	*0.845*

Source(s): Authors' own work

4.3 Assessment of structural model

The structural model was tested by the standards established by Hair *et al*. (2019, 2022). Bootstrapping with 5,000 subsamples was applied to test the significance of the path coefficients (Hair *et al*., 2022). Results for the structural model are presented in Table 5 and Figure 2, which represent the findings of the hypotheses. *T*-statistic values above 1.96 and *P*-values below the 0.05 level validate the significance of the relations under test, thus confirming the validity of every hypothesis.

The findings support the existence of positive, significant correlations among technological stimuli, service quality, marketing stimuli, and social influence on perceived value and trust in Q-commerce platforms. Furthermore, the relationships between perceived value and trust, perceived value and usage intention, and trust and usage intention were positive and significant. H1 is supported, as technological stimuli influence the perceived value of Q-commerce platforms ($T = 4.284$, $p < 0.05$). This suggests that app usability, platform features, and perceived security are vital in enhancing perceived value. H2 is supported, as technological stimuli also significantly affect trust in Q-commerce platforms ($T = 6.482$, $p < 0.05$), highlighting the roles of usability, support, and security in building consumer trust. H3 is supported, as service quality positively impacts perceived value ($T = 7.791$, $p < 0.05$), underscoring the importance of delivery speed, product availability, and customer support in shaping consumers' perception of value. H4 is supported, as service quality directly influences platform trust ($T = 6.752$, $p < 0.05$). H5 is supported, as marketing stimuli significantly enhance perceived value ($T = 6.052$, $p < 0.05$), emphasising the role of promotional offers, personalised deals, and bundled pricing in strengthening consumers' perception of value. H6 is supported, as marketing stimuli also significantly influence trust in Q-commerce platforms ($T = 4.461$, $p < 0.05$). H7 and H8 are supported, as social stimuli affect both perceived value ($T = 2.642$, $p < 0.05$) and trust ($T = 2.229$, $p < 0.05$), albeit to a lesser extent than other factors. H9 is supported, as perceived value plays a significant role in building trust in Q-commerce

Table 5. Structural model assessment

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T Statistics (|O/STDEV|)	*P* Values	Hypothesis
MKTG_ST → PER_VAL	0.276	0.275	0.046	6.052	0.000	H5 Supported
MKTG_ST → TRST	0.184	0.183	0.041	4.461	0.000	H6 Supported
PER_VAL → INT_USE	0.275	0.275	0.039	7.009	0.000	H10 Supported
PER_VAL → TRST	0.091	0.092	0.041	2.227	0.026	H9 Supported
SERV_Q → PER_VAL	0.281	0.281	0.036	7.791	0.000	H3 Supported
SERV_Q → TRST	0.233	0.234	0.035	6.752	0.000	H4 Supported
SOC_ST → PER_VAL	0.11	0.112	0.041	2.642	0.008	H7 Supported
SOC_ST → TRST	0.082	0.083	0.037	2.229	0.026	H8 Supported
TEC_ST → PER_VAL	0.206	0.206	0.048	4.284	0.000	H1 Supported
TEC_ST → TRST	0.305	0.305	0.047	6.482	0.000	H2 Supported
TRST → INT_USE	0.546	0.546	0.037	14.781	0.000	H11 Supported

Source(s): Authors' own work

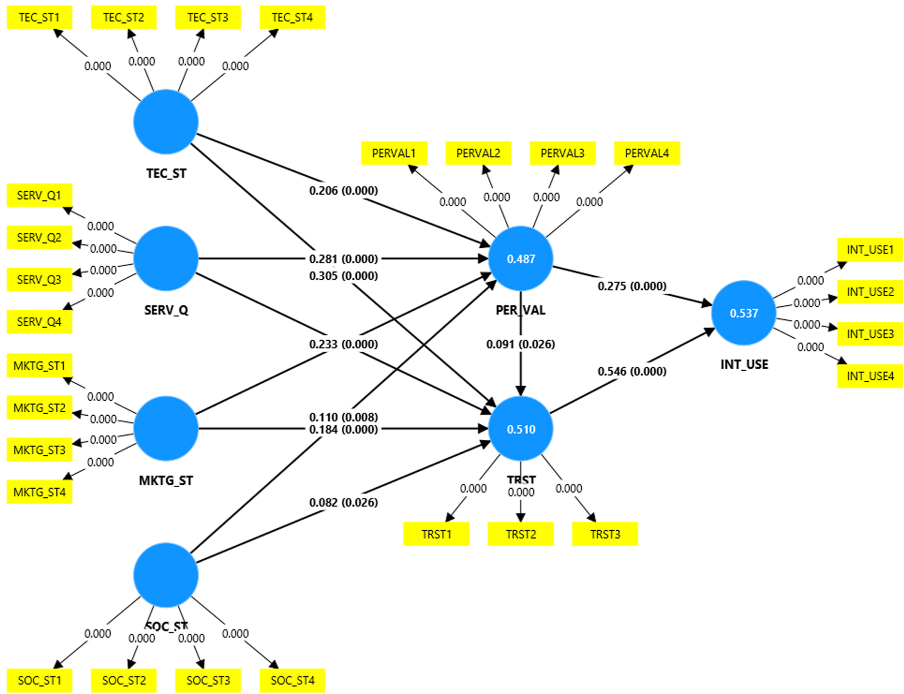

Figure 2. Path model. Source: Authors' own work

platforms ($T = 2.227$, $p < 0.05$). H10 is supported, as perceived value strongly influences consumers' intention to use Q-commerce platforms ($T = 7.009$, $p < 0.05$), reinforcing the idea that when consumers perceive value in a product or service, their intention to purchase or use it is strengthened. H11 is supported, as trust within the platform encourages consumers to use it ($T = 14.781$, $p < 0.05$). Overall, these findings confirm the acceptance of all hypotheses with varying significance levels, reinforcing the positive impact of technological stimuli, service quality, marketing strategies, and social influence on perceived value and trust. Ultimately, these factors drive consumers' intention to use Q-commerce platforms.

4.4 Measuring the coefficient of determination (r^2) *and effect size* (f^2)

Chin (2010) explains that the coefficient of determination (r^2) quantifies the amount of variance explained by a model. According to marketing research by Henseler *et al.* (2009), r^2 values greater than 0.75, 0.50, and 0.25 are generally categorised as "substantial," "moderate," and "weak," respectively, when analysing endogenous latent variables. In the context of consumer behaviour, r^2 values as low as 0.20 are often considered significant, as highlighted in other studies (Hair *et al.*, 2017).

The r^2 values in this study range from 0.485 to 0.535, indicating a moderate coefficient of determination. Specifically, the r^2 value for Q-commerce usage intention is 0.535, indicating that perceived value and trust exert a moderate influence on consumers' intention to use these platforms (see Table 6).

Another approach to evaluating structural models is the f^2 effect size, which measures the influence of latent variables (Hair *et al.*, 2019). If the f^2 effect size is below 0.02, it is considered insignificant or "negligible." Values between 0.02 and 0.15 indicate a weak influence, while those between 0.15 and 0.35 suggest a moderate effect. An f^2 value of 0.35 or higher signifies a strong effect (Cohen, 1988).

The findings of this study indicate a range of effects, from "negligible" to "weak" to "strong", as reflected in the f^2 effect size values presented in Table 7.

This study employs the standardised root mean square residual (SRMR) as a measure of approximate fit for the model, assessing the discrepancy between the observed and model-implied correlation matrices. Traditionally, a model is considered to have a suitable fit when the SRMR is below 0.08 (Hu and Bentler, 1999). The SRMR was introduced by Henseler *et al.* (2016) as a goodness-of-fit measure for partial least squares structural equation modelling to

Table 6. Coefficient of determination (r^2)

	R-square	*R*-square adjusted
INT_USE	0.537	0.535
PER_VAL	0.487	0.485
TRST	0.51	0.507

Source(s): Authors' own work

Table 7. Effect size (f^2)

	INT_USE	MKTG_ST	PER_VAL	SERV_Q	SOC_ST	TEC_ST	TRST
INT_USE							
MKTG_ST			0.063 (W)				0.028 (W)
PER_VAL	0.116 (W)						0.009 (N)
SERV_Q			0.119 (W)				0.076 (W)
SOC_ST			0.013 (N)				0.007 (N)
TEC_ST			0.044				0.096 (W)
TRST	0.457 (S)						

Note(s): (N-negligible, W-weak, S-strong)

Source(s): Authors' own work

prevent model misspecification. A model is considered to fit well when the difference between the model-suggested and the observed empirical correlation matrices is not significant ($p > 0.05$) (Ramayah *et al*., 2017).

According to Henseler *et al*. (2016), while bootstrapping, the *d*ULS < bootstrapped HI 95% of *d*ULS and *dG* < bootstrapped HI 95% of *dG* indicate that the data fit the model well. The model is saturated, with zero free parameters, since the estimated (structural model) fit values and the saturated (measurement model) fit values were identical. The SRMR value in the estimated model is 0.077, which is less than 0.08. The data still fit the model well, as shown by the d_ULS < bootstrapped HI 95% of d_ULS (0.566 < 0.66) and d_G < bootstrapped HI 95% (0.263 < 0.279) (as shown in Table 8). In the present study, since the difference between the model-implied and empirical correlation matrices is non-significant ($p > 0.05$), the model is considered to be fit.

Another important statistic for assessing a model's predictive significance is Q^2 (Stone-Geisser's Q-square), which measures how well the model reconstructs observed values via blindfolded cross-validation (Geisser, 1974; Stone, 1974). Q^2 will be positive if the model correctly anticipates the missing portions. Otherwise, Q^2 will be negative or zero. Only reflecting endogenous constructs and single-item endogenous variables are eligible for Q^2. The Q^2 value is the basis for the predictive relevance of the model; a Q^2 value > 0.35 indicates better predictive relevance, followed by a Q^2 value < 0.35 and >0.15 for moderate relevance, a Q^2 value < 0.15 and >0.02 for weak predictive relevance, and a Q^2value < 0.02 for negligible predictive relevance (Geisser, 1974; Stone, 1974). Table 9 displays the Q^2 value for INT_USE, PER_VAL, and TRST in the current study. Based on Q^2, the model has high predictive relevance, as the Q2 values for each of the three endogenous variables exceed 0.35.

Table 8. Model fit indices values (SRMR, d_ULS, d_G)

	Original sample (O)	Sample mean (M)	95%	99%
SRMR				
Saturated model	0.064	0.037	0.039	0.04
Estimated model	0.077	0.039	0.042	0.044
d_ULS				
Saturated model	1.528	0.505	0.575	0.609
Estimated model	2.254	0.566	0.666	0.725
d_G				
Saturated model	0.473	0.262	0.278	0.285
Estimated model	0.525	0.263	0.279	0.287

Source(s): Authors' own work

Table 9. Predictive relevance (Q^2 – geisser value)

Endogenous variable	Q^2 predict
INT_USE	0.499
PER_VAL	0.477
TRST	0.499

Source(s): Authors' own work

5. Discussion

In the fast-paced world of Q-commerce, where digital transactions are driven by technological, service quality, marketing, and social stimuli, concurrent validity is essential for verifying the relationships among the constructs. In response to RQ1, the current study validates 11 hypotheses, examining how these factors shape perceived value, trust, and usage intention in Q-commerce. Thus, among the four antecedents—technological, marketing, and social stimuli, as well as service quality —marketing and social stimuli have a greater influence on perceived value than on trust. In contrast, technological stimuli have a greater influence on building trust in Q-commerce platforms. Technological factors play a key role in shaping the user experience in Q-commerce. Advanced AI-driven personalisation, seamless payment systems, user-friendly app interfaces, and robust security measures all contribute to perceived value (H1) and trust (H2) (Pemayun and Alfirdaus, 2024). Research confirms that a seamless digital platform enhances customer satisfaction, reinforcing their perceived value of Q-commerce platforms (Dakhili *et al.*, 2024). Similarly, robust security and privacy protections significantly impact consumer trust, as users are likelier to engage with platforms that ensure safe transactions and data protection (Pemayun and Alfirdaus, 2024). Service quality is a key driver of both perceived value (H3) and trust (H4) in Q-commerce platforms (Yapinski *et al.*, 2024). Factors such as fast delivery, order accuracy, responsive customer support, and fair refund policies enhance user satisfaction, strengthening the link between service quality and perceived value (Tecoalu *et al.*, 2021). Additionally, platforms that consistently meet customer expectations earn greater consumer trust, leading to higher retention rates (Mudaim and Dirgiatmo, 2024). Empirical evidence supports a strong correlation ($p < 0.001$) between service quality and perceived trust, reinforcing the validity of these constructs within the Q-commerce landscape. Marketing efforts—such as discounts, loyalty programs, and limited-time promotions—are influential in shaping perceived value (H5) and trust (H6) (Tecoalu *et al.*, 2021). Research shows that well-executed promotional campaigns enhance consumers' perception of value, increasing their likelihood of repeat purchases (Balouchi *et al.*, 2024). Moreover, platforms that maintain transparency in their marketing practices, particularly regarding pricing, discount authenticity, bundled pricing, and return policies, foster greater consumer trust (Aryoko and Dirgiatmo, 2025). Social factors, such as customer reviews, community engagement, and social influence, play a crucial role in shaping the perceived value (H7) and trust (H8) associated with Q-commerce (Mudaim and Dirgiatmo, 2024). Consumers rely on peer recommendations and online ratings to assess a platform's reliability (Vazquez *et al.*, 2023). A strong online community where users share experiences and rate products further reinforces perceived value and trust (Busalim *et al.*, 2024). Studies indicate that platforms that integrate real-time customer feedback and interactive social engagement experience higher adoption rates, confirming the impact of social stimuli on user behaviour. Perceived value influences trust (H9) and usage intention (H10). When consumers perceive high benefits relative to costs, they are more likely to develop trust in a platform (Balouchi *et al.*, 2024). A substantial perceived value instils confidence, making users more likely to return to the platform (Aryoko and Dirgiatmo, 2025). Trust is a major predictor of a user's intention to continue using a Q-commerce platform (H11). Consumers who trust a platform's payment security, service reliability, and overall dependability are likelier to remain engaged over the long term (Pemayun and Alfirdaus, 2024). Research confirms that higher trust levels directly translate to increased user adoption rates, further validating its influence on usage intention. In response to RQ2, trust plays a more significant role in building usage intention for Q-commerce platforms than perceived value. This finding provides a way forward for developers and service providers to build user trust, motivating users to use the platforms. The findings highlight strong interconnections between technological, service quality, marketing, and social factors, demonstrating their influence on perceived value, trust, and the intention to adopt Q-commerce platforms.

6. Conclusions

This study makes valuable theoretical contributions by exploring how technological factors, service quality, marketing efforts, and social influences influence perceived value, trust, and usage intention in Q-commerce. The research reinforces key theoretical models, such as the Stimulus-Organism-Response (S-O-R) framework, by demonstrating concurrent validity. These findings confirm that external stimuli significantly influence consumer decision-making and behavioural intent (Aryoko and Dirgiatmo, 2025; Mudaim and Dirgiatmo, 2024). The study also highlights the critical role of perceived value as a bridge between external stimuli and trust, emphasising that factors such as competitive pricing, seamless user experience, and personalised services are crucial for driving consumer engagement in digital commerce (Pemayun and Alfirdaus, 2024). Additionally, this research deepens understanding of how trust is formed on Q-commerce platforms, identifying technological reliability, service efficiency, marketing efforts, and social influence as key factors in building customer confidence and intention to use the platform. Unlike traditional e-commerce, where service quality drives consumer satisfaction, Q-commerce relies on real-time interactions, user-generated content, and influencer endorsements to build credibility and trust (Busalim *et al*., 2024). Furthermore, this study reinforces the strong link between trust and usage intention, showing that platforms prioritising security, transparency, and social validation are more likely to retain customers in the long run (Yapinski *et al*., 2024).

For Q-commerce platforms and developers, these findings underscore the importance of innovation, customer experience, and trust-building strategies to enhance user engagement and foster long-term adoption. Investing in technology should be a top priority, focusing on AI-driven personalisation, strong cybersecurity measures, seamless mobile integration, and fast-loading interfaces—all crucial in enhancing perceived value and user confidence. Integrating real-time tracking, AI-powered customer support chatbots, and multi-layer payment authentication can strengthen trust in digital transactions. The adoption of AI-agentic systems can enhance supply chain and inventory management in Q-commerce stores. AI adoption can also anticipate the customer needs, thus reducing delivery times and improving customer satisfaction. Optimising service quality is equally essential, as speed and efficiency are key differentiators in Q-commerce. Platforms should build reliable last-mile delivery networks, form strategic partnerships with third-party logistics providers, and implement real-time inventory management systems to maintain consistent service reliability. Features such as automated order fulfilment, AI-driven demand forecasting, and dynamic route optimisation can enhance delivery speed and reduce operational inefficiencies. Providing 24/7 customer support, flexible refund policies, and real-time issue resolution will also help sustain consumer satisfaction and trust.

Marketing strategies must be highly personalised and interactive, leveraging data analytics and AI to deliver customised promotions, flash sales, loyalty rewards, and exclusive discounts. Unlike traditional marketing approaches, Q-commerce platforms should focus on real-time engagement tactics, such as location-based offers, push notifications, and gamified shopping experiences to drive customer participation. However, maintaining transparency in marketing is essential—misleading advertisements can quickly erode consumer trust and damage platform credibility. Social influence plays a key role in shaping purchasing decisions, making it essential for Q-commerce platforms to integrate social commerce features. Allowing peer reviews, influencer recommendations, community discussion forums, and interactive product conversations can enhance consumer confidence in making purchasing decisions. Investing in AI-powered sentiment analysis tools can help platforms track customer feedback in real-time and proactively address concerns. Additionally, incorporating live shopping events, influencer-led Q&A sessions, and user-generated content contests can increase engagement and conversion rates.

Building long-term trust and retaining customers is equally important. Developers should implement strict privacy policies, adhere to ethical data management practices, and maintain transparency in AI-driven decisions to foster consumer confidence. Features such as verified seller programs, product authenticity certification, and robust payment systems can further minimise fraud risks. A well-structured customer loyalty program, personalised incentives, and a tiered membership system can encourage repeat purchases and long-term platform engagement. By embracing these strategic improvements, Q-commerce platforms can enhance user engagement, foster lasting trust, and maintain a strong competitive position in the rapidly evolving digital commerce landscape.

Despite offering valuable insights, this research has several constraints. While this study focuses on Delhi and Gurugram, its geographical scope limits the broader applicability of the findings to other regions. Additionally, response bias is a potential concern because the research relies on self-reported data. Future studies should expand to diverse demographics and incorporate longitudinal research to track changes in consumer behaviour over time. Future research could explore how cultural and economic contexts shape consumers' intentions to use Q-commerce, offering a more holistic view of user behaviour. Cultural traits—such as individualism versus collectivism, uncertainty avoidance, and power distance—may influence how people perceive convenience, trust, and risk. In collectivist societies, recommendations from family members and peer groups drive adoption, whereas in individualist cultures, independent decision-making and personal preferences may be more influential. Likewise, consumers in cultures with high uncertainty avoidance might hesitate to embrace new digital services unless strong security and reliability measures are evident. In contrast, those in more open, risk-tolerant cultures may readily adopt innovative platforms and features. Future research should further examine the interplay between AI-driven personalisation, sustainability imperatives, and blockchain-enabled security to understand how technological innovation intersects with ethical and cultural expectations in Q-commerce adoption. A comparative investigation between metropolitan and non-metropolitan contexts could also uncover regional variations in adoption patterns. Metropolitan areas, characterised by higher population density, accelerated lifestyles, and advanced digital infrastructure, are likely to demonstrate higher levels of Q-commerce utilisation and a distinct preference for rapid delivery services. Conversely, in non-metropolitan regions, adoption may progress more gradually due to limited logistical infrastructure, lower digital literacy, and divergent purchasing habits. Consumers in these regions may emphasise affordability and community trust over immediacy. Understanding such contextual distinctions is essential for Q-commerce enterprises to formulate localised strategies, ensuring that marketing, pricing, and service delivery models align with the socio-economic realities and cultural expectations of diverse consumer segments.

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