International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)

Vol. 11-No.3 (2025) pp. 3793-3807
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

The Adaptive Consumer: Social Media, Q-Commerce, and Dark Warehouses Drive Purchase Flexibility in Indian Cities

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Article Info:

DOI: 10.22399/ijcesen.2557
Received : 05 March 2025
Accepted : 19 May 2025

Keywords :

Social Media
Warehouse Management
Marketing
Quick commerce
Management

Abstract:

Focusing on the effects of social media, fast commerce (Q-commerce), and dark warehouses on consumer buying flexibility, this paper investigates the changing dynamics of consumer behaviour in urban India. Data was gathered from three representative samples spread throughout four major metropolitan cities—Hyderabad, Chennai, and Bangalore—using a quantitative method. The effect of every variable was examined using structural equation modelling. Findings show that social media (β = 0.734, $p < 0.001$) exerts the strongest positive impact on customer purchase flexibility, followed by Q-commerce (β = 0.980, $p < 0.001$), while dark warehouses show a significant yet negative influence (β = -0.536, $p < 0.001$). With t-values far above the crucial threshold, all relationships were statistically significant. These results emphasize the flexible character of the contemporary Indian customer and show how important internet infrastructure and new retail concepts are in influencing buying choices. For marketers and logistics planners trying to improve consumer response in fast digitizing metropolitan areas, the study provides strategic insights.

1. Introduction

The contemporary retail landscape is undergoing a profound metamorphosis, propelled by the convergence of social media, quick commerce, and the strategic deployment of dark warehouses within metropolitan areas [1]. This transformation is reshaping consumer expectations and necessitating retailers to adopt innovative strategies to enhance customer satisfaction and ensure expeditious delivery services [2]. The rise of mobile technologies and social networks has cultivated a new breed of digitally savvy consumers who leverage multiple shopping channels to procure products and services at their convenience and desired price points [3]. The integration of digital technologies into the retail sector has blurred the lines between physical and online channels, compelling retailers to embrace omnichannel strategies to cater to the evolving needs of their customer base [4]. The proliferation of social media platforms has significantly influenced consumer behaviour, providing individuals with unprecedented access to information and facilitating seamless interactions with retailers, competitors, and fellow consumers [5]. Consumers now actively engage with brands on social media, seeking product recommendations, sharing feedback, and participating in online communities, enabling companies to glean valuable insights into consumer preferences and tailor their marketing efforts accordingly [6]. The advent of e-commerce, mobile shopping, and smart technologies has intensified competition, challenging the traditional dominance of brick-and-mortar retailers [7]. The shift towards online platforms empowers consumers to compare prices, read reviews, and make purchases from the comfort of their homes, diminishing the influence of physical stores as the primary interface for customer engagement [7]. Furthermore, interactive digital technologies implemented in brick-to-click, click-to-brick and brick-and-mortar retailing offer customers a variety of experiential qualities that allow them to co-create products and engage in personalized shopping experiences [8]. In essence, the retail landscape is no longer segmented by physical and digital lines but is instead an interconnected ecosystem where consumer journeys are fluid and multidimensional [9]. Quick commerce has emerged as a disruptive force in the retail industry, promising ultra-fast delivery of goods and services within a localized geographic area. Q-commerce leverages a network of strategically positioned dark warehouses, also known as micro-fulfilment centers, to store inventory and facilitate rapid order fulfilment. Dark warehouses, typically located in densely populated urban areas, are optimized for efficient picking, packing, and dispatching of orders, enabling retailers to minimize delivery times and cater to the demands of time-sensitive consumers. These facilities, which prioritize speed and efficiency over traditional retail aesthetics, enable businesses to fulfil online orders with unprecedented speed, often within minutes of placement, directly impacting customer satisfaction [10]. The integration of e-commerce with physical channels creates opportunities and synergies: companies can offer multiple services through different channels and for different target segments [11].

The strategic placement of dark warehouses in metropolitan areas plays a pivotal role in optimizing delivery logistics and ensuring timely order fulfilment. Dark warehouses are strategically positioned to minimize the distance between inventory and consumers, reducing delivery times and transportation costs. The efficiency of last-mile logistics, the final stage of the delivery process, is crucial for Q-commerce providers, as it directly impacts customer satisfaction and operational profitability. By delaying the decisions on how to fulfil customer orders, companies can make better operational decisions to utilize their resources and information more efficiently [12]. Efficient last-mile delivery is critical for e-commerce success, influencing customer experience and repeat purchases [13]. Last-mile logistics for e-commerce can present many unexpected dangers that could affect delivery time and accuracy, customer satisfaction, and ultimately the profitability of the e-commerce organization [14]. The goal of urban freight distribution is to supply specific items on time and in the right way, guaranteeing low costs and offering good customer service [15].

However, the pursuit of ever-faster delivery times introduces a complex set of operational challenges and cost considerations. Meeting customer expectations for quick delivery necessitates significant investment in infrastructure, technology, and human resources, straining retailers' profitability. As customers got accustomed to faster delivery timelines, new challenges have arisen in the middle-mile space to be able to design a transportation network that allows aggressive delivery promises while keeping operations cost-effective [12]. Moreover, the environmental impact of Q-commerce operations, particularly the use of delivery vehicles in congested urban areas, raises sustainability concerns. The volume of last-mile delivery services is increasing because of urbanization and e-commerce [16]. Urban delivery services are crucial for both economic and social sustainability, as their effectiveness directly affects the well-being of urban inhabitants. Logistics operations in urban areas, notably urban fulfilment and last-mile delivery, tend to be the most expensive of the entire logistic process while being the most critical in shaping customer experience [17]. Last-mile delivery is known to account for approximately 70% of the total cost of e-commerce logistics [18].

Income disparities and security issues in emerging market cities pose additional challenges for Q-commerce providers [19]. The sustainability issues contain the problems of air pollution, congestion, and sub-contractors [20]. Low distribution service quality during the "last mile" can be seen in three ways: first, the delivery person does not deliver the packages to the customer on time, which lowers distribution efficiency; and second, the customer may receive packages that were damaged in transit [21]. Also, an issue of inadequate car park which is not adjusted to the needs of e-commerce needs to be pointed out, especially in the context of vehicle size compared to the volume of delivery [22]. To mitigate these challenges, Q-commerce providers are exploring innovative solutions, such as electric vehicles [23], route optimization algorithms [24], and delivery drones, to enhance efficiency and minimize environmental impact.

The integration of social media platforms into the Q-commerce ecosystem has emerged as a potent catalyst for driving customer engagement and fostering brand loyalty. Social media platforms serve as a dynamic channel for retailers to connect with consumers, promote products and services, and gather valuable feedback. By leveraging social media data, Q-commerce providers can gain deeper insights into consumer preferences, tailor marketing campaigns, and personalize the shopping experience.

2. Background of the study

As Q-commerce gains traction, further research is needed to evaluate the role of logistics, platforms, and customer behaviour in shaping its trajectory [25]. There is a need for developing suitable measures that would overcome last mile distribution challenges, especially for e-commerce retailers in South Africa [26]. The key practices adopted by e-retailers in last-mile logistics can develop a sustainable network in economic, social, and environmental terms [27]. By examining real-world case studies and analysing quantitative data, researchers can gain a more nuanced understanding of the factors that drive success in the Q-commerce landscape [28]. The rapid development of e-commerce and the increasing demand for fast delivery have spurred the growth of Q-commerce, which emphasizes quick order fulfillment and delivery, thus resulting in increased delivery business [29]. E-commerce platforms that offer fresh and perishable goods are growing, and the quality of their logistics services is becoming increasingly important [30]. Logistics service speed is the most important determinant of customer satisfaction [31]. E-commerce success depends on things like trust, security, ease of use, and good service [32]. The growth of e-commerce depends on things like good internet, dependable delivery, and affordable prices. Last mile delivery options could involve a variety of transportation choices depending on the location, the consumer needs, and the product features. [26]

Q-commerce success depends on the location of dark warehouses, effective last-mile delivery, and use of social media for marketing and feedback [26]. Also, companies can ensure they can add value by directly connecting with customers and creating a strong image and culture through their last-mile service [33]. Customer satisfaction plays a pivotal role in shaping the success and sustainability of Q-commerce ventures in metropolitan areas. A customer wants more free time, so the goods home delivery option significantly shortens the time required for shopping, leading to preference for online sellers who make delivery as a standard part of their offer [22]. Logistics companies must strike a balance among customer needs, their own competitiveness, and the public interest to create a sustainable concept for urban last-mile delivery [34]. Retailers typically aim for a consistent and reliable delivery process to fulfill orders as agreed with logistics service providers and suppliers [35]. The ultimate moment of truth lies in last-mile logistics, necessitating precise planning to ensure timely and accurate deliveries to customers at the right place, quantity, quality, and cost [28]. Last-mile logistics is the crucial link that directly interacts with the final customer [28].

The rise of e-commerce has amplified the significance of last-mile delivery, which involves transporting goods from a distribution hub to the end customer's doorstep [36]. Last-mile delivery, the final leg of the supply chain, is often the most challenging and inefficient segment [28]. Last mile delivery concepts and the decision problems solved when setting up and operating each concept should be emphasized [37]. It accounts for a substantial portion of the total supply chain cost and is susceptible to various challenges, including traffic congestion, complex urban landscapes, and demanding customer expectations [38] [16]. The implementation of efficient last-mile delivery systems is crucial to address its inherent complexities, such as the large number of geographically dispersed delivery locations that are constantly changing [39]. Furthermore, it is crucial for minimizing transportation costs and mitigating environmental effects [40].

Compared to traditional home delivery, unattended delivery presents notable convenience for consumers, eliminating the need for them to be physically present to receive their orders [41]. Parcel lockers have emerged as an efficient last-mile delivery solution [42]. They offer the advantages of reducing delivery failures, increasing delivery efficiency, and providing consumers with greater flexibility in retrieving their parcels. The rapid growth of Q-commerce has led to the emergence of dark warehouses, which are strategically located fulfilment centers that cater specifically to online orders. These warehouses are designed to optimize picking, packing, and dispatching processes, enabling rapid order fulfilment and delivery [43]. Dark warehouses offer advantages such as proximity to urban centers, streamlined operations, and technology integration, all of which contribute to faster delivery times and improved customer satisfaction. To improve the service quality in the last part, express delivery industry develops the “last mile” strategy, which is particularly used to illustrate the interaction between people and goods from transportation centre to homes [21]. Express delivery companies have come up with two models for the "last mile" [21].

Social Media Influence: Social media has significantly impacted consumer behaviour in India, particularly in urban areas. Platforms like Facebook, Instagram, and WhatsApp have transformed how consumers interact with products and brands, providing instant access to information and peer reviews, which are crucial for making quick and reliable purchase decisions. This constant stream of information helps consumers make informed choices, enhancing their purchase flexibility. While not directly citing this point, a study on digital consumers and the foodservice market notes that social commerce has a significant influence on consumer behavior [44]. Additionally, the impact of social influence in e-commerce decision making is an area of active research [45].

Q-Commerce and Dark Warehouses: Quick commerce has emerged as a revolutionary model in the Indian retail sector, promising near-instant delivery of goods, typically within 20 minutes. This model relies heavily on dark warehouses, small store-like facilities strategically located to ensure rapid delivery. The convenience offered by Q-commerce has driven consumer expectations for faster and more flexible purchasing options, especially in urban areas. However, this convenience comes with environmental costs, such as increased carbon emissions and packaging waste, which need to be addressed for sustainable growth. Q-commerce is expected to be a metro-first phenomenon, with gradual adoption in tier 1 markets. The rise of quick commerce has provided new business opportunities to entrepreneurs and established e-commerce players (Q-Com, n.d.).

E-Commerce and Warehousing: The growth of e-commerce in India has been exponential, driven by increased internet penetration and the rise of platforms like Amazon and Flipkart. This surge has led to a higher demand for warehousing and logistics services, particularly from third-party logistics providers (3PLs). The ability to store and quickly dispatch goods from these warehouses has enhanced the flexibility of consumer purchases, allowing for a seamless shopping experience across metro cities and smaller towns. One paper examines how online shopping integrates into the everyday practices of shoppers in India [46]. The diffusion of the internet has changed advertising, sales, and delivery channels in the retailing industry [47].

Consumer Behaviour and Purchase Flexibility: The Indian consumer market has evolved significantly, with a new middle class driving increased consumption and changing purchase habits. The convenience of online shopping, combined with the ability to compare products and read reviews, has made consumers more flexible in their purchasing decisions. Additionally, the integration of forward and reverse logistics in e-commerce platforms has streamlined the returns process, further enhancing purchase flexibility. - It is important to analyse consumer's attitudes towards shopping products online to gain competitive advantage Gap: While the existing literature provides a comprehensive overview of e-commerce, social media impact, and Q-commerce in India, there are notable gaps that need to be addressed. Firstly, there is a lack of research on the specific environmental impacts of Q-commerce and dark warehouses in the Indian context. There is research on environmental implications of e-commerce that identifies pressing knowledge gaps . Secondly, there is limited empirical evidence on how customer satisfaction is directly influenced by the speed and reliability of Q-commerce deliveries in metro cities.

3. Literature Review

E-commerce and Q-Commerce: A Conceptual Overview: E-commerce, or electronic commerce, refers to the buying and selling of goods and services over the internet [47]. It encompasses a wide range of activities, including online shopping, electronic payments, and digital marketing. E-commerce has experienced exponential growth in recent years, driven by factors such as increasing internet penetration, mobile device adoption, and changing consumer preferences. Q-commerce, or quick commerce, is a subset of e-commerce that focuses on providing fast delivery, typically within an hour or less [48]. It leverages a network of strategically located micro-fulfilment centers, also known as dark warehouses, to enable rapid order fulfilment. Q-commerce caters to consumers' increasing demand for convenience and immediacy, offering a wide range of products, including groceries, household essentials, and prepared meals. The rise of e-commerce has significantly altered how consumers shop, and businesses operate [49]. E-commerce has become essential for countries aiming to transition into information societies; however, its adoption in developing countries like India is still evolving . Dark Warehouses and the Logistics of Fast Delivery: Dark warehouses are small-scale fulfilment centers strategically located in urban areas to facilitate rapid delivery. These facilities are not open to the public and are optimized for efficient order processing and last-mile delivery. Dark warehouses play a crucial role in Q-commerce by enabling companies to fulfil orders quickly and efficiently. The efficiency of supply chain management is lacking in Indian retail, hindering practices like Quick Response and Efficient Consumer Response [50]. Social media and Consumer Behaviour in E-Commerce: social media has become an integral part of the e-commerce landscape, influencing consumer behaviours in various ways. Social media platforms provide businesses with opportunities to reach a large audience, promote their products, and engage with customers. Social commerce, a subset of e-commerce, involves conducting transactions through social media platforms. [51]; Social media platforms have transformed the way consumers discover and interact with brands, and e-commerce businesses are increasingly leveraging social media to drive sales and build customer loyalty. Social commerce integrates online communities with social technologies to enhance e-commerce, emphasizing the adaptability of social media and aiming to transition e-commerce to social commerce [52]. Social networking sites have become key tools for marketing and selling products online. Customer Satisfaction in the Digital Age: Customer satisfaction is a critical factor for the success of any e-commerce business, and Q-commerce is no exception. In the context of e-commerce, customer satisfaction refers to the extent to which customers are happy with their online shopping experience. Factors that contribute to customer satisfaction in Q-commerce include fast delivery, product availability, ease of use of the platform, and customer service. Furthermore, social media enhances online shopping experiences, especially amid crises like the pandemic, by enabling cost-effective communication and management of customer relations. The messages conveyed in social media activities should improve customer attitudes towards the brand, which can be achieved through vivid and interactive posts that increase shares and likes [53].

4. Objectives of the Study

To assess the influence of social media on consumer purchase decisions in the context of Q-commerce.

To evaluate the role of dark warehouses in enabling fast delivery and enhancing customer satisfaction.

Scope of the Study

This study focuses on the metro cities in India, given their higher adoption rates of e-commerce and Q-commerce. The research encompasses an analysis of consumer behaviour, logistical operations, and environmental impacts, providing a holistic view of the Q-commerce ecosystem. The scope of your study focuses on metro cities in India, given their higher adoption rates of e-commerce and Q-commerce. This is a sound approach, as these cities are at the forefront of these trends [54].

Here are some considerations for refining the scope:

- Specific Metro Cities: Consider specifying which metro cities you will focus on (e.g., Chennai, Hyderabad, Bangalore). This will help to narrow down your research and make it more manageable.
- Demographic Focus: Within these metro cities, are you targeting a specific demographic (e.g., Gen Z, millennials, working professionals)? Mentioning this can provide further clarity.

5. Limitation

This study focuses on the metro cities of Bangalore, Hyderabad, Chennai and Bangalore, given their higher adoption rates of e-commerce and Q-commerce. The research will target Gen Z and millennial consumers who regularly use Q-commerce platforms for grocery and essential item purchases. Data will be collected over a three-month period to assess current trends in consumer behaviour. By clearly defining the scope, you can ensure that your research is focused and relevant, as there has been an increased purchasing rate in metro and Tier I cities in India due to the fastest delivery of groceries and other products, driving the quick commerce market in the country [54].

6. Significance of the study

This study holds significant implications for various stakeholders, including e-commerce companies, logistics providers, policymakers, and consumers. For e-commerce companies, the findings will provide insights into optimizing their Q-commerce strategies, enhancing customer satisfaction, and improving supply chain management [55]. For logistics providers, the study will offer guidance on improving delivery efficiency and reducing environmental impact. For policymakers, the research will inform the development of regulations and incentives to promote sustainable e-commerce practices. For consumers, the study will shed light on the benefits and drawbacks of Q-commerce, helping them make informed purchasing decisions. This study will contribute to the academic literature by providing empirical evidence on the impacts of Q-commerce in a developing country context, specifically India [56]. The study will also highlight the importance of considering both the economic and environmental dimensions of e-commerce, fostering a more sustainable approach to online retail. The study examines consumer attitudes towards online shopping, contributing to a deeper understanding of consumer behaviour in the digital age . The growth of e-commerce in India necessitates a thorough understanding of consumer behaviour to leverage the expanding online market. Additionally, the increasing usage of the internet has significantly connected customers to online buying portals, reflecting a growing trend in online shopping (Venice et al 2022). The study aims to fill the research gap by providing insights into the specific dynamics of Q-commerce in India, where limited studies have explored the nuances of this rapidly evolving market segment [48]. It seeks to understand how system quality, website features, and other factors influence customer satisfaction, which is a key element for success in the Indian online market [57]. In India, the online market is experiencing rapid growth, driven by technological advancements, increased internet access, and rising incomes, making it crucial to understand customer perceptions of online services. Furthermore, this research aims to contribute to the theoretical foundations of e-commerce by extending existing models, such as the Technology Adoption Model, to incorporate the unique characteristics of the Indian market (Arumugam et al 2024). The study will also explore how social media influences consumer purchase decisions in the context of Q-commerce, an area that has not been extensively researched. The rise of e-commerce has transformed the retail industry by changing advertising, sales, and delivery channels.

Hypothesis

- H1: Social media marketing has a significant positive influence on Q-commerce adoption.
- H2: Efficient dark warehouse operations significantly enhance customer satisfaction in Q-commerce.
- H3: Fast delivery speed positively impacts customer loyalty in Q-commerce within metro cities.

The use of analytic hierarchy process can help to find out the main factors of affecting the quality of delivery service in the "last kilometre" [29]. Website innovativeness, content usefulness, and ease of use can impact overall service quality of mobile commerce platforms [58]. Ease of use, design, responsiveness and security of a website can lead to increased levels of perceived value, while ease of use, responsiveness and personalization lead to an increase in the overall satisfaction of consumers [59].

7. Research Methodology

The study employs quantitative data collection technique to provide a comprehensive understanding of the research problem. The research design utilized in this study is descriptive research design, which aims to describe the characteristics of a population or phenomenon. The independent variables are social media (SM), Q-Commerce (QC), and Dark Warehouses (DW) and Dependent Variable was Customer Purchase Flexibility (CPF)

- Data collection is done using survey questionnaires.
- Data analysis is done using descriptive and inferential statistics.
- Type of sample design used is stratified random sampling.
- Target group of the sample from customers who have experience using q-commerce platforms in metro cities.
- Sample size of 412 respondents.
- testing- correlation and regression analysis.

8. Concept Framework

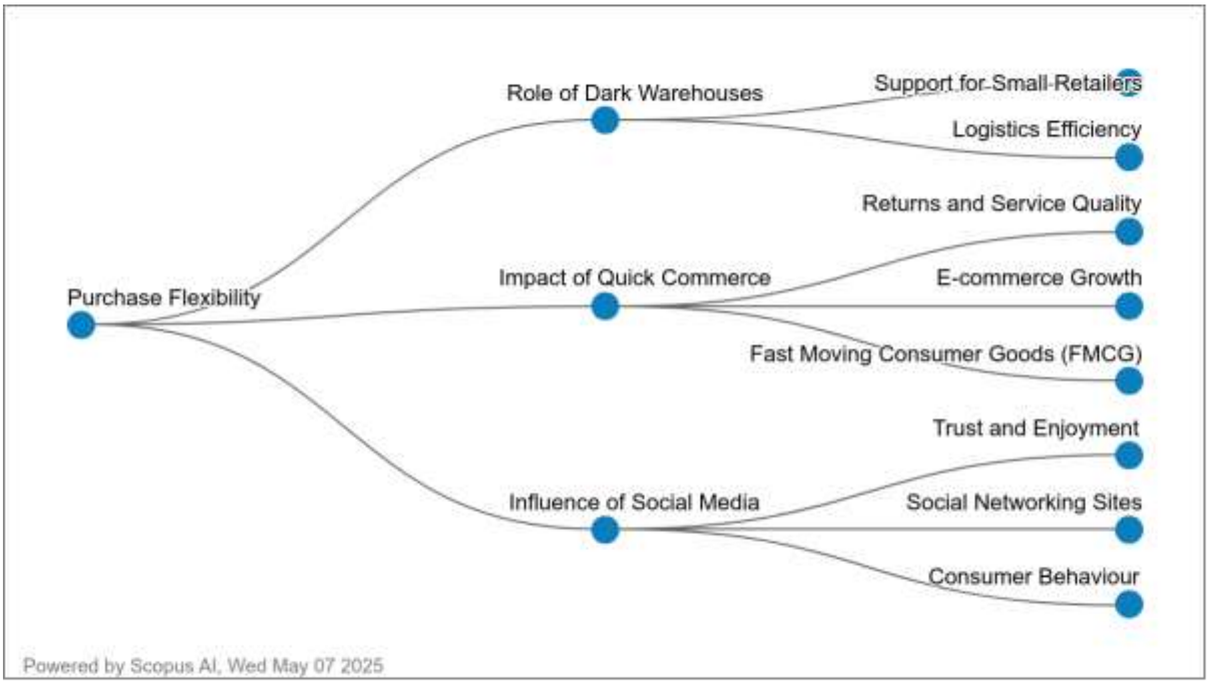

Figure 1. *The concept framework on purchase flexibility on dark warehouses, quick commerce social media.*

The conceptual map illustrates various interconnected factors influencing buy flexibility—the ability of consumers to obtain things at their convenience. Dark warehouses significantly boost logistics efficiency and offer essential support to small enterprises by facilitating faster and more reliable distribution networks. Especially in urban areas, these micro-fulfilment centers bridge the gap between demand and delivery. The impact of rapid commerce, which facilitates the swift delivery of fast-moving consumer goods (FMCG) and thus propels the growth of e-commerce, is another significant aspect. Quick commerce enhances service quality and returns, fulfilling customers' expectations for convenience and reliability. In addition to logistical enhancements, the influence of social media is significant in shaping consumer behaviour. Platforms such as Instagram and Facebook enhance the reliability and enjoyment of online shopping by promoting products and generating trends. These social networking platforms facilitate alterations in client behaviour by encouraging impulsive purchases and enhancing brand engagement. The integration of advanced storage, rapid commerce, and social influence establishes a dynamic system that enhances customer purchasing possibilities and accelerates the advancement of contemporary retail.

9. Data Analysis:

Table 1. *Mean and Standard Deviation of the Variables i.e., social media (SM), Quick Commerce (QC), Dark Warehouse (DW) and CPF (Customer Purchase Flexibility)*

Descriptive Statistics			
	Mean	Std. Deviation	N
Social media (SM)	3.2204	.54676	412
Quick Commerce (QC)	2.7976	.61663	412
Dark Warehouse (DW)	3.2617	.56567	412
Customer Purchase Flexibility (CPF)	2.8498	.55331	412

Interpretation: Table 1 displays the descriptive statistics—mean and standard deviation—for four principal variables obtained from 412 respondents: social media (SM): Average: 3.22, and Standard Deviation: 0.55. The average score for social media is moderately high, indicating that participants usually view social media influence or interaction in a somewhat positive manner. The low standard deviation signifies that responses are tightly grouped around the mean, indicating consistency in perceptions. Quick Commerce (RC): Average: 2.80, Standard Deviation: 0.62; Quick Commerce possesses the lowest average score among the variables, signifying a comparatively diminished level of agreement or familiarity among responders. The standard deviation is slightly higher than SM, indicating slightly more variability in how participants perceive or experience quick commerce services. Dark Warehouse (DW): Mean:

3.26, Standard Deviation: 0.57: DW exhibits the highest mean, indicating that respondents predominantly hold good or positive attitudes of dark warehouse operations (e.g., efficiency, utility in logistics). The standard deviation is moderate, signifying consistent replies. Customer Purchase Flexibility (CPF): Mean: 2.85, Standard Deviation: 0.55: CPF exhibits a moderate mean, somewhat beneath the neutral middle on a 5-point Likert scale, indicating that respondents see restricted flexibility in client purchasing alternatives. The diversity in replies resembles that of SM, indicating uniform opinions among participants, show in the table 2.

Table 2. *Variables Mean & Standard deviation's interpretation*

Variable	**Mean**	**Std. Deviation**	**Interpretation**
Customer Purchase Flexibility (CPF)	2.85	0.55	Respondents showed **moderate agreement** with statements related to purchase flexibility. The score is slightly below the neutral midpoint (on a 5-point Likert scale), suggesting **limited perceived flexibility** in purchasing options.
Social media (SM)	3.22	0.55	SM scored relatively high, indicating **positive perceptions or frequent use** of social media in the context studied. The responses are relatively consistent.
Quick Commerce (QC)	2.80	0.62	This variable had the **lowest mean**, suggesting that respondents have **neutral to slightly negative views or limited familiarity** with quick commerce services. Slightly higher variability in responses is observed.
Dark Warehouse (DW)	3.26	0.57	This variable had the **highest mean**, indicating **stronger agreement or favourable views** of dark warehouse operations. Participants are generally consistent in their perceptions.

Model Fit Analysis (R-Test)

Regression analysis's Model Summary table shows Dark Warehouse (DW), social media (SM), and Quick Commerce (QC) as the independent variables and Customer Purchase Flexibility (CPF) as the dependent variable.

Table 3. *Statistic of the Values of R, R square, Durbin-Watson for model fit*

Statistic	**Value**	**Interpretation**
R	0.526	This is the multiple correlation coefficient. It indicates a **moderate positive relationship** between the independent variables (DW, SM, QC) and CPF.
R Square (R^2)	0.277	About **27.7% of the variance** in **Customer Purchase Flexibility** is explained by the model. This suggests a **moderate explanatory power** of the predictors.
Adjusted R Square	0.271	Adjusted R^2 accounts for the number of predictors and sample size. It confirms that the model remains **robust and generalizable**, explaining about **27.1%** of the variance.
Standard Error of the Estimate	0.47228	This reflects the average distance that the observed values fall from the regression line. A lower value indicates better model fit; here it is moderate.
F Change / F Value	52.045	This is the **F-statistic** used to test the overall significance of the regression model.
Sig. F Change	0.000	The **p-value is < 0.001**, indicating the regression model is **statistically significant**—i.e., the combination of predictors significantly predicts CPF.
Durbin-Watson	0.686	This statistic tests for **autocorrelation** in the residuals. A value close to 2 is ideal. A value of **0.686 indicates positive autocorrelation**, which might suggest that residuals are not independent and could be a potential issue in time-series or sequential data.

Table 4. *ANOVA Test*

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34.826	3	11.609	52.045	.000[b]
	Residual	91.004	408	.223		
	Total	125.830	411			
a. Dependent Variable: CPF						
b. Predictors: (Constant), DW, SM, QC						

Table 4, ANOVA tests whether the overall regression model is a good fit for the data. **F-value = 52.045**, **Sig. = 0.000.** The **p-value < 0.001** indicates that the regression model is **statistically significant**. That is, the combination of the predictors—**SM, QC, and DW**—**significantly predicts Customer Purchase Flexibility (CPF)**. This confirms the model explains a significant amount of variance in the dependent variable.

Table 5. *Coefficients Table Interpretation*

Predictor	**B (Unstandardized)**	**β (Standardized)**	**t**	**Sig.**	**Interpretation**

Constant	0.466	–	2.417	0.016	The baseline CPF score when all predictors are zero.
SM	0.399	**0.394**	**9.087**	**0.000**	Strongest and significant positive predictor of CPF. A 1-unit increase in Social Media perception increases CPF by 0.399 units.
QC	0.102	0.113	1.753	0.080	Not statistically significant at the 0.05 level. While positive, the effect of Quick Commerce is weak.
DW	0.249	**0.255**	**3.964**	**0.000**	Significant positive predictor. DW perception contributes positively to CPF.

Residuals Statistics Interpretation from the table 5, This provides insight into how well the model fits the data. **Predicted CPF Values** range from **2.20 to 3.25**, with a mean of **2.85**, which aligns well with the actual mean of CPF. **Residuals** range from **-0.75 to 0.60**, indicating relatively small prediction errors. **Standardized residuals** range from **-1.58 to 1.28**, which falls within the acceptable range (±3), suggesting **no major outliers**.

Table 6. *Reliability Test for all the four variables:*

Statistic	Value	Interpretation
Cronbach's Alpha	**0.613**	This indicates **acceptable reliability**, though on the lower end. Values above **0.7** are preferred, but for exploratory research or newly developed scales, values between **0.6–0.7** are often acceptable.
Number of Items	4	The reliability is measured across 4 constructs: **SM, QC, DW** and **CPF.**

Table 7. *ANOVA with Cochran's Q Test:*

ANOVA with Cochran's Test						
		Sum of Squares	df	Mean Square	Cochran's Q	Sig
Between People		248.309	411	.604		
Within People	Between Items	72.676	3	24.225	248.927	.000
	Residual	288.182	1233	.234		
	Total	360.858	1236	.292		
Total		609.166	1647	.370		
Grand Mean = 3.0323						

Table 6 & 7 show that Cochran's Q test, a non-parametric test often used to examine whether **multiple related samples (e.g., different items or treatments measured on the same subjects)** have **statistically significant differences in responses**.

Table 8: *Statistic Cochran's Q and Significance (Sig):*

Statistic	Value	Interpretation
Cochran's Q	**248.927**	This is the test statistic value for Cochran's Q test.
Significance (Sig.)	**0.000**	Since **p < .05**, the result is **statistically significant**.
df (Between Items)	3	There are **4 items** being compared (hence 4-1 = 3 df).
Mean Squares Between Items	24.225	Indicates **substantial variability** between the items (constructs).
Residual Mean Square	0.234	Represents the error variance within respondents across the items.
Grand Mean	3.0323	This is the **overall average** of the item means.

According to the table 8; There is a significant difference among the four measured items (SM, QC, DW, CPF) in terms of how respondents rated them. This result **supports the earlier descriptive and correlation analyses**, which showed varying means and differing relationships between the constructs. The high **Q value (248.927)** combined with a **significance of .000** confirms that these items are not equally perceived or endorsed by participants. The constructs (social media, Quick Commerce, Dark Warehouse, and Customer Purchase Flexibility) are **perceived differently by respondents**, warranting individual attention in strategic decisions or further research.

Table 9. *Factor Analysis*

Measure	Value	Interpretation
KMO (Kaiser-Meyer-Olkin)	**0.532**	Acceptable but **marginal**. Values > 0.5 are the minimum threshold for factor analysis to be considered suitable.
Bartlett's Test of Sphericity	χ^2 = 484.751, **Sig. = .000**	Highly significant (p < .001), indicating sufficient correlations among variables for factor analysis.

Table 10. *Communalities of the Variables:*

Variable	Extraction Value	Interpretation

SM	0.812	81.2% of its variance is explained by the extracted factor(s).
QC	0.873	Very high communal variance explained.
DW	0.851	Also strongly represented in the factor(s).
CPF	0.721	Over 72% of variance accounted for.

The dataset is **adequately suited for factor analysis**, though the KMO value is barely above the threshold. The **Bartlett's test confirms significant inter-item correlation**, making factor extraction valid. The **variables are well represented** in the factor solution (high communalities), indicating a **strong latent structure**. The high correlation between **DW and QC** may suggest they load on the same latent factor.

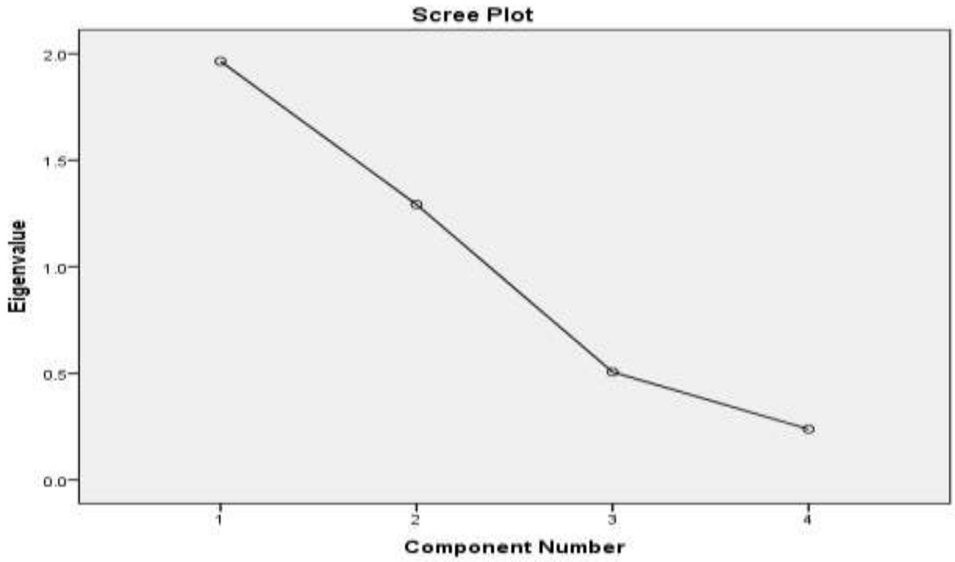

Figure 2. *Total Variance Explained:*

Table 11. *Total Variance Explained*

Total Variance Explained							
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	1.964	49.099	49.099	1.964	49.099	49.099	1.886
2	1.292	32.301	81.399	1.292	32.301	81.399	1.431
3	.506	12.653	94.052				
4	.238	5.948	100.000				
Extraction Method: Principal Component Analysis.							
a. When components are correlated, sums of squared loadings cannot be added to obtain a total variance.							

According to the figure 2, and table 11;Components with **eigenvalues > 1** are typically retained (Kaiser's criterion). In this case: **Component 1:** Eigenvalue = 1.964 → Retained, **Component 2:** Eigenvalue = 1.292 → Retained, Components 3 and 4 have eigenvalues < 1 → **Not retained.** These two components **together explain 81.4% of the total variance** in the data, which is **very high** and indicates a strong factor solution. This means most of the information (variability) in your four variables is captured by these two latent components. The scree plot supports the decision to retain **2 components**, as they account for the majority of variance and the rest are likely noise or minor variation. **According to the figure 3; the relation between the variables i.e.,Dark Warehouse -> Customer Purchase Flexibility:** The original sample (-0.536) is very close to the sample mean (-0.531), but it is still significantly different. The t-statistic of 3.630 indicates that the observed sample is 3.63 standard deviations away from the mean. The p-value of 0.000 is very small, meaning there's a very low probability that this result is due to chance, suggesting a strong effect of "Dark Warehouse" on "Customer Purchase Flexibility."

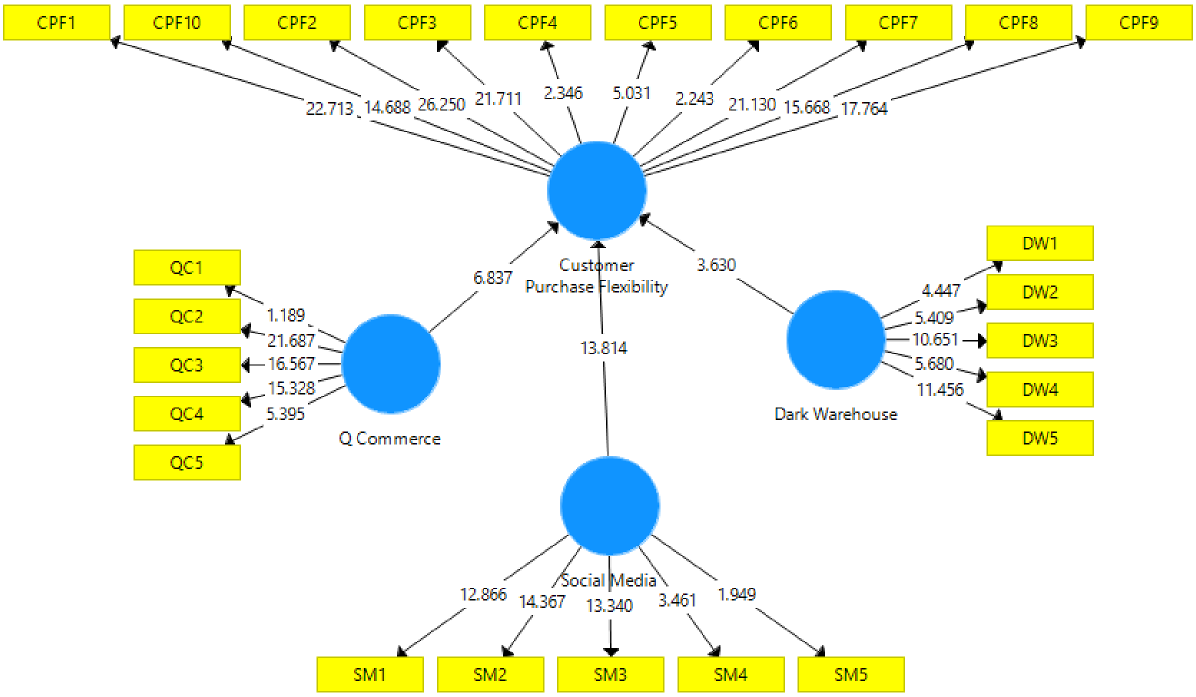

Figure 3. *SEM (Structural Equation Model) between the Variables using SmartPLS: The relationship between the variables independent variable i.e., Quick Commerce (QC), Dark warehouse (DW), social media (SM) influence on Customer purchase flexibility (CPF).*

2. Q Commerce -> Customer Purchase Flexibility: The original sample (0.980) is very close to the mean (0.970), but the t-statistic of 6.837 shows a much stronger deviation from the mean compared to the previous result. This indicates a stronger relationship between "Q Commerce" and "Customer Purchase Flexibility." The p-value again is 0.000, which confirms the result is statistically significant.

3. Social media -> Customer Purchase Flexibility: The original sample (0.734) is extremely close to the mean (0.732), but the t-statistic of 13.814 indicates an even greater deviation from the mean. With a t-statistic this high, the effect is extremely strong, and the result is statistically significant (p-value = 0.000).

I.e., T Statistics: All the t-statistics are large (greater than 2), suggesting that the observed differences are substantial compared to the variation within the sample. **P Values**: The p-values are all 0.000, meaning each relationship is statistically significant at the 0.05 level, indicating strong evidence against the null hypothesis (i.e., that the relationships between the variables are not meaningful). **Effect Strength**: The strongest effect is found with **social media** (t-stat of 13.814), followed by **Q Commerce** (t-stat of 6.837), and then **Dark Warehouse** (t-stat of 3.630), suggesting that **social media** has the most significant impact on "Customer Purchase Flexibility."

10. Discussion and Conclusion

The research implies that the ideas have a major influence on "Customer Purchase Flexibility." As the effect size is quite strong, social media and Customer Purchase Flexibility are discovered to be more closely related. Dark Warehouse and Q Commerce were also discovered to be related to Customer Purchase Flexibility. The findings show that the advantages of social media do positively correlate with consumers' buying choice [60]. Performance is positively influenced by social media [61]. The statistical study shows notable links between dark warehouses, Q-commerce, social media, and consumer buying flexibility. All the t-statistics are high, suggesting that the noted differences are significant relative to the variation inside the sample. Uniformly 0.000, the p-values indicate that every relationship is statistically relevant at the 0.05 level. This offers good proof against the null hypothesis, hence confirming the assertion that these elements significantly affect consumer buying flexibility. The findings indicate that, after Q-commerce and dark warehouses, social media most significantly affects client buying flexibility. This is in line with the knowledge that social media channels have become essential to the e-commerce scene, therefore affecting customer behaviour by means of direct interaction, advertising, and community development [8]. With social media playing a major role in boosting sales and developing customer loyalty, especially during crises, the growth of e-commerce has greatly changed how people shop, and companies run [62]. Q-commerce shows a close link with consumer purchase flexibility as well. The prospect of almost-instant delivery and the ease it provides meet consumers' growing need for immediacy, therefore improving their buying flexibility [63]. Although still important, dark warehouses have the least impact when compared to social networking and Q-commerce. Their smart placement and quick order processing, however, help to fast delivery, which indirectly improves consumer buying flexibility. Dark warehouses, Q-commerce, and social media have been shown in this paper to greatly influence consumer buying flexibility in metro areas. Of all the factors, social media has the most influence; next comes Q-commerce and dark warehouses. These results underline the need of companies using social media tools to improve consumer interaction and increase revenue [45]. Q-commerce's emphasis on quick delivery and convenience also helps to satisfy consumer needs and improve purchasing flexibility (2024). Although dark warehouses help to fulfil orders quickly, their influence is less noticeable than that of social media and Q-commerce. Retailers have changed their business plans to welcome additional digital/online channels and reexamine their supply networks in view of the significant developments in the previous years [64]. E-commerce retailing has seen incredible expansion over the last decade, and flexible logistics solutions can help both consumers and merchants [65]. These revelations offer useful direction for e-commerce companies aiming to improve customer happiness and performance in the Indian market. As e-commerce develops, companies must change their plans to stay competitive and fulfil evolving customer expectations (Raj et al (2024). The COVID-19 epidemic pushed companies to digitalize their processes to match evolving customer buying behaviour, hence hastening the expansion of e-commerce [66]. E-commerce affects many facets of city life beyond only transactions; sustainable urban development depends on a thorough knowledge of these consequences [67].

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper

- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.

- **Author contributions:** The authors declare that they have equal right on this paper.

- **Funding information:** The authors declare that there is no funding to be acknowledged.

- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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