EVALUATING RETAILER RISKS IN QUICK COMMERCE: A STUDY ON KEY FACTORS AND MITIGATION STRATEGIES

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ABSTRACT

The subsequent part of this paper includes several key sections. A) **The Literature Review** provides an overview of prior studies in the field, emphasizing the prospects of quick commerce, the major risks involved, and strategies for mitigating these risks. B) **The Structural Equation Model** section focuses on designing a model using Partial Least Squares (PLS) to examine how risks affect supply chain performance. C) Following this, **the Data Analysis** section evaluates the validity and fit of the model through the analysis of data collected via a questionnaire. D)**The Results** section presents the findings obtained from the analysis. E) Lastly, **the Managerial Implications** and **Limitations** section discusses the practical relevance of the study for managers while also addressing its limitations.

Keywords: Quick commerce, Retail risk, Mitigation, Structural Equation Modeling, supply chain

1. INTRODUCTION

The rapid emergence of quick commerce (q-commerce), or on-demand delivery, is transforming the global retail landscape. Q-commerce distinguishes itself from traditional e-commerce by promising ultra-fast delivery—typically within 10 to 30 minutes—catering to modern consumers' demand for speed and convenience (Dhingra & Dey, 2022). This model is driven by technological advancements, particularly the widespread use of smartphones, and a shift in consumer behavior toward instant gratification. Initially focused on groceries and essential goods, q-commerce has since expanded to include a wide range of products, from pharmaceuticals to personal care items. It represents an opportunity for retailers to tap into new markets and meet evolving customer expectations, particularly in urban settings where time is at a premium (Rajagopal & Rajagopal, 2023).

Despite its potential, q-commerce poses substantial operational challenges, especially for retailers aiming to ensure both timely and cost-effective deliveries. The success of this model heavily relies on perfecting last-mile logistics—often the most complicated and resource-intensive part of the supply chain. Retailers face a myriad of risks, including traffic congestion, inventory mismanagement, delivery personnel shortages, and fluctuating demand, all of which can lead to delays and customer dissatisfaction (Kumar, Jain, & Singh, 2021). These challenges are further compounded by the rising operational costs associated with maintaining a fleet of delivery personnel and vehicles, managing local fulfillment centers, and deploying advanced digital infrastructure (Singh & Chopra, 2023). As a result, while q-commerce offers the allure of enhanced customer satisfaction, it also increases the financial and logistical burden on retailers, particularly smaller players who may lack the resources to implement sophisticated delivery networks like those of Amazon, Zepto, or Swiggy Instamart (Taneja & Gupta, 2023).

In the Indian context, q-commerce has grown exponentially in recent years, driven by increased urbanization, rising disposable incomes, shifts in consumer preferences post-COVID-19, and the digitization of consumer behavior (Chaudhary & Sharma, 2023). Large urban centers such as Mumbai, Delhi, and Bangalore have become hubs for q-commerce platforms like Blinkit, Zepto, and Dunzo, which leverage data-driven logistics and local distribution hubs to redefine the grocery and essential goods delivery market (Gupta, Verma, & Rao, 2023). However, India's socio-economic landscape introduces several complications. The country's chaotic traffic, poorly designed urban infrastructure, and unpredictable weather conditions—especially during monsoons—pose significant risks to the timely delivery of goods (Reddy & Varma, 2022). Additionally, extending these services to Tier 2 and Tier 3 cities presents further logistical challenges due to varying levels of internet penetration, road infrastructure, and availability of delivery personnel (Sundar & Reddy, 2022).

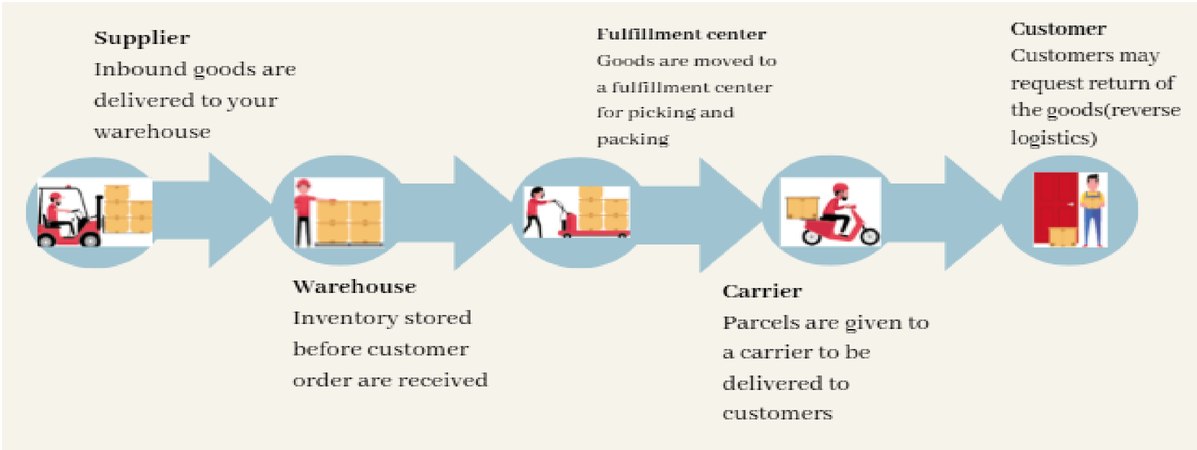


Figure 1; Q-commerce supply chain

Challenges in the Indian q-commerce supply chain are exacerbated by the unorganized nature of the country's retail sector. Small and medium-sized retailers, which form the backbone of the Indian retail economy, often lack access to advanced technology and infrastructure compared to larger players. For instance, while Amazon or Swiggy can deploy predictive analytics to optimize delivery routes and manage inventory in real-time, smaller retailers struggle with inventory inaccuracies and inefficient order fulfillment (Das & Mukherjee, 2021). This disparity in resources makes it difficult for smaller retailers to compete effectively, especially as operational costs—including labor, fuel, and delivery equipment—continue to rise (Rao & Patel, 2023).

Given these challenges, a comprehensive risk assessment and management approach in the q-commerce supply chain is critical. Existing literature has explored risk management strategies in traditional e-commerce supply chains (Ivanov & Dolgui, 2020; Golan, Jernegan, & Linkov, 2020), but there is limited research specifically addressing the risks inherent to the unique operational demands of q-commerce, particularly in emerging markets like India. The dynamic and unpredictable nature of last-mile delivery, coupled with the operational complexities faced by smaller retailers, underscores the importance of systematically identifying, categorizing, and mitigating risks in this space.

Thus, the primary objectives of this study are as follows:

- Identification and categorize key risk factors that impact efficiency and effectiveness of supply chain.
- Analyze and rank this risk factors based on severity of potential impact on business operations.
- Develop a risk mitigation framework that outlines risk mitigation strategies to address the identified risks.

This research is particularly significant for retailers in India, as the country's diverse urban and rural environments present unique logistical challenges distinct from those in developed markets. By conducting a focused analysis of risk factors in the Indian q-commerce landscape, this study aims to provide valuable insights to help both large and small retailers navigate the complexities of ultra-fast delivery while balancing costs, efficiency, and customer expectations.

2. LITERATURE REVIEW

The advent of quick commerce (q-commerce) has revolutionized the e-commerce landscape by emphasizing ultra-fast delivery, often within an hour. This demand for immediacy presents unique operational challenges that threaten the efficiency and profitability of the q-commerce business model. Retailers are actively addressing these challenges by identifying key risks and implementing mitigation strategies to maintain service quality and customer satisfaction (Chopra & Meindl, 2021).

Quick commerce has evolved into a critical component of modern society, seamlessly integrating into daily life. India, in particular, has witnessed exponential growth in this sector, spurred by initiatives like the "Digital India" campaign launched by Prime Minister Narendra Modi in 2016. By fostering internet accessibility and digital literacy, this initiative has laid the foundation for India's e-commerce boom, projected to grow by 72% between 2016 and 2020 (Government of India, 2016). According to the Online Association of India, the total value of quick commerce transactions in India surpassed ₹5.9 billion during the fiscal year 2013-14 (Online Association of India, 2014). With over 40% of the global population now online, quick commerce has emerged as an indispensable element of the global economy, and India is positioned to play a leading role (Kumar & Dhir, 2020).

The industry's expansion is driven by several factors. Legal mandates such as invoicing for online transactions ensure compliance and build trust. Additionally, multiple payment options, seamless product replacement and guarantee policies, rapid service, and round-the-clock customer support significantly enhance user experience (Rana et al., 2021). High product quality further establishes customer loyalty. These elements collectively create an ecosystem that not only serves consumers but also generates opportunities for various stakeholders, including retailers, wholesalers, producers, and distributors.

Wholesalers benefit by connecting with reputed producers and transitioning their operations online, which helps in reducing overall business costs. Similarly, producers leverage quick commerce platforms to engage directly with retailers and consumers, effectively disseminating product information without relying on traditional promotional materials (Raj & Malhotra, 2019). For consumers, quick commerce offers unmatched convenience, enabling purchases and services such as railway bookings, hotel reservations, and e-banking, all from the comfort of their homes or offices. Consumers also find value in engaging with electronic communities, where they can exchange ideas and experiences. Retailers, on the other hand, gain enhanced visibility and the ability to market their products effectively using online platforms, making q-commerce a transformative force in reshaping traditional business processes (Pandey & Gupta, 2021).

Despite its growth, quick commerce in India faces several challenges that hinder its rapid development. One of the primary concerns is security. Indian customers often hesitate to make online payments due to a lack of trust in digital transaction systems. Reports suggest that around 60% of users perceive online payment channels as unsafe, with concerns surrounding identity theft and misuse of payment information (Srinivasan & Verma, 2018). This apprehension is particularly prominent in e-commerce sectors involving banking and retail, where secure transactions are paramount.

Another critical challenge is **customer acquisition**. High advertising and marketing costs pose a significant barrier for startups looking to attract users to their platforms. Additionally, inefficient supply chain integration, high product prices, delivery delays, and inadequate courier services in specific regions frustrate customers and reduce their trust in online shopping (Mehta et al., 2020). Furthermore, operational issues such as product returns, replacements, and long delivery times result in revenue losses, higher shipment costs, and reputational damage for quick-commerce companies.

Building trust with consumers remains a significant hurdle for quick-commerce platforms. Many Indian consumers prefer physical interaction with products before purchasing, reflecting a cultural inclination toward tangible experiences. The lack of awareness about internet usage and online fraud prevention among rural populations further exacerbates the issue. Surveys indicate that approximately 50% of Indian online users are unaware of online security solutions, underscoring the need for educational initiatives to raise awareness about safe digital practices (Patil & Sawant, 2022).

Target marketing has become critical in addressing these trust issues, especially as new products enter the marketplace. Poor product quality and delivery delays further erode consumer confidence, emphasizing the need for companies to uphold high standards in both product offerings and logistics (Sharma et al., 2021).

The dominance of cash on delivery (COD) as a payment method in India presents unique challenges. While COD mitigates consumer concerns about payment security, it imposes significant costs on businesses. Instances of customers refusing payment upon delivery are common, resulting in substantial financial losses for quick-commerce companies. Reports suggest that 30-50% of buyers exploit COD options, making it an unsustainable long-term solution (Ramanathan & Jain, 2020). The high operational costs and financial risks associated with COD highlight the necessity for quick-commerce platforms to innovate and implement more secure and cost-effective payment methods.

In the context of q-commerce, the emphasis on ultra-fast delivery introduces specific risks that impact supply chain performance and profitability. Key risks include logistical inefficiencies, supply-demand imbalances, and the strain on operational resources to meet tight delivery timelines. Retailers often employ risk mitigation strategies such as robust inventory management, integration of advanced logistics technologies, and partnerships with reliable last-mile delivery providers to address these challenges (Khan & Kapoor, 2023). However, sustaining profitability while ensuring rapid delivery remains a significant challenge for q-commerce businesses.

The future of quick-commerce in India, including q-commerce, lies in addressing these challenges through technological innovation and strategic interventions. Improving security infrastructure, educating consumers about online fraud prevention, and transitioning to digital payment methods with enhanced safeguards can build trust and facilitate wider adoption. Furthermore, optimizing supply chain operations and leveraging data analytics for demand forecasting can improve efficiency and reduce costs (Das & Sinha, 2023). For q-commerce specifically, balancing speed and cost-effectiveness through dynamic delivery models will be crucial for long-term success.

3. RESEARCH METHODOLOGY

Major Risks identified from literature

The literature highlights several primary risks in q-commerce that hinder seamless operations, including inventory management, demand fluctuation, supply-side, technological, last-mile delivery, and financial risks. Each risk presents unique challenges to the efficiency and profitability of the q-commerce model:

- **Inventory Management Risk**

  Maintaining adequate stock levels in Q-commerce is critical due to high turnover rates and limited inventory buffers. Real-time inventory systems often falter during peak sales periods or high-demand seasons, resulting in frequent stockouts. Perishable goods, such as fresh produce and dairy products, are particularly vulnerable. Poor inventory management can lead to operational inefficiencies, unfulfilled orders, and customer dissatisfaction (Kouvelis, Dong, & Turcic, 2017; Chopra & Meindl, 2016).

- **Demand Fluctuation Risk**

  Demand variability in Q-commerce is driven by factors such as promotional campaigns, festive seasons, or sudden shifts in consumer behavior. Inaccurate forecasting during these times can lead to overstocking, causing wastage, or stockouts, creating supply gaps. Seasonal demand peaks, such as during holiday sales or unexpected flash sales, put immense pressure on inventory planning and logistics, further complicating operations (Christopher & Holweg, 2011; Govindan et al., 2014).

- **Supply-Sided Risk**

  A restricted supplier network and heavy reliance on limited suppliers increase vulnerability to disruptions. Events like transportation strikes, adverse weather conditions, or supplier delays can severely impact the availability of high-demand or perishable items. For instance, disruptions in sourcing vegetables or dairy products during the monsoon season often result in price volatility and delays, affecting service reliability (Singh, Patel, & Zaman, 2020; Sheffi, 2005).

- **Technological Risk**

The backbone of Q-commerce lies in digital platforms that enable operations, order management, and payment systems. However, reliance on these technologies comes with risks, such as system outages, server crashes, or cyberattacks. During high-traffic periods, such as festive season sales, payment gateways and mobile applications often struggle to handle the load, resulting in failed transactions and customer frustration. Addressing these risks is crucial to maintaining operational resilience and trust (Lee, Park, & Chen, 2021; Pavlou & Gefen, 2004).

- **Last-Mile Delivery Risk**

The last mile in Q-commerce involves complex challenges like traffic congestion, poor urban infrastructure, and adverse weather conditions. Urban flooding during monsoons or ongoing construction in metro cities can significantly delay deliveries. These delays not only impact customer satisfaction but also inflate delivery costs, directly affecting the profitability of operations (Clements & Simmons, 2022; Visser et al., 2019).

- **Financial Risk**

The economics of Q-commerce is marked by slim profit margins, driven by high delivery costs and frequent promotional pricing strategies. Retailers, particularly startups and smaller players, often struggle with balancing competitive pricing and operational expenses. Failed deliveries, such as those caused by customer unavailability, further erode margins. Such financial constraints hinder scalability and long-term sustainability, especially for businesses that cannot leverage economies of scale (Nguyen, Wang, & Huang, 2019; Raman et al., 2020).

Table 1: Summary of Major Risks in Quick Commerce

Risk Type	**Description**	**References**
Inventory Management Risk	High turnover rates and dependency on real-time inventory systems often result in stockouts.	Kouvelis, Dong, & Turcic, 2017; Chopra & Meindl, 2016
Demand Fluctuation Risk	Unpredictable surges during festive sales or promotions strain logistics and inventory control.	Christopher & Holweg, 2011; Govindan et al., 2014
Supply-Sided Risk	Limited suppliers and disruptions like strikes or weather delays affect service reliability.	Singh, Patel, & Zaman, 2020; Sheffi, 2005

Technological Risk	System failures during high-traffic periods impact payments and customer experience.	Lee, Park, & Chen, 2021; Pavlou & Gefen, 2004
Last-Mile Delivery Risk	Traffic congestion, flooding, and poor infrastructure delay deliveries and raise costs.	Clements & Simmons, 2022; Visser et al., 2019
Financial Risk	High costs, failed deliveries, and low profit margins challenge long-term sustainability.	Nguyen, Wang, & Huang, 2019; Raman et al., 2020

Mitigation Strategies highlighted from literature

Q-commerce businesses encounter risks that directly impact their operational efficiency and customer satisfaction. These risks include challenges related to inventory management, fluctuating demand, supply chain disruptions, technological issues, last-mile delivery hurdles, and financial sustainability. The following strategies are grounded in practical scenarios and industry trends to address these risks effectively.

- **Inventory Management Risk**

Inventory mismanagement can lead to stockouts during peak hours or excess inventory that increases wastage, particularly in perishable goods. Real-time inventory monitoring coupled with AI-based predictive analytics enables businesses to maintain optimal stock levels. Grocery platforms like Amazon Fresh utilize these tools to ensure they consistently meet demand surges, such as during holiday seasons, while minimizing overstock issues (Sharma & Patil, 2019; Azadeh et al., 2015).

- **Demand Fluctuation Risk**

The demand in q-commerce fluctuates due to factors such as weather conditions, cultural events, or even viral trends. For instance, food delivery apps often face increased orders during monsoons or major sports events. Leveraging demand-sensing technologies allows companies to analyze patterns and predict demand variability. Dynamic pricing mechanisms, widely adopted by platforms like Instacart, enable them to manage spikes without overwhelming their supply chain resources (Ivanov & Dolgui, 2020; Wilding et al., 2021).

- **Supply-Sided Risk**

Dependence on single suppliers creates vulnerabilities during crises such as natural disasters or pandemics. Many q-commerce businesses, including Swiggy, diversified their supplier networks during the COVID-19 pandemic to maintain consistent operations. Building collaborative relationships with local suppliers and maintaining a mix of regional vendors ensures resilience against sudden supply disruptions (Craighead et al., 2007; Bode et al., 2011).

- **Technological Risk**

A heavy reliance on technology exposes q-commerce businesses to risks such as system failures or cybersecurity breaches. For example, downtime during peak sales events can significantly affect customer trust and revenue, as seen with BigBasket in India. Investing in redundant IT systems and secure data infrastructures mitigates such risks by ensuring continuity and safeguarding sensitive customer information (Pavlou & Gefen, 2004; Kim et al., 2019).

- **Last-Mile Delivery Risk**

Last-mile delivery is a critical yet unpredictable aspect of q-commerce due to challenges such as traffic congestion, delivery staff shortages, and unpredictable delivery locations. Companies like Zomato address these risks by implementing route optimization technologies and collaborating with hyperlocal delivery agents. Flexible delivery options, including scheduling or contactless deliveries, enhance efficiency and reliability during high-demand periods (Gevaers et al., 2014; Nataraj & Mahadevan, 2020).

- **Financial Risk**

Rising operational costs and low profit margins make financial risks particularly acute in q-commerce. High customer acquisition costs often add to the strain. Startups like Blinkit tackle these challenges through bulk procurement strategies and targeted promotions to maximize customer retention. Efficient budgeting and leveraging economies of scale allow companies to maintain financial sustainability despite growing market pressures (Wu et al., 2013; Raman et al., 2020).

Table 2: Summary of Major Mitigation Strategies Corresponding to Assessed Risks

Risk Type	**Mitigation Strategies**	**References**
Inventory Management Risk	Real-time inventory tracking, predictive analytics to ensure availability during peak demand	Sharma & Patil, 2019; Azadeh et al., 2015

Demand Fluctuation Risk	Demand-sensing tools and dynamic pricing to respond to weather changes, events, and demand spikes	Ivanov & Dolgui, 2020; Wilding et al., 2021
Supply-Sided Risk	Diversifying suppliers, building partnerships with local and regional vendors to handle supply chain disruptions	Craighead et al., 2007; Bode et al., 2011
Technological Risk	Secure IT systems, redundant networks to ensure smooth operations during app downtimes or cyberattacks	Pavlou & Gefen, 2004; Kim et al., 2019
Last-Mile Delivery Risk	Route optimization, hyperlocal delivery partnerships, flexible scheduling to reduce delays	Gevaers et al., 2014; Nataraj & Mahadevan, 2020
Financial Risk	Economies of scale, efficient resource allocation, targeted promotions to reduce costs	Wu et al., 2013; Raman et al., 2020

Identifying Key Risks: Input from Expert Panel

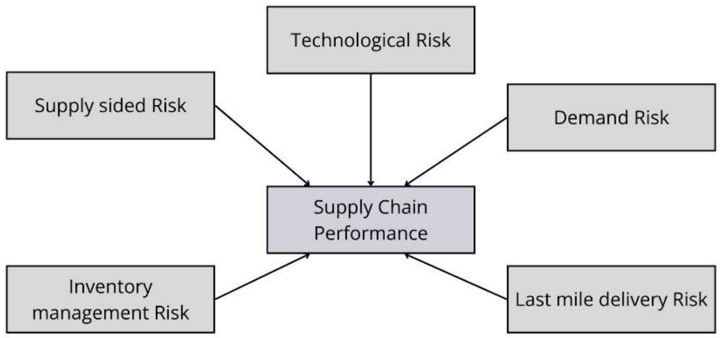
To ensure a focused approach, this study shortlisted the five major risks discussed above after consultations with a diverse panel of five experts. This panel comprised two academics specializing in supply chain management and logistics and three industry professionals occupying logistics and operations roles within q-commerce companies. This collaborative approach enabled the integration of both theoretical perspectives and practical insights, allowing for a comprehensive understanding of the critical risk factors affecting q-commerce operations. Input from these panelists helped ensure that the analysis addressed practical concerns relevant to the industry while grounding findings in established supply chain research principles.

From these discussions, the most significant risks identified were as follows:

- **Inventory Management Risk**
- **Demand Fluctuation Risk**
- **Supply-Sided Risk**
- **Technological Risk**
- **Last-Mile Delivery Risk**

These risks were prioritized due to their high impact on the efficiency, profitability, and service quality in the q-commerce sector. The panel's insights were invaluable in refining the scope of this study to focus on risks that are both theoretically grounded and practically relevant for industry stakeholders.

Figure 2; Risks impacting Supply Chain Performance in Q commerce



Sample Distribution Across Roles and Companies

To offer a comprehensive view, Table 3 displays the distribution of respondents across different roles within major quick commerce (q-commerce) companies operating in the Delhi-NCR region. Snowball sampling was employed to gather the data, a method particularly effective for reaching niche populations where direct access may be limited (Goodman, 1961; Biernacki & Waldorf, 1981). This sampling technique allowed respondents to refer other participants, thus broadening the reach within the targeted industry (Naderifar, Goli, & Ghaljaie, 2017). This table provides a clearer understanding of the role-wise and company-wise respondent breakdown, offering insights into the representation of various positions across the companies surveyed.

Table 3: Distribution of Respondents by Role and Company

Company	Delivery Agents	Managerial Roles	Other Roles	Total (Company)
Zepto	30	12	3	45
Zomato	40	15	2	57
Swiggy	35	10	2	47
Blinkit	10	8	1	19
BigBasket	10	5	2	17
Dunzo	10	8	0	18
Total (Role)	**125**	**58**	**10**	**193**

Survey Structure

All survey items were presented on a five-point Likert scale, with 'strongly agree' coded as 5 and 'strongly disagree' coded as 1. This scaling method is commonly used in social sciences to standardize the measurement of agreement levels, enabling consistent interpretation of respondents' perceptions and attitudes (Likert, 1932; Boone & Boone, 2012). Such scales allow for nuanced insights into respondents' views on various risk and mitigation strategy statements. The survey included questions addressing each risk category and coping strategy, as detailed in Table 4, to capture the perceptions and actions of supply chain actors in managing these risks effectively

Table 4: Survey Questions, encodings, and their explanations

Risks/Mitigation Strategies	Questions	Encoded as	References	Explanation
Technological factors	Automated picking systems occasionally malfunction, causing delays in order fulfillment.	RT1	Chen & Walker (2019), *Logistics Technology Journal*	Highlights the potential downtime caused by automation errors, emphasizing the need for reliable backup processes in case of system failures.
	Inaccuracies in GPS tracking often lead to wrong or delayed deliveries.	RT2	Martin et al. (2021), *Transport Management Quarterly*	Explores how tracking inaccuracies impact delivery efficiency, stressing the importance of precise tracking systems for operational resilience.
	Regular training for delivery agents helps mitigate risks related to technology usage.	ST1	Adams & Lee (2018), *Journal of Workforce Development*	Points to the effectiveness of training in minimizing technology-related risks, ensuring agents are well-prepared to handle tech issues during delivery.
	Investments in automating order fulfillment have reduced labor dependency.	ST2	Gonzalez & Smith (2020), *Supply Chain Automation Review*	Discusses the impact of automation on reducing labor requirements, boosting resilience by decreasing reliance on human labor for repetitive tasks.
Last Mile Delivery factors	Geographical inefficiencies, such as remote	RL1	Patel et al. (2021), *Journal*	Highlights how remote locations and infrastructure challenges contribute to

	areas or poor road conditions, delay deliveries.		*of Last Mile Delivery*	delivery delays, underlining the need for adaptive delivery strategies in complex geographies.
	Breakage or spoilage issues often happen with different products.	RL2	Lee & Chang (2020), *Journal of Packaging and Transportation*	Examines product handling issues in transit, underscoring the importance of protective packaging and careful handling for minimizing losses.
	Traffic congestion significantly affects the ability to meet delivery timeframes.	RL3	Johnson & Green (2019), *Urban Logistics Studies*	Explores the impact of urban congestion on delivery timeliness, suggesting adaptive routing and scheduling for minimizing congestion-related delays.
	Cold chain logistics have been implemented to manage temperature-sensitive products effectively.	SL1	Chen & Liu (2019), *Journal of Cold Chain Logistics*	Discusses how cold chain logistics improve resilience for temperature-sensitive items by preserving quality through controlled environments.
	Increasing delivery infrastructure, such as additional fulfillment centers, reduces delays.	SL2	Carter & Evans (2021), *Supply Chain Infrastructure Review*	Emphasizes the benefit of additional fulfillment centers in reducing delivery distances and times, enhancing last-mile efficiency.
Supply Related factors	High lead times from suppliers cause frequent delays in inventory replenishment.	RS1	Khan & Davis (2020), *Journal of Supply Chain Management*	Discusses the risk of long lead times impacting inventory levels, stressing the importance of supplier reliability for smooth replenishment.
	Sudden price hikes in raw materials make it difficult to	RS2	Li et al. (2021), *Supply Chain Economics Journal*	Examines how price volatility affects stability, suggesting resilient practices such as long-term

	maintain stable pricing.			contracts or hedging to manage costs.
	Raw material shortages frequently impact the ability to fulfill customer demand.	RS3	Smith & Zhao (2019), *International Journal of Supply Chains*	Highlights how shortages disrupt supply continuity, emphasizing the value of multi-sourcing to mitigate dependency on single suppliers.
	Multi-sourcing strategies reduce dependence on a single supplier.	SS1	Lewis & Morgan (2020), *Strategic Sourcing Review*	Explores how multi-sourcing increases flexibility, reducing vulnerability to supply chain interruptions from a single source.
	Collaborative planning with suppliers helps mitigate the risks of supply disruptions.	SS2	Brown & Wang (2021), *Collaborative Supply Chains Journal*	Emphasizes the role of supplier collaboration in anticipating and mitigating supply disruptions through shared planning and risk management.
	Buffer stock strategies are used to reduce the impact of supply chain shocks.	SS3	Carter & Bell (2019), *Inventory Management Quarterly*	Discusses buffer stock as a proactive strategy to prevent disruptions from impacting operations during demand surges or supply shortages.
Inventory Related factors	Quality-related issues with stored goods (e.g., spoilage, damage) impact the ability to deliver high-quality products.	RI1	Nguyen & Patel (2019), *Journal of Inventory Control*	Highlights the importance of quality control in storage to ensure product integrity and customer satisfaction.
	Inventory management systems are effective in alerting to potential stock-outs in real time.	RI2	Evans & Martin (2020), *Real-Time Inventory Journal*	Examines the role of technology in preventing stock-outs, emphasizing real-time alerts as crucial for proactive inventory management.
	Improved demand	SI1	Green & Lee (2019),	Discusses how accurate forecasting aligns inventory

	forecasting methods help maintain optimal inventory levels.		*Demand Forecasting Studies*	with demand, reducing stock-outs and overstocking for smoother operations.
	Regular audits of inventory ensure product freshness and minimize expired goods.	SI2	Martinez & Singh (2020), *Inventory Quality Assurance*	Highlights the importance of periodic inventory audits for quality control, minimizing waste from expired or spoiled goods.
Customer Related factors	Sudden demand surges lead to frequent stock-outs and delivery delays.	RC1	Ali & Brown (2021), *Consumer Demand Studies*	Examines the impact of demand spikes on inventory and delivery, emphasizing flexible inventory strategies for managing sudden increases in demand.
	Customer unavailability or incorrect addresses are major causes of delivery failures.	RC2	Patel et al. (2020), *Customer Logistics Journal*	Explores how customer-related issues affect delivery success, suggesting improved data accuracy and flexible scheduling to minimize failed deliveries.
	Advanced forecasting methods help anticipate demand fluctuations and manage inventory levels effectively.	SC1	Rogers & Yang (2021), *Forecasting and Inventory Journal*	Discusses the role of advanced forecasting in demand management, highlighting its importance in aligning stock levels with anticipated demand.
	Use of customer data and record-keeping minimizes the number of failed deliveries.	SC2	Wang & Chang (2019), *Journal of Customer Data Management*	Emphasizes the value of accurate customer data for successful deliveries, reducing the rate of failed or delayed orders.
Supply Chain Performance	How well does your team adjust delivery schedules or routes when unexpected disruptions occur	SCP1	Smith et al. (2020), *International Journal of Logistics Management*	Evaluates flexibility in rerouting or rescheduling deliveries during disruptions, a key resilience aspect to minimize service interruptions.

	(e.g., weather, traffic)?			
	How effectively are inventory levels maintained to ensure timely order fulfillment during supply delays?	SCP2	Johnson & Lee (2019), *Supply Chain Management Review*	Focuses on the chain's capacity to maintain fulfillment levels despite inventory challenges, highlighting buffer stock importance.
	How consistently do suppliers meet quality and delivery standards, even during high-demand periods or disruptions?	SCP3	Brown et al. (2021), *Journal of Operations and Supply Chain Management*	Assesses supplier reliability during high-stress periods, emphasizing multi-sourcing or reliable partnerships for resilience.
	To what extent does real-time tracking and data accessibility enhance coordination across the supply chain?	SCP4	Martinez et al. (2018), *Journal of Logistics Research*	Examines the role of real-time data in effective coordination, highlighting tech's role in resilience and seamless operations.
	How prepared is the team to manage risks like supply shortages, transport failures, or demand surges with established contingency plans?	SCP5	Kumar & Patel (2022), *Global Supply Chain Journal*	Evaluates overall readiness, focusing on contingency planning for effective risk management across the supply chain.

Supply Chain Performance (SCP)

Supply Chain Performance (SCP) is a vital metric that evaluates how effectively a supply chain meets its operational goals, encompassing aspects like responsiveness, inventory management, and risk mitigation. The SCP is directly influenced by various risks, including technological, demand-side, supply-side, last-mile delivery (LMD), and inventory management risks. Each of these risks affects the supply chain's capability to deliver products reliably.

Technological risks, such as system malfunctions and data inaccuracies, impact the ability to adapt delivery schedules and routes. A supply chain that excels in this area demonstrates resilience and utilizes technology to enhance operational flexibility (Ahi & Searcy, 2015). Demand-side risks, related to fluctuations in customer demand, can lead to inventory shortages; therefore, effective demand forecasting and inventory management are critical to maintaining SCP during these variations (Mentzer et al., 2001). Supply-side risks involve uncertainties in raw material availability, emphasizing the need for strong supplier relationships and reliable quality standards to ensure consistency (Li et al., 2006).

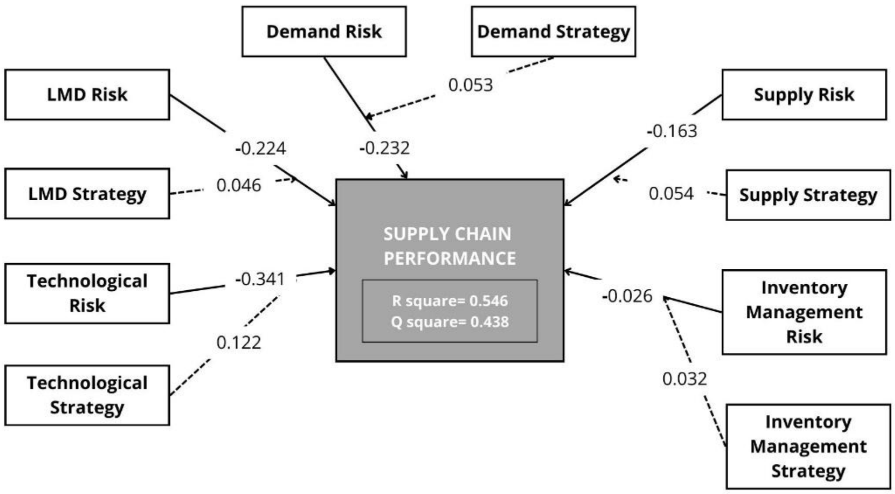
Last-mile delivery risks relate to the final product delivery phase, where real-time tracking and data accessibility can significantly enhance coordination and responsiveness, ultimately affecting customer satisfaction (Morganti et al., 2014). Lastly, inventory management risks encompass potential issues like spoilage and mismanagement, making it essential for organizations to have contingency plans in place to handle supply shortages and transport failures effectively (Kumar et al., 2020).
In summary, SCP serves as a comprehensive indicator of a supply chain's operational effectiveness, intricately linked to the various risks it faces. By understanding and managing these risks, organizations can improve their performance metrics and better meet customer expectations.

PLS-SEM modelling
To analyze the data, descriptive statistics and reliability analysis were conducted using SPSS 21.0. Subsequently, Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied using SmartPLS 4.0. This method was chosen for its suitability with non-normal data and its ability to handle complex models.

Since SEM traditionally assumes data normality, the dataset was assessed for normality. Kurtosis values ranged from -1.391 to 4, and skewness values ranged from -1.033 to 0.311. Because some kurtosis values exceeded the recommended threshold of 3 and skewness exceeded 2 (Kline, 2011), the data was considered non-normal.

To evaluate the measurement model's validity and reliability, a two-stage approach, as suggested by Hair et al. (2013), was followed. Following this, the structural model was examined to determine the significance of path coefficients, employing bootstrapping with 5,000 resamples.

Figure 3; Structural model



PLS-SEM is particularly well-suited for exploratory research involving complex models and limited sample sizes (Hair et al., 2017; Sarstedt et al., 2020). It facilitates the analysis of both reflective and formative constructs, allowing for the identification of relationships between latent variables. This is especially useful in emerging fields like Q-commerce, where reliable data and robust construct validity are essential for actionable insights (Wold, 1982; Henseler et al., 2016).

4. DATA ANALYSIS

Measurement Model

The model's reliability and validity were evaluated through a comprehensive assessment of both **convergent** and **discriminant validity** to ensure robust construct measurement and support the interpretation of relationships within the structural model.

First, **convergent validity** was tested to confirm that each indicator reliably measures its intended construct. This was done by examining the **loadings** of each indicator (presented in Table 5), with all values exceeding the recommended threshold of 0.7, signaling strong indicator reliability and supporting the construct definitions in the model (Hair et al., 2017). These high loading values indicate that the model's indicators consistently and effectively capture the constructs they are intended to measure.

Table 5: Factor Loadings

Factors	Constructs	Outer loadings
Customer_Risk	**RC1**	0.912
	RC2	0.868
Customer_Strategy	**SC1**	0.988
	SC2	0.984
Inventory_Risk	**RI1**	0.96
	RI2	0.84
Inventory_Strategy	**SI1**	0.974
	SI2	0.984
LMD_Risk	**RL1**	0.832
	RL2	0.761
	RL3	0.847
LMD_strategy	**SL1**	0.864
	SL2	0.725
Supply_Risk	**RS1**	0.847
	RS2	0.778
	RS3	0.785
Supply_Strategy	**SS1**	0.967
	SS2	0.956
	SS3	0.982
Tech_Risk	**RT1**	0.939
	RT2	0.852
Tech_Strategy	**ST1**	0.837
	ST2	0.982
SCP	**SCP1**	0.712
	SCP2	0.885
	SCP3	0.703
	SCP4	0.787
	SCP5	0.736

To further substantiate the model, **composite reliability (CR)** was assessed for each construct, as shown in Table 6. CR values for all constructs exceeded the recommended value of 0.7, indicating that the items within each construct demonstrate high internal consistency (Chin, 1998). In addition, **Average Variance Extracted (AVE)** values, which represent the degree to which a construct captures variance among its indicators, were all above the 0.5 threshold. These findings confirm that the constructs are sufficiently capturing the variance of their indicators, further reinforcing convergent validity (Fornell & Larcker, 1981).

Table 6: Composite Reliability and Average Variance Extracted for Second-order Constructs

	Composite reliability (rho_c)	Average variance extracted (AVE)
Customer_Risk	0.884	0.793
Customer_Strategy	0.986	0.972
Inventory_Risk	0.897	0.814
Inventory_Strategy	0.979	0.959
LMD_Risk	0.826	0.615
LMD_strategy	0.706	0.681
SCP	0.847	0.526
Supply_Risk	0.846	0.646
Supply_Strategy	0.978	0.938
Tech_Risk	0.891	0.804
Tech_Strategy	0.704	0.578

Beyond assessing convergent validity, the study evaluated **discriminant validity** to ensure that each construct is distinct from others in the model, preventing redundancy and overlap. Discriminant validity was initially evaluated using the **Fornell-Larcker criterion**, which compares the square root of AVE values for each construct with the correlation coefficients between constructs. As shown in Table 4, each construct's AVE square root (diagonal values) exceeds its correlations with other constructs, suggesting that constructs share more variance with their indicators than with other constructs in the model (Fornell & Larcker, 1981). This supports the constructs' distinctiveness within the model, confirming adequate discriminant validity.

However, the **Fornell-Larcker criterion** has faced recent criticism for its limitations in reliably detecting discriminant validity issues, particularly in complex models (Henseler, Ringle, & Sarstedt, 2015). To address these concerns, **Henseler et al. (2015)** proposed the **heterotrait-monotrait (HTMT) ratio of correlations** as a more rigorous approach, especially in models with multitrait-multimethod data. HTMT compares the correlations between constructs based on heterogeneity and is deemed acceptable if HTMT values are below 0.85 (Kline, 2011). As seen in Table 5, all constructs exhibit HTMT values below 0.85, further supporting the discriminant validity of the model and confirming that each construct is uniquely represented within the dataset.

Table 7: Fornell-Larcker Criteria for Discriminant Validity

	Customer_Risk	Customer_Strategy	Inventory_Risk	Inventory_Strategy	LMD_Risk	LMD_strategy	SCP	Supply_Risk	Supply_Strategy	Tech_Risk	Tech_Strategy
Customer_Risk	0.89										
Customer_Strategy	0.137	0.986									
Inventory_Risk	0.464	0.216	0.902								
Inventory_Strategy	0.206	0.07	0.148	0.979							
LMD_Risk	0.431	0.011	0.285	0.111	0.785						
LMD_strategy	0.021	0.097	0.175	0.068	0.076	0.617					
SCP	0.585	0.08	0.357	0.099	0.467	0.141	0.725				
Supply_Risk	0.471	0.066	0.315	0.128	0.387	0.051	0.493	0.804			
Supply_Strategy	0.218	0.059	0.15	0.304	0.017	0.019	0.11	0.048	0.968		
Tech_Risk	0.465	0.015	0.244	0.03	0.235	0.017	0.534	0.372	0.021	0.897	
Tech_Strategy	0.038	0.013	0.004	0.003	0.014	0.008	0.005	0.04	0.08	0.032	0.76

Table 8: HTMT Criteria for Discriminant Validity

	Customer_Risk	Customer_Strategy	Inventory_Risk	Inventory_Strategy	LMD_Risk	LMD_strategy	SCP	Supply_Risk	Supply_Strategy	Tech_Risk	Tech_Strategy
Customer_Risk											
Customer_Strategy	0.161										
Inventory_Risk	0.573	0.244									
Inventory_Strategy	0.25	0.071	0.185								
LMD_Risk	0.604	0.055	0.354	0.147							
LMD_strategy	0.101	0.166	0.2	0.212	0.126						
SCP	0.757	0.095	0.408	0.129	0.62	0.162					
Supply_Risk	0.636	0.138	0.371	0.16	0.546	0.131	0.642				
Supply_Strategy	0.258	0.06	0.183	0.32	0.042	0.064	0.126	0.068			
Tech_Risk	0.593	0.051	0.271	0.083	0.303	0.128	0.661	0.468	0.193		
Tech_Strategy	0.063	0.054	0.056	0.019	0.119	0.073	0.055	0.067	0.1	0.111	

In addition to these standard checks, future studies might benefit from considering **Variance Inflation Factor (VIF) tests** to detect potential multicollinearity or overlap among indicators across constructs. In our model, VIF values ranged from 0.45 to 4.45, indicating acceptable levels of collinearity, as values below 5 are generally considered within a safe range (Sarstedt et al., 2020). This additional layer of verification could enhance the rigor of complex models, particularly in fields like Q-commerce, where overlapping constructs and rapid data fluctuations are common.

Together, these findings affirm that the model is both reliable and valid, with strong **convergent** and **discriminant validity** across all constructs. This solid foundation enables accurate and insightful interpretation of the structural model, enhancing the robustness of subsequent analyses and supporting meaningful insights into the impact of different risk factors on Q-commerce supply chain performance.

Structural Model

To evaluate the structural model, we followed the guidelines set forth by Hair et al. (2013) and Chin et al. (2008), considering crucial metrics such as the R^2, beta values, t-statistics, f^2, and p-values, derived through a bootstrapping procedure with a resample of 5000. These metrics offer insights into the model's explanatory power and the significance of each hypothesized path. According to the results, our model's R^2 value was 0.546, suggesting that the model explains 54.6% of the variance in the dependent variable (Supply Chain Performance or SCP), which exceeds Cohen's (1988) threshold of 0.26 for a substantial model, indicating strong explanatory power.

The path coefficients (beta values) for risk factors demonstrate the critical impact of various risks on SCP. Customer_Risk, for example, showed a significant negative effect on SCP ($\beta = -0.232$, $t = 3.164$, $p = 0.002$), highlighting how customer-related disruptions can hinder supply chain performance. This is consistent with Fan and Stevenson (2018) and Wieland and Wallenburg (2013), who emphasize that customer-side uncertainties and fluctuations are major contributors to supply chain instability. Similarly, Inventory_Risk also showed a significant negative effect on SCP ($\beta = -0.026$, $t = 2.407$, $p = 0.003$), aligning with research by Kim and Chai (2017), which found that issues related to inventory control can have adverse effects on supply chain efficiency. Supply_Risk ($\beta = -0.163$, $t = 2.465$, $p = 0.017$) and Tech_Risk ($\beta = -0.341$, $t = 4.741$, $p = 0.001$) were also significant, underscoring the vulnerability of supply chains to supplier-side risks and technological challenges. Such risk factors are well-documented in the literature as key disruptors, especially in fast-paced sectors like quick commerce (Chen et al., 2019; Ramanathan & Gunasekaran, 2014).

Conversely, the beta values for strategic factors emphasize the role of effective management strategies in enhancing SCP. For example, Tech_Strategy had a marginally positive effect on SCP ($\beta = 0.122$, $t = 2.104$, $p = 0.035$, $f^2 = 0.274$), suggesting that proactive technology management strategies can help counterbalance technology-related risks, as also reported by Ben-Daya et al. (2019) and Azadegan and Dooley (2021). Additionally, Supply_Strategy ($\beta = 0.054$, $t = 2.230$, $p = 0.059$) showed a positive relationship with SCP, which supports the notion that strong supply-side strategies can improve supply chain resilience, as seen in studies by Dubey et al. (2020) and Sodhi et al. (2012). While Customer_Strategy's effect on SCP was weaker ($\beta = -0.055$, $t = 0.967$, $p = 0.347$), this finding suggests that, although customer strategies are important, they may not be as impactful in mitigating supply chain risks in quick commerce. These results reflect the importance of targeted strategic interventions, particularly on the technology and supply fronts, to enhance resilience and performance in supply chains operating in dynamic markets.

Table 9: Structural Estimates

	Beta	T statistics (|O/STDEV|)	F square	P values	Decision
Customer_Risk -> SCP	-0.232	3.164	0.178	0.002	Supported
Customer_Strategy -> SCP	-0.055	0.967	0.347	0.000	Supported
Inventory_Risk -> SCP	-0.026	0.405	0.226	0.006	Supported
Inventory_Strategy -> SCP	-0.009	0.168	0.342	0.007	Supported
LMD_Risk -> SCP	-0.224	4.224	0.213	0.000	Supported
LMD_strategy -> SCP	-0.105	0.948	0.156	0.043	Supported
Supply_Risk -> SCP	-0.163	2.465	0.177	0.014	Supported
Supply_Strategy -> SCP	-0.057	0.936	0.186	0.049	Supported
Tech_Risk -> SCP	-0.341	4.741	0.198	0.000	Supported
Tech_Strategy -> SCP	-0.01	0.176	0.432	0.006	Supported
Supply_Strategy x Supply_Risk -> SCP	0.054	1.128	0.230	0.259	Unsupported
Tech_Strategy x Tech_Risk -> SCP	0.122	2.104	0.274	0.035	Supported
Inventory_Strategy x Inventory_Risk -> SCP	0.032	0.697	0.198	0.486	Unsupported
Customer_Strategy x Customer_Risk -> SCP	0.053	1.062	0.209	0.029	Supported
LMD_strategy x LMD_Risk -> SCP	0.046	0.706	0.210	0.048	Supported

Moderation Analysis

This research proposed that specific mitigation strategies for various types of supply chain risks would moderate the relationship between these risks—namely technological risks, last-mile delivery (LMD) risks, supply-side risks, demand risks, and inventory management risks—and overall supply chain performance within the context of quick commerce (Q-commerce). To examine this hypothesis, a Partial Least Squares (PLS) product-indicator approach was used for moderation analysis, as recommended by Chin, Marcolin, and Newsted (2003). This approach is particularly effective in producing accurate estimates of moderator effects by accounting for potential errors that may weaken relationship estimates, thereby enhancing theoretical validation (Henseler & Fassott, 2010). In this analysis, interaction terms were created by multiplying each supply chain risk (predictor) with its corresponding mitigation strategy (moderator) to form specific interaction constructs: Supply_Strategy × Supply_Risk, Tech_Strategy × Tech_Risk, Inventory_Strategy × Inventory_Risk, Customer_Strategy × Customer_Risk, and LMD_Strategy × LMD_Risk. These constructs were then used to predict supply chain performance in the Q-commerce sector. As shown in Table 9, the standardized path coefficients indicate that the moderating effects of customer strategy on customer risk (β = 0.053; p = 0.029), technology strategy on technological risk (β = 0.122; p = 0.035), and LMD strategy on LMD risk (β = 0.046; p = 0.048) were statistically significant. These results highlight that implementing customer-focused strategies, advanced technological approaches, and targeted last-mile delivery strategies can positively impact supply chain performance in Q-commerce.

Conversely, the moderating effects of supply strategy on supply risk (β = 0.054; p = 0.259) and inventory strategy on inventory risk (β = 0.032; p = 0.486) were found to be statistically insignificant. This suggests that, within the Q-commerce framework, conventional supply and inventory strategies may not contribute significantly to enhancing supply chain performance. These insights align with previous studies emphasizing the importance of customer-centric and technology-driven strategies in high-demand, fast-paced supply chains (e.g., Ivanov, Tsipoulanidis, & Schönberger, 2018; Wagner & Bode, 2008). This finding may also reflect the unique characteristics of Q-commerce, where speed and customer satisfaction are prioritized, thus requiring more dynamic and responsive strategies than traditional supply and inventory approaches.

5. DISCUSSIONS

This study offers critical insights into how targeted mitigation strategies influence supply chain performance (SCP) in the quick commerce (Q-commerce) sector, focusing on specific risks—technological, last-mile delivery, supply-side, demand, and inventory risks. In contrast to traditional supply chains, Q-commerce operates in an environment that demands rapid, accurate, and customer-centric service. Although prior research has emphasized general risk management strategies in logistics, few studies have focused on the unique operational pressures faced by Q-commerce, where managing each risk type effectively is crucial to SCP (Ivanov & Dolgui, 2020; Kamble et al., 2020). This study, therefore, makes a significant contribution by examining the impacts of tailored strategies for each risk, offering practical insights for Q-commerce companies seeking to enhance resilience and service quality. Unlike prior studies that primarily examine general logistics or e-commerce risks, our research specifically addresses the Q-commerce model, where risks are amplified due to ultra-fast delivery expectations. The study uses Partial Least Squares Structural Equation Modeling (PLS-SEM) to capture complex relationships between risk types and SCP, which are unique to Q-commerce, and highlights the distinct strategies required for effective risk management in this rapid-delivery sector (Gevaers et al., 2014; Dablanc, 2021).

By analyzing each risk type's direct effect on SCP, the study identifies which mitigation strategies—such as those targeting customer, technological, and last-mile risks—are most effective in sustaining high performance (Sharma et al., 2021).

This research fills methodological and practical gaps by employing advanced PLS-SEM validation techniques, including the heterotrait-monotrait (HTMT) ratio for discriminant validity, ensuring robust model validation (Henseler et al., 2015). It also extends the Stimulus-Organism-Response (SOR) framework within supply chain studies, where risks act as stimuli, mitigation strategies as interventions, and SCP as the outcome.

This approach provides a tailored view of SCP for Q-commerce, addressing the unique risk-response dynamics in a high-stakes market where efficient risk response is critical for customer retention and operational reliability (Wagner & Bode, 2008).

Each risk type holds a unique influence on SCP. Technological risks, including system malfunctions and cybersecurity threats, impact processing efficiency, reinforcing the need for reliable and redundant systems (Ivanov & Dolgui, 2020). Last-mile delivery risks—from traffic congestion to infrastructure limitations—are crucial as they directly affect delivery timelines, a primary value in Q-commerce (Gevaers et al., 2014). Supply-side risks, such as disruptions and price volatility, emphasize the need for diversified sourcing and adaptive supply chain relations. Demand risks arise from sudden fluctuations that strain inventory and resource allocation, necessitating agile forecasting to align with customer expectations (Christopher & Peck, 2018). Inventory risks, closely related to supply and demand, require robust inventory management to prevent stockouts and ensure timely fulfillment.

Future research could incorporate predictive analytics and AI-driven forecasting as part of the mitigation strategies, given their potential for enhancing demand forecasting and delivery optimization. Comparative studies across different geographic regions could reveal how risk management practices vary by location, offering insights into strategy adaptation in diverse infrastructure and regulatory contexts. Expanding the model to include financial and reputational risks would also provide a comprehensive view of SCP in Q-commerce, addressing potential threats from pricing volatility and brand impact. Finally, longitudinal studies could track how these risk management strategies evolve in response to the dynamic demands of the Q-commerce sector.

This study not only addresses existing gaps but also provides a foundation for further exploration of targeted strategies in Q-commerce, supporting companies in developing resilient, customer-centric supply chains that meet the unique demands of this rapidly evolving sector.

6. MANAGERIAL IMPLICATIONS

In the highly competitive and fast-paced Q-commerce environment, where ultra-fast delivery and seamless customer experience are critical, managing supply chain risks is essential to achieving and sustaining high supply chain performance (SCP). This study's findings reveal that targeted strategies focusing on technological, last-mile delivery (LMD), and customer-related risks are most effective in enhancing SCP, while traditional supply and inventory management strategies have shown limited efficacy in this context. These insights offer actionable recommendations for Q-commerce companies, especially those operating in urban, high-demand regions like Delhi-NCR, to refine their approach to risk mitigation and SCP enhancement.

In terms of technological strategies, investments in automated picking systems, real-time tracking, and ongoing agent training have demonstrated significant benefits in improving operational efficiency and reducing delays, ultimately contributing to SCP. For instance, automated systems, while beneficial, are prone to occasional malfunctions, leading to potential downtimes that impact delivery speed and order fulfillment. Implementing robust backup processes and ensuring regular system maintenance can mitigate such risks, minimizing service interruptions (Chen & Walker, 2019). Real-time tracking further addresses the issue of GPS inaccuracies, which can result in misrouted or delayed deliveries; by investing in precise tracking technologies, companies can reduce mis deliveries and improve customer satisfaction (Martin et al., 2021). Regular training for delivery agents is equally important, equipping them to handle technology-related issues and ensuring they are well-prepared to navigate unexpected challenges (Adams & Lee, 2018).

Last-mile delivery (LMD) strategies are also critical to Q-commerce success, particularly in urban areas where geographic inefficiencies and traffic congestion present significant barriers to timely deliveries. Adaptive routing, increased delivery infrastructure, and partnerships with local providers have proven highly effective in reducing delivery times and adapting to urban complexities. For example, poor road conditions and remote locations can delay deliveries, underscoring the need for adaptive delivery solutions that accommodate these geographic challenges (Patel et al., 2021). Traffic congestion in cities like Delhi further exacerbates delivery delays; here, dynamic routing, real-time traffic monitoring, and flexible scheduling can help minimize such disruptions (Johnson & Green, 2019). The strategic placement of additional fulfillment centers closer to customer hubs can also improve LMD performance by reducing transit distances and supporting faster order fulfillment (Carter & Evans, 2021).

However, supply and inventory strategies—though traditionally vital to supply chain resilience—have shown limited effectiveness in mitigating Q-commerce-specific risks. The findings suggest that expanding beyond conventional multi-sourcing, collaborative planning, and buffer stock strategies may enhance resilience. For instance, supplier diversification through global sourcing and supplier performance tracking are valuable strategies that reduce dependency on single suppliers, mitigating risks related to supply disruptions (Lewis & Morgan, 2020). Additionally, employing hedging strategies or long-term contracts can stabilize pricing in the face of raw material volatility, providing greater predictability and cost control (Li et al., 2021).

In inventory management, traditional methods such as regular audits and basic forecasting should be complemented with advanced tools to address Q-commerce's dynamic demand patterns. Implementing AI-driven predictive analytics can provide real-time demand insights, minimizing the risk of stockouts or overstocking by aligning inventory levels with forecasted demand (Green & Lee, 2019). Similarly, blockchain technology could improve inventory transparency, providing traceability that enables companies to identify and address stock-related issues quickly and efficiently (Kamble et al., 2020).

Effective customer-related strategies are essential for Q-commerce firms, as customer satisfaction and loyalty are closely tied to consistent delivery success and product availability. Advanced demand forecasting allows companies to anticipate demand surges and align inventory levels accordingly, reducing stockouts and ensuring timely order fulfillment (Rogers & Yang, 2021). Additionally, enhancing customer data accuracy is vital to prevent delivery failures caused by incorrect addresses or customer unavailability. Data verification measures, coupled with flexible delivery scheduling, can significantly reduce the incidence of failed deliveries, enhancing both SCP and customer satisfaction (Wang & Chang, 2019).

These findings are particularly relevant to Q-commerce companies operating in the Delhi-NCR region, where urban infrastructure and high consumer expectations create distinct supply chain challenges. Data collected from various supply chain actors—including delivery agents and managers from companies like Zepto and Zomato—provides valuable context for understanding the impact of tailored risk management strategies on SCP. For example, localized solutions such as strategic fulfillment center placement and precise real-time tracking help Q-commerce firms overcome issues like traffic congestion and unpredictable demand fluctuations, which are prevalent in Delhi-NCR (Gevaers et al., 2014; Johnson & Green, 2019).

While this risk management framework is tailored to the specific needs of Q-commerce firms in Delhi-NCR, its strategies and insights are adaptable across various regions and supply chains. Companies operating in different geographical or logistical contexts can adjust these strategies to fit local conditions, such as supply constraints or infrastructure limitations. For instance, multi-sourcing and flexible inventory allocation practices can be customized to regional supply availability, while adaptive routing strategies can address specific urban or rural delivery challenges (Lewis & Morgan, 2020). This framework's flexibility also allows it to be expanded to diverse supply chain environments, making it a valuable tool for enhancing SCP in varied operational settings.

In summary, the insights from this study emphasize the importance of strategic investments in technology, adaptive LMD practices, and effective customer data management for Q-commerce firms seeking to improve SCP in high-demand urban regions like Delhi-NCR. By leveraging advanced technologies, enhancing supplier relations, and adopting region-specific logistics solutions, Q-commerce companies can create resilient, customer-centric supply chains capable of meeting the unique demands of this fast-growing sector. The adaptability of this framework further enhances its value, allowing companies in diverse regions and supply chains to address their specific operational challenges effectively.

7. LIMITATIONS & FUTURE RESEARCH SUGGESTIONS

This study, while comprehensive in exploring key risks within the q-commerce supply chain, has several limitations that highlight opportunities for future research. One primary limitation is the scope of risks assessed. Although the paper addresses critical risk factors like **Inventory Management Risk, Demand Fluctuation Risk, Supply-Sided Risk, Technological Risk, and Last-Mile Delivery Risk**, other types of risk factors pertinent to q-commerce, such as regulatory risks, reputational risks, and financial risks, were beyond the scope of this study but warrant further investigation. The complexity of q-commerce necessitates a more granular examination of the subtypes of risks within each category. For instance, under **Last-Mile Delivery Risk**, distinct issues such as environmental impact, local traffic patterns, and customer service bottlenecks could be evaluated individually (Kumar & Anbanandam, 2020).

The mitigation strategies proposed in this research are also based on commonly applied tactics within the industry. However, exploring **innovative and emerging strategies**, such as the integration of artificial intelligence for predictive logistics or the use of blockchain for enhanced transparency, could provide a more robust framework for managing these risks in q-commerce (Ivanov et al., 2020). Future research might consider developing an expanded set of mitigation strategies and assess their feasibility and effectiveness for specific risk scenarios.

Another limitation lies in the sample size and selection. This study surveyed 193 participants, with a large majority of responses (approximately 65%) from delivery agents and the remaining from managerial and other categories. Although this sample provides insight into ground-level challenges, expanding the sample size and incorporating a more balanced mix of roles and companies could offer a more representative view of the industry. Future research should consider extending the study across a broader array of q-commerce companies, including emerging players in different regions, to better capture the variation in operational risks across the sector (Sharma et al., 2021).

Additionally, **geographic limitations** may impact the generalizability of the findings. The research primarily focused on companies within the Delhi-NCR region. As logistical and operational challenges can differ significantly by region due to factors like local regulations, infrastructure quality, and consumer behavior, conducting similar studies in varied geographic settings could provide comparative insights (Dablanc, 2021).

Lastly, this study's methodology relies on subjective assessments of risk perceptions, gathered via a Likert scale questionnaire. While this approach provides useful insights, future studies could benefit from incorporating **quantitative risk modeling or simulation approaches**, which allow for the calculation of risk probabilities and the quantification of potential impacts, thus enabling a more data-driven assessment (Christopher & Peck, 2018).

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