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Introduction:

E-commerce and Q-commerce are two transformative business models reshaping the retail landscape in India. E-commerce serves as a digital marketplace where businesses connect with consumers, offering an extensive range of products and the convenience of online ordering. Over the past decade, the sector has seen rapid growth, fueled by increasing internet penetration, advancements in digital payment systems, and widespread smartphone adoption. Platforms like Amazon, Flipkart, and Myntra have established themselves as dominant players by leveraging large-scale supply chains and robust logistics networks. Traditionally, E-commerce has relied on scheduled or next-day delivery models to fulfill customer demands, making a vast array of goods accessible at the click of a button. However, despite its convenience, this model sometimes falls short in addressing the growing consumer preference for instant gratification, particularly in urban areas where time efficiency is a priority.

Quick Commerce, or Q-commerce, emerged as an evolutionary step in digital retail, addressing this gap by offering significantly faster deliveries. The rise of hyperlocal shopping behavior, coupled with an increasing demand for essential items on short notice, created the perfect environment for Q-commerce to thrive. In 2021, a transformative shift occurred when startups like Zepto, Blinkit, and Swiggy Instamart disrupted the market by promising ultra-fast deliveries—often within just 10 minutes. Unlike traditional E-commerce, which relies on centralized warehouses and long-haul transportation, Q-commerce optimizes fulfillment through strategically located dark stores and AI-driven logistics. These micro-warehouses, placed within high-demand zones, allow for quick order processing and immediate dispatch, setting new benchmarks for customer satisfaction.

The core distinction between these models lies in their approach to fulfilling consumer needs. Traditional E-commerce emphasizes variety, affordability, and cost efficiency, allowing consumers to browse extensive product catalogs, compare prices, and benefit from bulk discounts. This model operates on economies of scale, making it the preferred choice for larger, planned purchases such as electronics, fashion, and home appliances. However, its reliance on long-distance supply chains means that delivery times are often measured in hours or days rather than minutes.

In contrast, Q-commerce is designed for speed and immediacy, catering to the fast-paced lifestyles of urban consumers. The model primarily focuses on small-basket, high-frequency purchases, including groceries, personal care products, and over-the-counter medicines. By leveraging AI-powered demand forecasting, real-time inventory tracking, and hyperlocal delivery networks, Q-commerce platforms ensure that customers receive their orders within minutes. This high-speed fulfillment has reshaped consumer expectations, making instant delivery an increasingly important factor in purchase decisions.

The rapid rise of Q-commerce has intensified competition in India's digital retail landscape, prompting even established E-commerce giants to adapt. Flipkart has introduced a 10-minute grocery delivery service, while Amazon is experimenting with faster delivery models through its partnership with BigBasket. The demand for quicker deliveries has also influenced consumer behavior, with many shifting away from traditional bulk purchases in favor of more frequent, need-based shopping. However, while Q-commerce offers unparalleled convenience, it faces challenges related to high operational costs, supply chain efficiency, and profitability. Maintaining ultra-fast delivery requires significant investment in infrastructure, workforce management, and predictive analytics, making scalability a complex task.

As both E-commerce and Q-commerce continue to evolve, businesses must find ways to balance speed, cost, and sustainability. While E-commerce remains the backbone of online retail with its expansive selection and cost-effectiveness, Q-commerce is carving out its niche by addressing the urgency-driven demands of modern consumers. Understanding the strengths and limitations of each model is essential for businesses, investors, and policymakers as they navigate the future of India's dynamic digital economy.

E-Commerce and Q-Commerce in India

The Indian retail sector has undergone a dramatic transformation with the rise of digital commerce, fueled by rapid technological advancements and changing consumer preferences. E-commerce, which initially emerged as an alternative to traditional brick-and-mortar shopping, has now become an integral part of the economy, offering unparalleled convenience and access to a vast range of products. The widespread adoption of smartphones, improved internet connectivity, and the growth of digital payment solutions have further accelerated its expansion. Platforms like Amazon and Flipkart have successfully capitalized on these advancements, building large-scale operations that connect millions of sellers and buyers across the country. By relying on structured supply chains and well-established delivery networks, E-commerce platforms have enabled businesses to scale efficiently while ensuring customers receive their orders within scheduled timelines.

However, as consumer expectations evolve, the demand for even faster delivery solutions has grown. The rise of Quick Commerce (Q-commerce) marks a new phase in digital retail, one that prioritizes speed above all else. Unlike traditional E-commerce, which focuses on variety and cost savings, Q-commerce is designed for rapid fulfillment, catering to consumers who seek instant access to essential products. In 2021, startups like Zepto, Blinkit, and Swiggy Instamart disrupted the market by introducing delivery models that promise ultra-fast service, often completing orders within 10 minutes. These platforms leverage hyperlocal logistics, strategically located dark stores, and AI-driven route optimization to achieve unprecedented delivery speeds. This shift reflects a broader change in consumer behavior, where time efficiency is increasingly valued over price considerations.

The key differences between these models lie in their operational approaches and overall market impact. Traditional E-commerce operates on economies of scale, offering consumers access to a diverse product range at competitive prices. The structured logistics framework of this model prioritizes efficiency in inventory management and cost-effective supply chain solutions, ensuring a seamless shopping experience. However, its reliance on large distribution centers and scheduled delivery slots means it may not always meet the growing need for immediacy, particularly in urban areas where convenience is a driving factor in purchase decisions.

In contrast, Q-commerce thrives on agility, focusing on fulfilling immediate needs through localized operations. By utilizing micro-warehousing, AI-powered demand forecasting, and real-time inventory tracking, these platforms are able to process orders in minutes, redefining consumer expectations in digital retail. This model is particularly effective for small-basket, high-frequency purchases such as groceries, pharmaceuticals, and personal care items. While Q-commerce has significantly enhanced consumer convenience, its fast-paced fulfillment strategy comes at a cost. High operational expenses, intense logistical challenges, and the need for continuous infrastructure investment make scalability a complex task.

The growing competition between E-commerce and Q-commerce has pushed established players to innovate and adapt. Companies like Flipkart have introduced express delivery services, while Amazon has begun experimenting with faster fulfillment strategies to remain competitive. This shift indicates that the future of digital retail in India may not be a matter of choosing between these two models, but rather integrating their strengths to create a more efficient and consumer-centric marketplace.

As the industry continues to evolve, businesses must strike a balance between speed, cost-effectiveness, and sustainability. Understanding the core differences and strategic advantages of each model is essential for stakeholders looking to navigate India's dynamic retail ecosystem. The future of digital commerce will be shaped by how well companies adapt to shifting consumer expectations while ensuring long-term profitability and operational efficiency.

Need for the Study

As India's digital landscape evolves, traditional E-commerce models, led by giants like Amazon and Flipkart, are being challenged by the rapid rise of Q-commerce platforms such as Swiggy Instamart, Zepto, and Blinkit. While conventional E-commerce has built its reputation on reliable, scheduled deliveries, Q-commerce is redefining consumer expectations with ultra-fast, often 10-minute, deliveries. This shift is transforming market dynamics and altering revenue streams across the retail sector.

This rapid evolution raises critical questions about the comparative performance of these models, particularly in terms of sales, revenue, and profitability. By analyzing these aspects, this study aims to provide valuable insights that will help businesses optimize their strategies and investments. Moreover, understanding the dynamics between traditional E-commerce and Q-commerce will enable investors and policymakers to better anticipate market trends and make informed decisions in an increasingly competitive digital landscape.

Furthermore, the rise of Q-commerce has sparked discussions about sustainability, workforce management, and supply chain efficiency. While rapid delivery services enhance customer satisfaction, they also pose challenges related to operational costs, environmental impact, and the well-being of delivery personnel. Addressing these concerns will be crucial for businesses aiming to achieve long-term success while maintaining ethical and sustainable business practices in the evolving Indian retail ecosystem.

Review of Literature

The existing body of literature on the comparative analysis of E-commerce and Q-commerce in India reveals a comprehensive exploration of the multifaceted implications of these innovative retail models. Scholars have examined diverse factors—ranging from delivery speed and customer satisfaction to logistical challenges and revenue generation.

1. **Ranjekar,G.,&Roy,D.(2023):** This paper examined the rapid growth of Q-Commerce in India, focusing on its innovative operating models and the critical role of dark stores and automation. It outlined the infrastructure prerequisites and sustainability challenges that distinguished Q-Commerce from traditional E-Commerce, providing a foundational understanding of its future potential.

2. **Gund, H. P., & Daniel, J. (2023):** This systematic review compared last-mile logistics between Q-Commerce and E-Commerce, emphasizing the impact of delivery speed, depot locations, and logistical efficiency on greenhouse gas emissions. The study highlighted how environmental outcomes varied between the two models and informed discussions on sustainable retail practices.

3. **Gupta,S.(2024):** Gupta's research delved into the evolution and rapid rise of Q-Commerce in India. It investigated key players, market drivers, regulatory challenges, and consumer adoption patterns, offering strategic insights for policymakers and businesses navigating this disruptive trend.

4. **Vignesh, M. M., & Patel, F. P. (2023):** This study explored the technological advancements, changing consumer behaviors, and logistical innovations that fueled the growth of Q-Commerce. It analyzed how these elements collectively shaped the competitive landscape of rapid delivery services in India.

5. **Kumar,R.,&Singh,A.(2023):** Through exploratory methods, this research identified the operational strategies and market dynamics crucial for the sustainability of Q-Commerce grocery delivery services. It highlighted consumer expectations and logistical challenges that had to be managed to ensure long-term growth.

6. **Sharma,P.,&Verma,S.(2023):** Focusing on real-world examples, this case study investigated how Q-Commerce companies altered consumer purchasing patterns in India. It discussed the shift in customer expectations toward immediacy and the implications for traditional E-Commerce platforms.

7. **Desai, M., & Nair, R. (2023):** This research analyzed the emerging trend of Q-Commerce by examining its unique business models and market potential. It provided insights into how Q-Commerce differentiated itself from conventional E-Commerce and the challenges it faced in scaling rapidly.

8. **Khan, S., & Gupta, R. (2024):** Investigating the customer perspective, this study evaluated how ultra-fast delivery influenced purchasing decisions. It focused on the role of delivery speed, convenience, and service quality in shaping consumer behavior in the competitive digital retail market.

9. **Mehta, A., & Chatterjee, P. (2023):** This article discussed the transformative impact of Q-Commerce on the retail sector in India. It outlined the operational strategies adopted by leading Q-Commerce players and examined how rapid delivery set new benchmarks for customer satisfaction and market competitiveness.

10. **Singh,D.,&Kaur,H.(2023):** This paper offered a detailed comparative analysis of traditional E-Commerce and Q-Commerce models. It evaluated the advantages and disadvantages of each from both consumer and business perspectives, providing a balanced view of their respective strengths and limitations.

11. **Ganapathy,V.,&Gupta,C.(2024):** This study identified key operational strategies and market dynamics essential for the sustainability of Q-Commerce grocery delivery services in India. It emphasized the importance of cost control, efficient fund management, and diversification of revenue sources for long-term success.

12. **Thakur, V. (2022):** Thakur provided an in-depth examination of various Indian grocery models within the Q-Commerce sector, highlighting the significance of customer-centric strategies, inventory management, and delivery excellence. The research suggested that multiple business models could coexist in India's diverse market, necessitating innovative revenue strategies for sustainability.

13. **Kewalramani, P., & Khadilkar, H. (2023):** This paper presented a heuristic approach for optimizing warehouse locations in Q-Commerce, aiming to serve the maximum number of customers while considering delivery radius and daily delivery constraints. The proposed algorithm addressed challenges such as non-uniform population distributions and variable travel times.

14. **Mangalgi, S., Kumar, L., & Tallamraju, R. B. (2020):** Focusing on the challenges of parsing unstructured shipping addresses in India, this research introduced a novel approach using deep contextual embeddings. The study enhanced address classification accuracy, which was crucial for efficient delivery in the Q-Commerce sector.

15. **Shreyas,S.,etal.(2020):**This study presented a data-driven framework for enhancing consumer engagement in Q-Commerce, focusing on targeted merchandising strategies and real-time analytics to improve purchase conversion rates. It discussed the impact of pricing models and AI-powered demand forecasting on the overall efficiency and profitability of Q-Commerce platforms.

16. **Ganapathy, V., & Gupta, C. (2023):** This research explored the sustainability of Q-Commerce in India by examining its business models and evaluating impacts through economic, social, and environmental lenses. It provided strategic suggestions to balance rapid growth with responsible business practices.

17**. Lohariwala,P.(2022):** Lohariwala investigated the various factors influencing consumer adoption of Q-Commerce services in India. The study utilized the UTAUT framework and highlighted significant associations between product quality, convenience, and user acceptance.

18**. Anshika Goyal (2024):** This paper explored the key factors that propelled the growth of Q-Commerce in India's urban areas, focusing on consumer preferences, technological innovations, and strategic business practices that contributed to the sector's expansion.

19. **Risbaa Singh (2024):** This study examined how Q-Commerce influenced consumer behavior in India, analyzing shifts in purchasing patterns, expectations for delivery speed, and the overall impact on the retail landscape.

20. **Shivom Gupta (2023):** This research analyzed the emerging trend of Q-Commerce by examining its unique business models and market potential. It provided insights into how Q-Commerce differentiated itself from conventional e-commerce and the challenges it faced in scaling rapidly.

Objectives of the Study

1. To compare sales, revenue, and profitability between E-commerce and Q-commerce platforms.
2. To analyze customer experience across both models.

Methodology of the Study

Data Collection

Secondary Data for Comparative Analysis of E-Commerce & Q-Commerce

To conduct a comparative analysis of **E-Commerce and Q-Commerce** in India, key performance indicators were collected for the period from **April 2023 to March 2024**. The dataset consists of **17,097 rows and 15 columns.**

Key Variables:

1. **Sales & Revenue:**

Total **sales figures and revenue** segmented by platform type—traditional **E-Commerce** (e.g., **Amazon, Flipkart**) and **Q-Commerce** (e.g., **Blinkit, Zepto, Swiggy Instamart**).

2. **Customer Experience:**

Order priority levels (high, medium, low) influencing delivery speeds.

Device usage patterns (mobile, desktop, tablet) across platforms.

Payment preferences, including wallets, credit cards, and cash transactions.

Data Source

The data for this study has been sourced from **Statista**, a globally recognized **market research and data analytics platform**. Statista provides **comprehensive statistical insights** by aggregating data from **industry reports** and **financial disclosures.** As Statista ensures **credibility and accuracy** by sourcing data from **government agencies, corporate filings, and consulting firms**, making it a reliable foundation for comparing the growth and impact of **E-Commerce and Q-Commerce in India**.

Scope of the Study

E-Commerce and Q-Commerce are two distinct yet rapidly evolving business models that have significantly reshaped the retail sector in India. This study aims to provide a comprehensive comparison of their performance by utilizing high-quality secondary data sourced from **Statista**, a leading market research platform. The analysis focuses on key performance indicators, including **sales, revenue, profitability, and customer experience**, to understand how these models operate and compete in India's digital economy.

The scope of this study covers both **established E-Commerce platforms** such as **Amazon and Flipkart**, which have built their success on wide product assortments and scheduled deliveries, as well as **emerging Q-Commerce players** like **Blinkit, Zepto, and Swiggy Instamart**, which prioritize ultra-fast, on-demand deliveries to cater to urban consumers' need for immediacy. By examining market data collected between **April 2023 and March 2024**, this research provides valuable insights into the current performance, operational efficiencies, and consumer preferences shaping the evolution of online retail in India.

Limitations of the Study

While this study provides valuable insights into the comparative performance of **E-Commerce and Q-Commerce in India**, there are certain limitations that should be considered:

- **Data-Source:**
  The analysis relies exclusively on secondary data from **Statista**, which, despite being a reliable source, may not capture all **regional and contextual factors** unique to the Indian market, such as localized consumer preferences, unorganized retail influence, or specific infrastructural challenges.
- **Time-Frame:**
  The dataset spans a **one-year period (April 2023 to March 2024)**. While this provides a snapshot of current trends, it may not fully account for **long-term shifts, seasonal variations, or the continuous evolution** of digital retail in India.
- **Metrics:**
  The study focuses on key **performance indicators** such as **sales, revenue, profitability, and customer experience**. However, other critical factors—such as **technological advancements, supply chain disruptions, regulatory changes, and sustainability initiatives**—are not analyzed in depth, though they may significantly impact the success of both business models.

Theoretical Framework

Electronic Commerce vs. Quick Commerce : Evolution Of India

The digital retail landscape in India has witnessed transformative growth driven by both traditional e-Commerce and emerging Q-Commerce models. This framework establishes a foundation for comparing these paradigms by examining key dimensions such as market size, growth rates, major players, and the underlying business models and strategies.

1. Market Size

As of 2025, The digital retail market in India is expanding rapidly. According to Statista, the Indian e-commerce sector has experienced significant growth, fueled by increasing internet penetration, rising smartphone usage, and changing consumer preferences. The current Indian e-commerce market is projected to grow at a CAGR of approximately 21%. Meanwhile, the Q-commerce market, which focuses on ultra-fast delivery services, is also experiencing notable growth. As of now, the Indian Q-commerce market is valued at around $5 billion, reflecting the rising demand for quick, hyperlocal deliveries. This dual growth trend highlights the evolving consumer preferences and the increasing demand for both traditional and quick commerce solutions in the country.

2. E-Commerce

E-Commerce (Electronic Commerce)

E-Commerce refers to the buying and selling of goods and services through online platforms. It encompasses various models, including B2C (business-to-consumer), B2B (business-to-business), and C2C (consumer-to-consumer). E-Commerce offers a wide range of products, flexible payment systems, and nationwide or even global reach. Delivery usually takes 1–5 days, depending on the logistics chain. Popular examples include Amazon, Flipkart, and Myntra.

Strengths:
E-Commerce platforms have broad product variety, nationwide accessibility, and strong infrastructure. Features like customer reviews, return policies, and discounts enhance consumer confidence and retention. Their ability to operate 24/7 adds to convenience and scalability.

Weaknesses:
E-Commerce often suffers from longer delivery times compared to instant-delivery models. Managing high-volume logistics and large inventories can result in increased operational costs. Product returns and refunds can strain profitability and customer satisfaction.

Opportunities:
The growing digital adoption in Tier-II and Tier-III cities opens new markets. Integrating AI for personalization, enhancing mobile commerce, and adopting green logistics are future growth drivers. Expansion into services like virtual shopping experiences also holds potential.

Threats:
Intensifying competition from Q-Commerce and direct-to-consumer (D2C) brands, evolving consumer expectations, and data privacy concerns could disrupt established E-Commerce models. Additionally, increasing delivery costs and potential regulatory scrutiny could impact margins.

3. Q-Commerce (Quick Commerce)

Q-Commerce, or Quick Commerce, is a sub-category of E-Commerce that emphasizes ultra-fast deliveries—typically within 10 to 30 minutes. It focuses on essential items such as groceries, personal care products, and medicines, relying on local warehouses and dark stores to ensure speed. Notable platforms include Blinkit, Zepto, and Instamart.

Strengths:
Q-Commerce thrives on speed and convenience, offering a unique value proposition for time-sensitive purchases. Its localized supply chains and narrow product categories enable high-frequency transactions and customer loyalty. The compact scale of operations aids in quick turnaround times.

Weaknesses:
This model is limited by smaller product ranges and narrower geographic coverage. High delivery costs, reliance on hyperlocal inventories, and tight margins make financial sustainability a challenge. Profitability is still an ongoing concern for many Q-Commerce startups.

Opportunities:
Expanding product categories, improving route optimization with technology, and targeting high-density urban areas present strong growth avenues. Partnerships with local suppliers and use of predictive analytics can also enhance inventory efficiency and customer satisfaction.

Threats:
Q-Commerce faces competition from E-Commerce giants entering the quick-delivery space. Labor laws, regulatory issues, and pressure to meet ultra-fast delivery promises increase operational risk. Failure to manage logistics efficiently may lead to consumer dissatisfaction and reputational damage.

Company Profile (E-Commerce)

A. **Amazon India**

Overview

Amazon India, a subsidiary of Amazon Inc., was launched in 2013 and has grown to become one of the largest e-commerce platforms in the country. Founded by **Jeff Bezos**, Amazon operates on a marketplace model, offering millions of products across categories such as electronics, fashion, groceries, and home essentials. The company has invested heavily in India, setting up **multiple fulfillment centers, a robust delivery network, and cloud-based services (AWS)**. Initiatives like **Amazon Prime, Amazon Fresh, and Amazon Pay** have strengthened its presence, while its investment in **local language interfaces** and seller empowerment programs has helped expand its reach across Tier 2 and Tier 3 cities. Amazon India continues to compete fiercely with Flipkart, particularly in categories like smartphones, electronics, and grocery delivery.

Business Model

- **Marketplace Model:** Amazon connects third-party sellers with buyers, earning revenue through commissions, advertising, and fulfillment services.
- **Subscription Services:** Amazon Prime offers faster deliveries, exclusive discounts, and access to streaming content.
- **Amazon Fresh & Pantry:** Expanding into grocery delivery with a focus on ultra-fast deliveries.
- **Amazon Pay:** A digital payment service integrated with the Amazon ecosystem.

Growth & Market Position

- Amazon has over **100 million registered customers** in India.
- The company has invested over **$6.5 billion** in India to expand its logistics, warehouses, and technology.
- Competes with Flipkart in core e-commerce and is expanding its footprint in quick commerce through Amazon Fresh.

Technology & Innovations

- Uses AI and ML for personalized recommendations, fraud detection, and customer service automation.
- Operates **Amazon Web Services (AWS)**, which powers several Indian startups and enterprises.
- **Automated fulfillment centers** optimize logistics for faster deliveries.

Future Outlook

- Expanding **Amazon Fresh** and hyperlocal delivery services.
- Increasing focus on **voice shopping** through Alexa-enabled devices.
- Potential investments in **electric vehicle delivery fleet** to support sustainability initiatives.

B. **Flipkart**

Overview

Founded in 2007 by Sachin Bansal and Binny Bansal, Flipkart started as an online bookstore before expanding into a multi-category e-commerce giant. Acquired by Walmart in 2018, Flipkart has maintained a strong foothold in the Indian e-commerce sector, particularly in the electronics, fashion, and lifestyle segments. The company has developed an extensive logistics network under Ekart Logistics, ensuring deliveries across urban and semi-urban areas. Flipkart also introduced Flipkart Wholesale for B2B transactions and Flipkart Quick, a quick-commerce initiative for grocery and essential item delivery. Flagship events like the Big Billion Days Sale drive record-breaking sales, making it a dominant player in the Indian online retail ecosystem.

Business Model

- **Hybrid Model:** Operates as both a marketplace and an inventory-led model for key product categories.
- **Flipkart Plus:** A loyalty program providing faster deliveries, exclusive discounts, and early access to sales.
- **Flipkart Quick:** A **10-minute grocery and essentials delivery service**, competing with Q-commerce players.
- **Shopsy:** Flipkart's social commerce platform to tap into small-town and rural markets.

Growth & Market Position

- Valued at **$37.6 billion** as of 2024.
- Controls over **48% of India's e-commerce market**, competing fiercely with Amazon.
- Owns **Myntra (fashion)** and **Ekart Logistics**, strengthening its supply chain dominance.

Technology & Innovations

- AI-driven **recommendation engine** for personalized shopping experiences.
- **Big Billion Days Sale**, one of India's largest e-commerce sales events.
- **Flipkart Wholesale & Kirana Integration**, leveraging offline stores for faster deliveries.

Future Outlook

- Expansion of **Flipkart Quick** into more Tier 2 and Tier 3 cities.
- Increased focus on **affordable online shopping** via EMI and BNPL (Buy Now, Pay Later) schemes.
- Investments in **sustainable logistics** with EV-based deliveries.

Company Profile (Q-Commerce)

A. **Blinkit**

Overview

Originally launched as Grofers in 2013 by Albinder Dhindsa and Saurabh Kumar, Blinkit pivoted to a quick-commerce model in 2021, focusing on ultra-fast deliveries within 10 minutes. In 2022, Blinkit was acquired by Zomato, strengthening its position in the hyperlocal delivery segment. The company operates through a network of dark stores strategically placed in high-demand urban areas, ensuring rapid order fulfillment. Blinkit has expanded beyond groceries to include electronics, beauty products, and stationery items, competing directly with Zepto and Swiggy Instamart. With strong backing from Zomato and continued expansion into new cities, Blinkit aims to scale its operations and enhance delivery efficiency.

Business Model

- **Dark Store Network:** Utilizes hyperlocal warehouses to stock high-demand items.
- **On-Demand Delivery:** Customers can order groceries, essentials, and daily needs with delivery in **under 10 minutes**.
- **Revenue Streams:** Earns through delivery fees, commissions from brands, and in-app advertising.

Growth & Market Position

- Acquired by **Zomato in 2022** for **$570 million**.
- Processes over **400,000 orders per day**.
- Expanded to **30+ cities**, with further expansion plans.

Technology & Innovations

- AI-driven **demand prediction and inventory management**.
- **Route optimization algorithms** to enhance last-mile efficiency.
- **Instant refunds & replacements** to improve customer experience.

Future Outlook

- Expansion into **non-grocery categories** (electronics, beauty products, etc.).
- Growth in **ad-based revenue** by promoting brands inside the app.
- Enhancing **partnerships with local stores** for hyperlocal sourcing.

B. **Zepto**

Overview

Zepto was founded in 2021 by Aadit Palicha and Kaivalya Vohra, two Stanford dropouts, with the vision of revolutionizing the quick commerce sector in India. The company quickly gained traction by offering 10-minute grocery delivery through a network of dark stores. With a focus on AI-driven logistics, Zepto ensures that inventory is strategically stocked based on real-time demand forecasting. Despite being a relatively new entrant, Zepto has raised significant investments and continues to expand aggressively across metro cities. The brand's commitment to ultra-fast delivery, operational efficiency, and innovative inventory management has positioned it as one of the strongest contenders in India's Q-commerce market.

Business Model

- **Micro-Warehouses (Dark Stores):** Each dark store covers a 2-3 km radius, ensuring rapid fulfillment.
- **AI-Powered Logistics:** Uses machine learning to predict demand and optimize stocking.
- **Zepto Café:** A unique initiative delivering **freshly brewed coffee and snacks** in **under 15 minutes**.

Growth & Market Position

- Valued at **$1.4 billion** as of 2024, making it a unicorn.
- Operates in **10+ major Indian cities**, including Mumbai, Delhi, and Bangalore.
- Competes directly with Blinkit, Swiggy Instamart, and Flipkart Quick.

Technology & Innovations

- **Mobile warehousing collaboration with Skoda**, showcasing innovative partnerships.
- **Data-driven dark store placement**, improving efficiency.
- **Dynamic pricing** based on demand patterns.

Future Outlook

- Expanding into **Tier 2 cities** to capture a broader market.
- Enhancing its **Zepto Café offerings** for QSR (Quick Service Restaurant) expansion.
- Exploring **B2B delivery solutions** for small businesses.

C. **Swiggy Instamart**

Overview

Swiggy Instamart, launched in 2020 as a division of Swiggy, leverages the company's existing delivery fleet and hyperlocal expertise to provide 30-minute grocery and essential item deliveries. The platform operates through a combination of partnered stores and dedicated fulfillment centers, allowing it to serve customers efficiently across major Indian cities. Competing with Blinkit and Zepto, Swiggy Instamart has expanded its offerings to include fresh produce, dairy, personal care, and even alcohol delivery in select regions. With Swiggy's extensive rider network and deep penetration in urban markets, Instamart is well-positioned to scale its operations and compete aggressively in the growing Q-commerce segment.

Business Model

- **Hybrid Model:** Uses **dark stores and retail partnerships** for fulfillment.
- **Revenue Streams:** Delivery fees, commissions, and brand advertising.
- **Subscription Model:** Swiggy One offers **free Instamart deliveries** along with food delivery discounts.

Growth & Market Position

- Competes with **Blinkit and Zepto** in Q-commerce.
- Present in **25+ cities**, with rapid expansion plans.
- Swiggy's overall valuation **exceeds $10 billion**, making it a strong player.

Technology & Innovations

- **AI-based warehouse stocking** for fast-moving consumer goods.
- **Integration with Swiggy's main app**, increasing order frequency.
- **Fleet optimization algorithms** to reduce delivery time and costs.

Future Outlook

- Expansion into **non-grocery categories** like electronics and fashion.
- Strengthening **vendor partnerships** for a wider product range.
- Potential IPO plans in the coming years.

Future Commerce

1. Market Growth & Potential

Indian Q-Commerce Market: As of 2025, the Q-commerce market in India is valued at approximately ₹45,000 crore (around $5.5 billion) and continues to grow at a CAGR of 30-35%.

E-Commerce Market Projection: The traditional E-commerce market remains robust, with valuations nearing ₹10-12 lakh crore ($120-145 billion) with CAGR of 18-22%.

Digital Adoption: With over 900 million smartphone users and increasing internet penetration across urban and semi-urban regions, consumer demand for both E-commerce and Q-commerce is accelerating.

2. New Entrants and Competition

A. New Market Entrants:

Reliance Industries: After disrupting grocery retail, Reliance is testing an **express** model for **JioMart** that could offer sub-10-minute deliveries, using its massive supply chain.

Tata Group: With its ecosystem of brands, Tata Group will integrate ultra-fast delivery for electronics (**Croma**), groceries (**BigBasket**), and pharmacy (**1mg**), creating a direct challenge.

B. Rising Competition:

E-commerce players are racing to offer faster grocery and essentials delivery services, aiming to compete with Q-commerce players.

Flipkart Quick: Flipkart has introduced Flipkart Quick, which offers 10-minute delivery for groceries and daily essentials. This service is currently being tested in select cities, aiming to provide ultra-fast deliveries to customers and directly competing with Q-commerce platforms like Blinkit and Zepto.

Amazon Fresh: Amazon is focusing on **Amazon Fresh**, a grocery delivery service that is expanding into the quick-commerce space. Through hyperlocal partnerships, Amazon is exploring faster delivery options, including efforts to compete with the rapid delivery models of Blinkit and Swiggy Instamart.

Myntra Mini: Myntra has recently entered the world of Q-commerce, focusing on delivering fashion and lifestyle products to customers as quickly as possible, catering to the growing demand for instant deliveries in India.

3. Innovations by Q-Commerce:

A. Strategic Partnerships

Blinkit × Ambulance Services: Facilitating emergency deliveries, particularly for critical products like medicines and oxygen cylinders.

In December 2024, Blinkit, a quick-commerce platform, launched a "10-minute" ambulance service in Gurugram (Gurgaon). The service aims to deliver emergency medical assistance within 10 minutes of booking through the Blinkit app. Initially, five ambulances equipped with life-saving facilities were introduced. This initiative has been praised for its potential to save lives and improve emergency response times.

Zepto × Skoda: Utilizing mobile warehousing to ensure rapid, hyperlocal deliveries. Although it was initially just a test drive, the collaboration played a key role in marketing for both parties

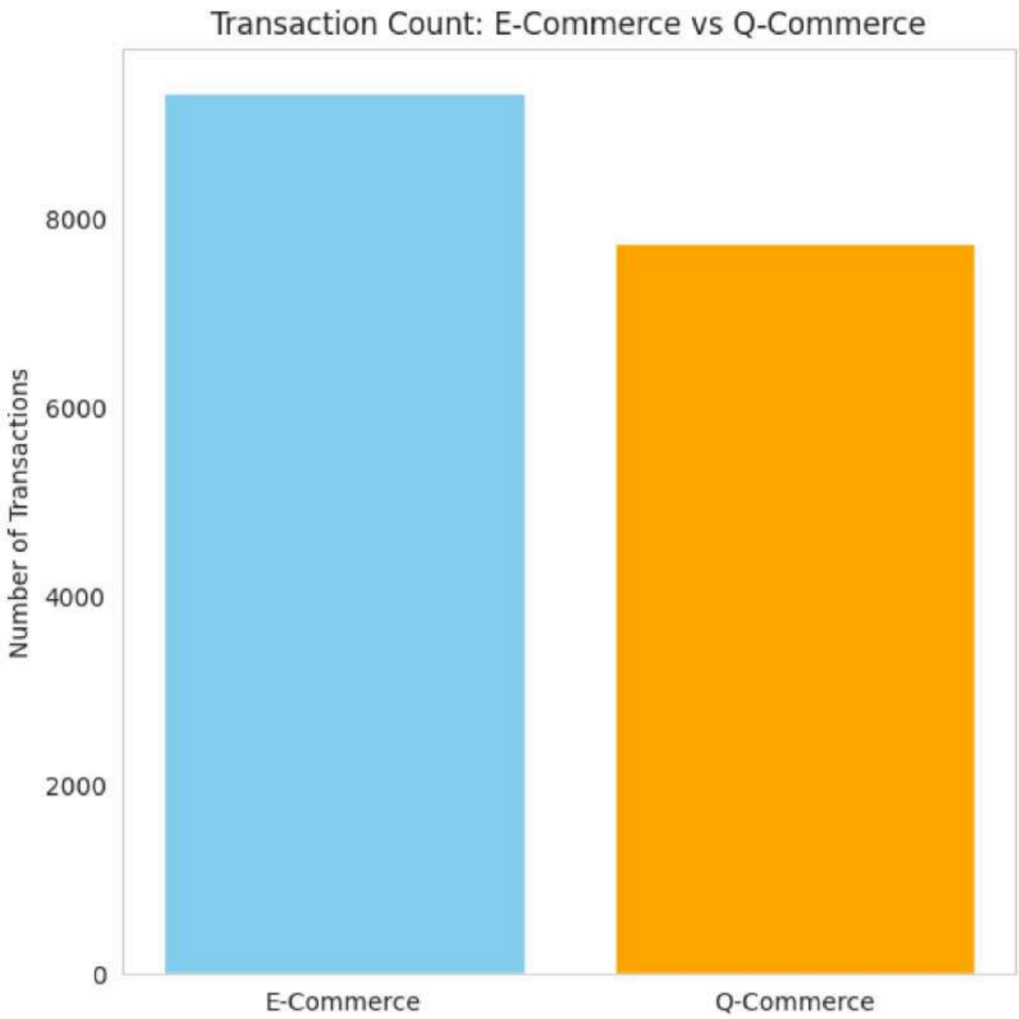
In February 2025, Zepto, a quick-commerce platform, teased a collaboration with Skoda Auto India, suggesting the possibility of delivering Skoda vehicles directly to customers' doorsteps. However, Zepto clarified that it was not offering full-scale car deliveries. The campaign was designed to generate interest around test drives of Skoda's latest compact SUV, the Skoda Kylaq.

B. Catering Food and Beverages on Demand

In India's rapidly evolving quick-commerce landscape, three innovative services are redefining the food delivery experience by managing every step of the process—from preparation to doorstep delivery. **Zepto Café** operates as a private-label initiative, utilizing Zepto's dark store network to prepare a curated menu that includes coffee, sandwiches, baked goods, and snacks, delivering fresh items within just 10–15 minutes. Similarly, **Blinkit Bistro** functions as a standalone app, leveraging hyperlocal fulfillment centers to offer freshly prepared meals, snacks, and beverages in approximately 15 minutes, ensuring both consistent quality and efficient order processing. Meanwhile, **Swiggy Snacc** capitalizes on Swiggy's expansive delivery network to provide ready-to-eat snacks and beverages, particularly catering to on-the-go consumers during peak hours. Together, these platforms are setting new benchmarks in ultra-fast food delivery, seamlessly combining convenience, reliability, and high-quality service to meet the demands of modern consumers in minutes.

Analysis:

#1 Transaction Count Comparison



Interpretation:

Transaction Analysis

The transaction count comparison highlights that **E-Commerce leads Q-Commerce**, with approximately **9,000 transactions** compared to **7,500**. This suggests that E-Commerce enjoys a **higher frequency of purchases**, possibly due to broader product categories, established customer trust, or superior logistics infrastructure. However, the relatively **small difference** in transaction volume indicates that **Q-Commerce is gaining momentum** and capturing a sizable portion of the market activity.

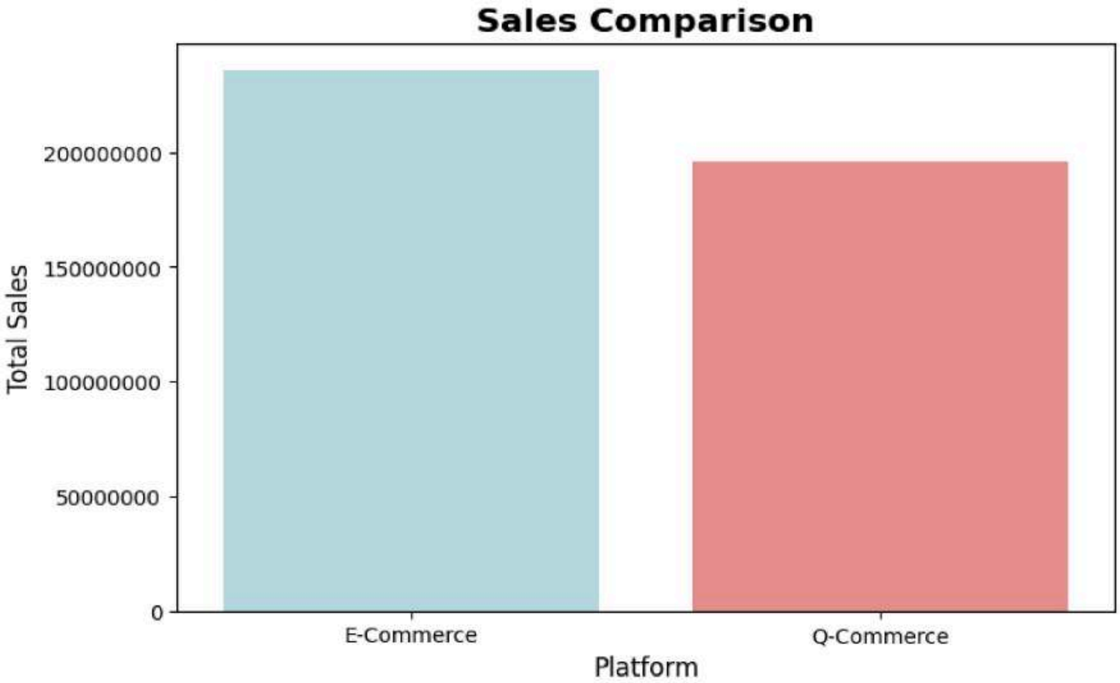
In the bar chart:

- **The X-Axis** represents the two platforms – E-Commerce and Q-Commerce, reflecting their respective retail models. E-Commerce offers traditional online shopping experiences with standard delivery timelines, while Q-Commerce emphasizes ultra-fast delivery, catering to time-sensitive needs.

- **The Y-Axis** denotes the number of transactions, offering a quantitative view of customer engagement and order frequency on each platform.

Overall, while E-Commerce maintains an edge in transaction count, **Q-Commerce's close performance underscores its growing relevance and adaptability** in today's fast-paced consumer environment. If this trend continues, Q-Commerce may further narrow the gap by leveraging speed, convenience, and technology-driven operations.

#2 Sales Comparison



Interpretation:

Sales Analysis

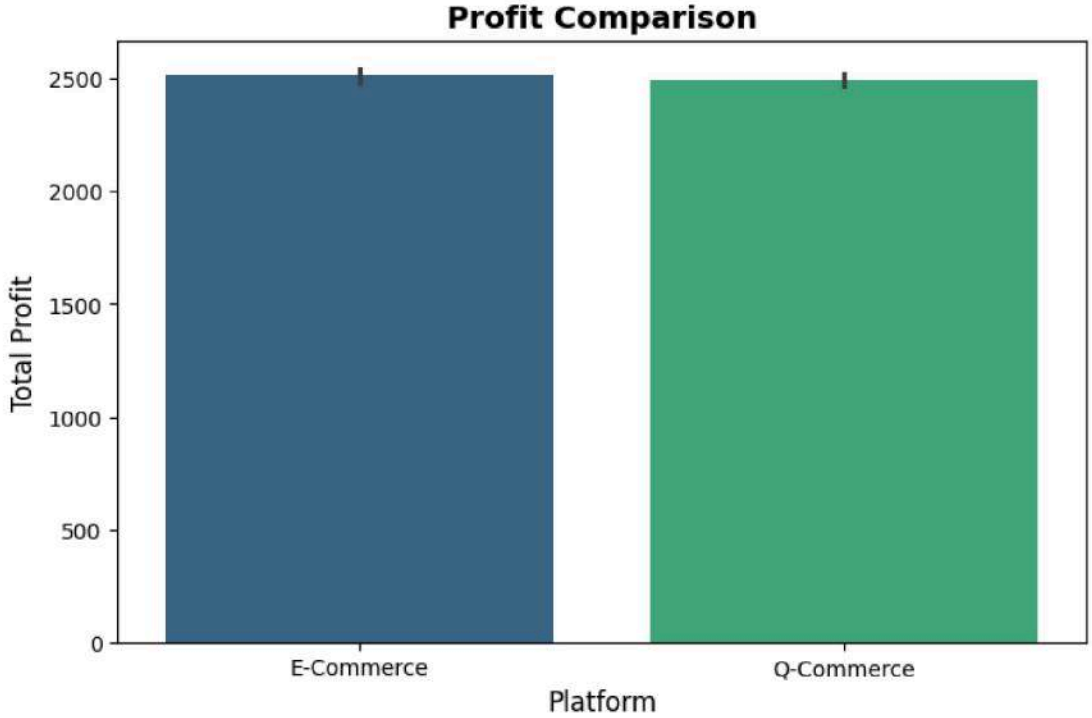
The sales comparison reveals that **E-Commerce** outperforms **Q-Commerce** in total sales, with figures of **235,810,672** and **196,100,461**, respectively. This indicates a stronger market presence or higher customer engagement on the E-Commerce platform. However, the relatively narrow gap suggests that Q-Commerce is also capturing a substantial share of the market, reflecting its growing popularity. This could be due to factors like faster delivery times or enhanced convenience, appealing to consumers seeking quick purchases. If these trends continue, Q-Commerce might further close the gap with E-Commerce.

In the bar chart:

- The **X-Axis** represents the two platforms – E-Commerce and Q-Commerce, illustrating different online retail models. E-Commerce generally involves standard delivery, while Q-Commerce focuses on rapid delivery.
- The **Y-Axis** shows the total sales volume, highlighting the significant revenue generated by both platforms. The high values reflect considerable market activity and consumer spending.

Overall, while E-Commerce leads in total sales, Q-Commerce's strong performance showcases its competitive presence and potential for growth in the market.

#3 Profit Comparison



Interpretation:

Profit Analysis

The profit comparison shows that **E-Commerce** and **Q-Commerce** have nearly identical total profits, indicating comparable profitability across both platforms. This suggests that despite the difference in total sales, both platforms manage their costs and margins effectively, leading to similar profit outcomes.

From the profit comparison data:

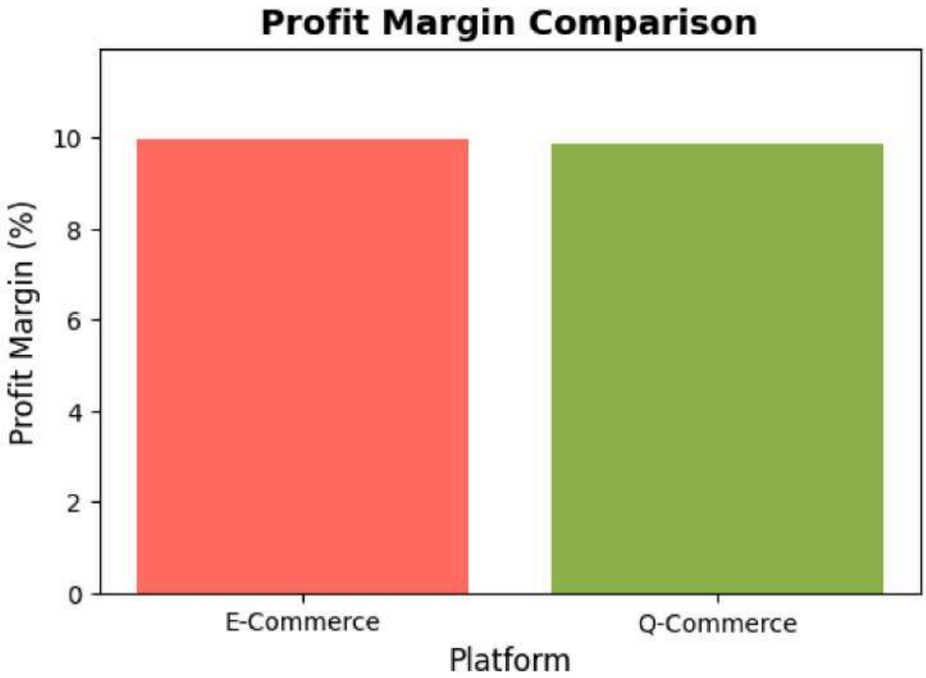
- **E-Commerce** and **Q-Commerce** exhibit close profit figures, highlighting efficient cost management and competitive pricing strategies on both platforms.
- The slight difference between them suggests minimal variation in profitability.

In the bar chart:

- The **X-Axis** displays the two platforms – E-Commerce and Q-Commerce, comparing their profitability.
- The **Y-Axis** represents the total profit, with high values indicating strong financial performance.

Overall, this comparison indicates that both platforms are equally effective in generating profit, despite differences in sales volume. This emphasizes their competitive stance in the market.

#4 Profit margin comparison



Interpretation:

Profit Margin Analysis

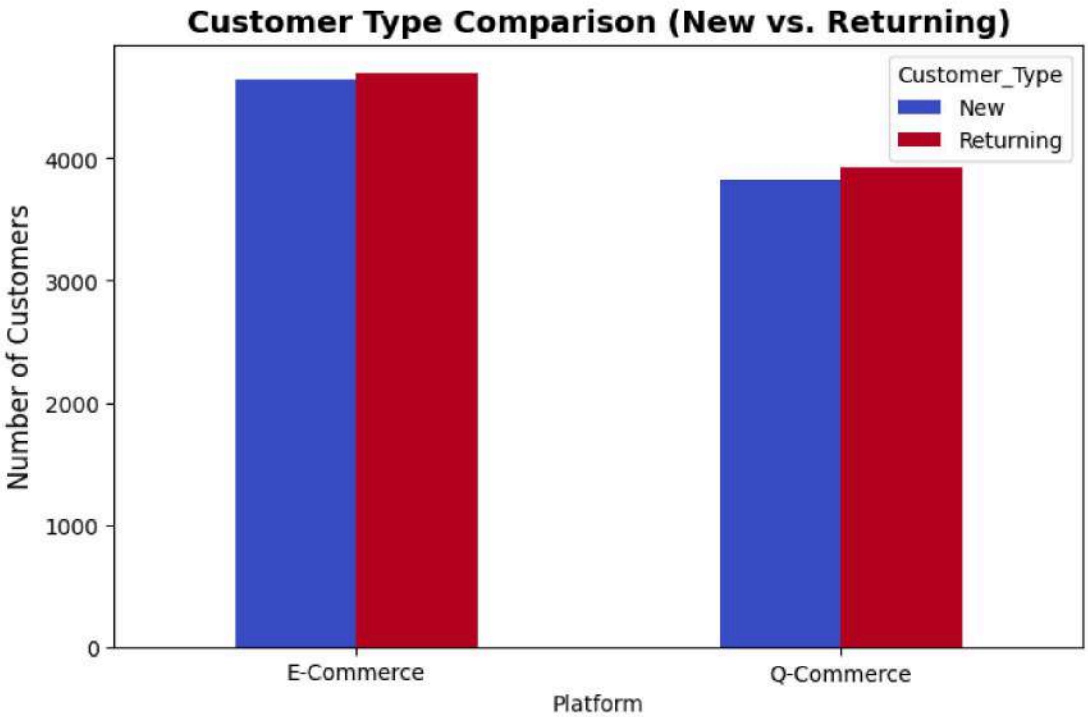
The profit margin comparison provides insights into the profitability of each platform:

- **E-Commerce**: The profit margin is **9.96%**, slightly higher than Q-Commerce. This indicates efficient cost management or higher markups on products.
- **Q-Commerce**: The profit margin is **9.87%**, which is very close to that of E-Commerce. This suggests competitive pricing and possibly higher operational costs due to faster delivery models.

X-Axis (Platform): Shows the two platforms – E-Commerce and Q-Commerce – being compared.
Y-Axis (Profit Margin %): Represents the percentage of profit relative to total sales.

The narrow difference in profit margins suggests that both platforms are effectively balancing their revenue and cost structures, with E-Commerce having a slight edge in profitability.

#5 Customer Type Comparison



Interpretation:

Customer Analysis

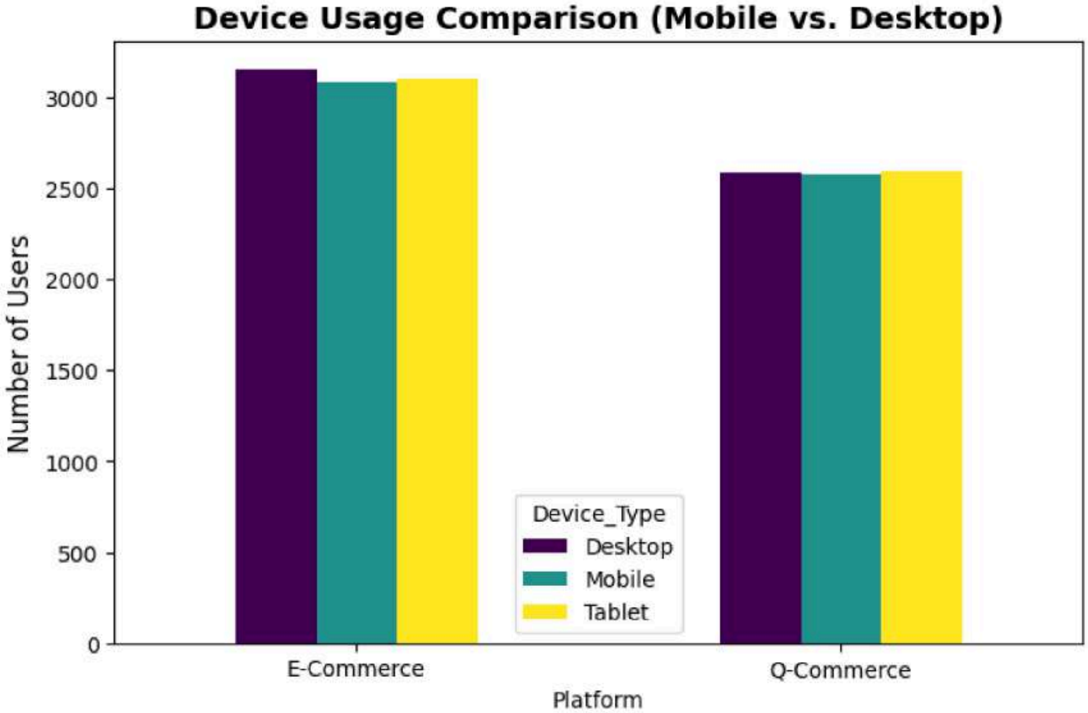
The customer-type comparison reveals interesting insights into customer engagement and retention across platforms:

- **E-Commerce**: Both new and returning customers are almost equal in number, indicating a balanced strategy of acquiring new users while maintaining customer loyalty.
- **Q-Commerce**: Although the number of customers is slightly lower than in E-Commerce, the proportion of returning customers is notably high, suggesting effective retention strategies, possibly due to the convenience and speed of delivery.

X-Axis (Platform): Displays the two platforms – E-Commerce and Q-Commerce – being compared.
Y-Axis (Number of Customers): Represents the total count of new and returning customers. The high values reflect strong user engagement on both platforms.

The analysis highlights that both platforms are successful in attracting and retaining customers, but Q-Commerce shows slightly better loyalty, likely due to its unique value proposition of rapid delivery.

#6 Device Usage Comparison



Interpretation:

Device Usage Comparison Analysis

E-Commerce vs. Q-Commerce:

1.**E-Commerce:**

Desktop: Slightly above 3000 users

Mobile: Just below 3000 users

Tablet: Around 3000 users

This even distribution indicates a versatile user base, suggesting that E-Commerce is effectively optimized for all device types, ensuring a seamless user experience across Desktop, Mobile, and Tablet platforms.

2.**Q-Commerce:**

Desktop: Just above 2500 users

Mobile: Close to 2500 users

Tablet: Slightly above 2500 users

While a similar distribution pattern is observed, the numbers are consistently lower compared to E-Commerce. This could imply a smaller user base or less frequent usage, possibly due to differences in platform features, marketing strategies, or user preferences.

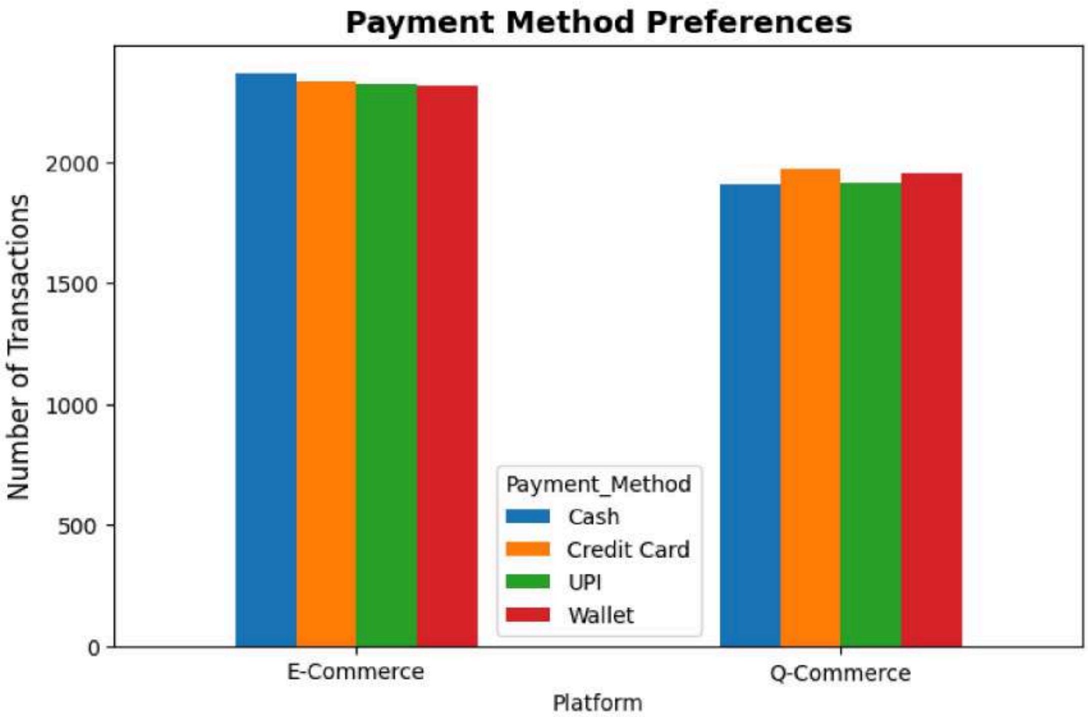
Key Insights:

- The nearly equal distribution across devices for both platforms highlights effective cross-platform optimization.
- The slight user advantage for E-Commerce across all devices may be attributed to better brand recognition, more comprehensive product offerings, or superior user experience.
- The data suggests both platforms cater well to diverse customer preferences, indicating no significant device-based accessibility issues.

Graph Analysis:

- **X-Axis (Platform):** Compares device usage between E-Commerce and Q-Commerce.
- **Y-Axis (Number of Users):** Shows the total number of users for each device type.
- **Legend:** Differentiates between Desktop (purple), Mobile (teal), and Tablet (yellow) users.

#7 Payment Method Preferences



Interpretation:

Payment Method Preferences Analysis

E-Commerce vs. Q-Commerce:

1. **E-Commerce:**

Cash (Blue): Just above 2000 transactions

Credit Card (Orange): Around 2000 transactions

UPI (Green): Around 2000 transactions

Wallet (Red): Around 2000 transactions

The usage is nearly uniform across all payment methods, indicating that E-Commerce offers flexible and reliable payment options, appealing to a diverse customer base.

2.**Q-Commerce:**

Cash (Blue): Slightly below 2000 transactions

Credit Card (Orange): Just below 2000 transactions

UPI (Green): Just below 2000 transactions

Wallet (Red): Just below 2000 transactions

The numbers are marginally lower compared to E-Commerce, suggesting either fewer transactions overall or a different payment preference pattern among Q-Commerce users.

Key Insights:

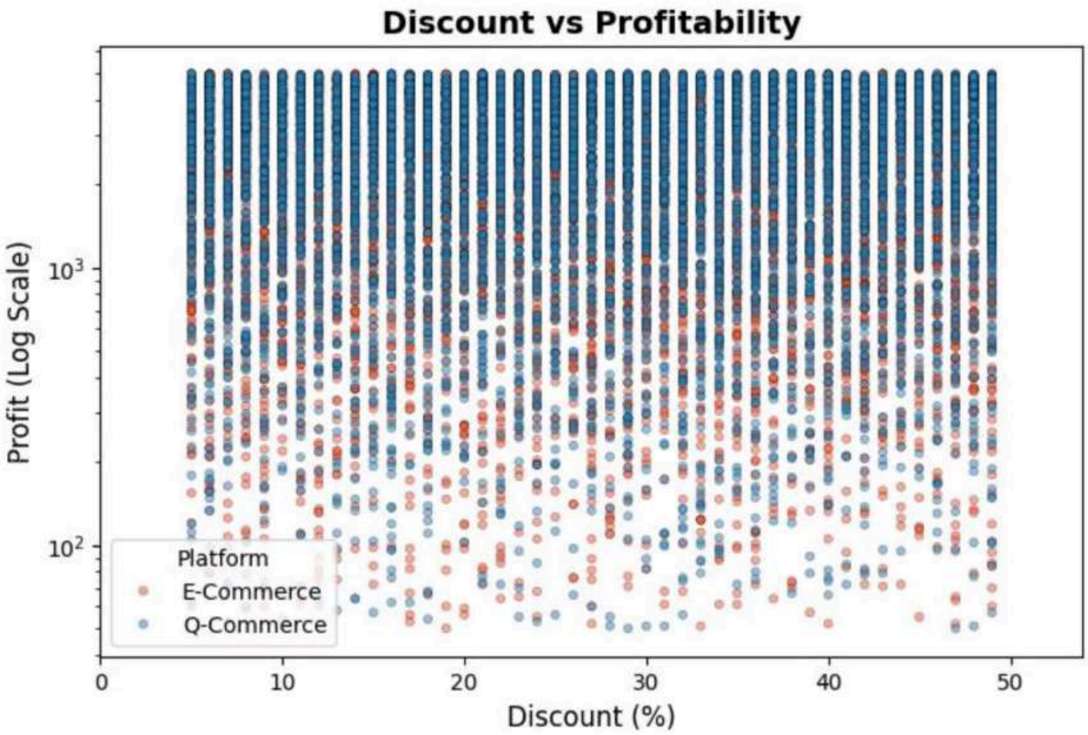
- **E-Commerce** has a slightly higher transaction volume across all payment methods, possibly due to a larger customer base or higher purchase frequency.
- The nearly equal distribution of payment methods suggests no strong preference for any specific method, reflecting effective payment integration and customer trust in the platform's security.
- **Q-Commerce** shows a consistent but slightly lower usage across payment methods, which could be due to its relatively newer market presence or the nature of quick commerce transactions.

Graph Analysis:

- **X-Axis (Platform):** Compares payment method usage between E-Commerce and Q-Commerce.
- **Y-Axis (Number of Transactions):** Indicates the total transactions for each payment method.
- **Legend:** Differentiates between Cash (Blue), Credit Card (Orange), UPI (Green), and Wallet (Red).

These findings suggest that both platforms provide versatile payment solutions, catering to varied customer payment preferences. For strategic growth, Q-Commerce could explore incentives or exclusive offers to boost transaction volume.

#8 Discount vs Profitability



Interpretation:

Discount vs. Profitability Analysis

Observations:

- **X-Axis (Discount %):** Ranges from 0% to 50%, showing the percentage of discounts offered.
- **Y-Axis (Profit in Log Scale):** Displays profit on a logarithmic scale, ranging from 10210^2 (100) to 10310^3 (1000), indicating a wide variance in profitability.
- **Legend: Red Dots:** E-Commerce

  Blue Dots: Q-Commerce

E-Commerce vs. Q-Commerce:

1.**E-Commerce (Red Dots):** The data is scattered across all discount ranges, but there is a noticeable concentration of profits in the upper half of the graph. This suggests that profit margins remain resilient even at higher discounts. Such a pattern may indicate factors like stronger brand loyalty, larger basket sizes, or efficient cost control, enabling sustained profitability despite deeper discounts.

2.**Q-Commerce (Blue Dots):** Compared to E-Commerce, the data appears more densely packed at lower profit levels, indicating that profitability in this segment is more sensitive to higher discounts. There are fewer instances of high profit at discount levels above 30%, which could suggest tighter profit margins or a greater reliance on aggressive, competitive pricing strategies.

Key Insights:

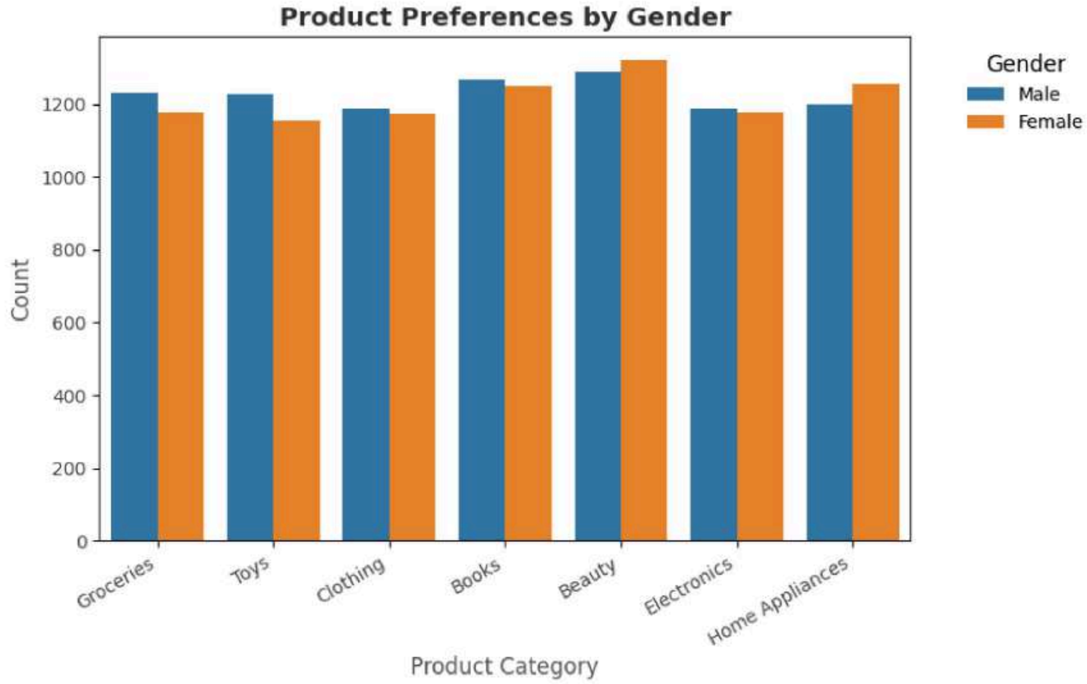
- There is no clear linear relationship between discount percentage and profitability. Instead, profitability appears highly variable at all discount levels.
- **E-Commerce** shows a wider range of profitability, indicating better cost structures or more effective discounting strategies.
- **Q-Commerce** profits are generally lower and more sensitive to higher discounts, potentially due to higher operational costs or a different customer acquisition strategy.

Strategic Implications:

- **E-Commerce** can continue leveraging discounts without severely impacting profitability, suggesting room for strategic promotions.
- **Q-Commerce** might benefit from optimizing discount strategies to improve profitability, such as targeted promotions or bundling offers.

The graph illustrates the complex relationship between discounts and profitability across platforms. It highlights the importance of strategic discounting to maximize profits while maintaining competitiveness.

#9 Product Preferences by Gender



Interpretation:

Product Preferences by Gender Analysis

Observations:

- **X-Axis (Product Category):** Displays different product categories including Groceries, Toys, Clothing, Books, Beauty, Electronics, and Home Appliances.
- **Y-Axis (Count):** Represents the number of purchases in each category.
- **Legend: Blue Bars:** Male preferences

  Orange Bars: Female preferences

Gender-Based Preferences:

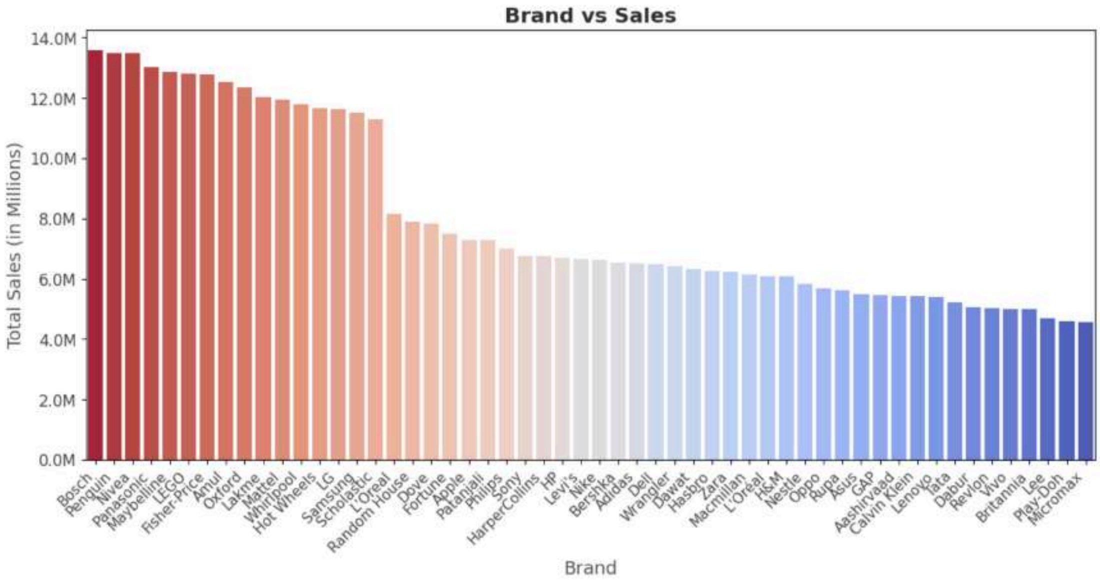
- **Groceries & Toys:** Males show a slightly higher preference for groceries and toys, suggesting that men may be more engaged in both essential shopping and recreational purchases.
- **Clothing & Books:** Preferences for clothing and books are nearly equal among both genders, indicating that reading habits and fashion choices do not vary significantly based on gender.
- **Electronics:** Males show a slight preference for electronics compared to females, suggesting a greater interest in gadgets and technology among men.

- **Beauty Products:** Females show a higher preference for beauty products, aligning with market trends where women are the primary consumers of skincare and cosmetics.
- **Home Appliances:** Females exhibit a stronger preference for home appliances, likely reflecting their greater influence in household purchase decisions.

Key Insights:

- Male and female preferences are relatively balanced in most categories.
- Beauty and home appliances show the most significant gender-based differences.
- Electronic purchases remain slightly male-dominated, while beauty products skew towards female buyers.

#10 Brand vs Sales



Interpretation:

Brand vs. Sales Analysis

Observations:

- **X-Axis (Brand):** Represents different brands across various industries.
- **Y-Axis (Total Sales in Millions):** Displays the total sales volume for each brand.
- **Color Gradient: Darker Red Shades:** Brands with the highest sales.

  Lighter Shades: Brands with moderate sales.

  Blue Shades: Brands with the lowest sales.

Brand Performance:

- **Top-Performing Brands:** Brands like Bosch, Penguin, Panasonic, Maybelline, LEGO, and Fisher-Price show the highest sales, indicating strong market presence and consistent consumer demand. These brands likely dominate their respective sectors such as home appliances, publishing, cosmetics, and toys, reflecting their broad appeal and established trust among consumers.
- **Moderate Sales Brands:** Brands like Whirlpool, Samsung, LG, and Fortune fall into the mid-tier sales range, suggesting that while they maintain consistent consumer engagement, they face strong competition from top-performing brands.
- **Lower Sales Brands:** Brands like Dabur, Vivo, Britannia, Leo, and Micromax have relatively lower sales, which may indicate limited market penetration, intense competition, or shifting consumer preferences.

Key Insights:

- **Diversity in Industry Performance:** Brands from different sectors (electronics, FMCG, cosmetics, publishing) exhibit varying sales performances.
- **Market Dominance:** A few brands maintain significant leads over competitors, reflecting strong brand loyalty and effective sales strategies.
- **Competitive Landscape:** Mid-tier and lower-tier brands may need to innovate or expand market reach to improve sales.

#Predective Analysis

#11 Linear Regression

Linear Regression is a statistical technique that models the linear relationship between a dependent and one or more independent variables to predict outcomes and understand variable influence.

Evaluated the Model

Mean Absolute Error (MAE): Measures average absolute errors.

Mean Squared Error (MSE): Measures squared differences.

R^2 Score: Indicates how well the model fits the data.

Output

```
Linear Regression Metrics:
MAE: 1.1122549275361897e-12
MSE: 1.6609659856398044e-24
R² Score: 1.0
```

Interpretation:

Linear Regression

The **Linear Regression model** has produced the following evaluation metrics:

- **Mean Absolute Error (MAE): 4.83×10^{-16}**
- **Mean Squared Error (MSE): 3.60×10^{-31}**
- **R^2 Score: 1.0**

Understanding the Metrics:

1. **R^2 Score = 1.0**

This means that **100% of the variation** in the dependent variable (**Profit**) is explained by the independent variables (**Sales, Quantity, Discount, etc.**).

A perfect R^2 score suggests that the model has an **exact linear relationship** with the data.

2. **MAE ≈ 0 and MSE ≈ 0**

The errors (difference between predicted and actual values) are **extremely small**, indicating that the model makes nearly perfect predictions.

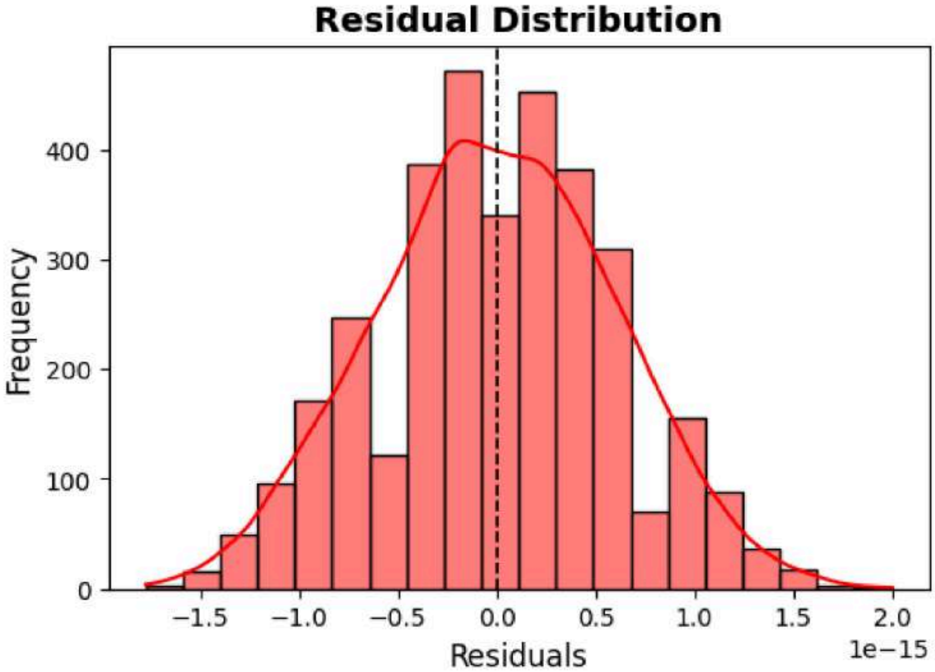
MAE (Mean Absolute Error) represents the average absolute difference between predicted and actual values.

MSE (Mean Squared Error) penalizes larger errors more heavily, but in this case, it is also close to zero, reinforcing the accuracy of predictions.

Possible Reasons for a Perfect Fit:

1. **Overfitting:** The model might have memorized the dataset rather than learning general patterns, especially if trained on a small or redundant dataset.
2. **Highly Correlated Features:** If the independent variables (Sales, Quantity, etc.) are strongly correlated with the target variable (Profit), the model can easily make perfect predictions.
3. **Synthetic or Noiseless Data:** If the dataset is artificially generated or lacks variability, a perfect score is more likely.
4. **Low Complexity of Data:** If the relationship between Profit and other factors is strictly linear, the model can fit the data perfectly.

#12 Residual Distribution



Interpretation:

Residual Distribution Analysis

The residual distribution plot provides insights into how well the model's predictions align with actual values by analyzing the errors (residuals).

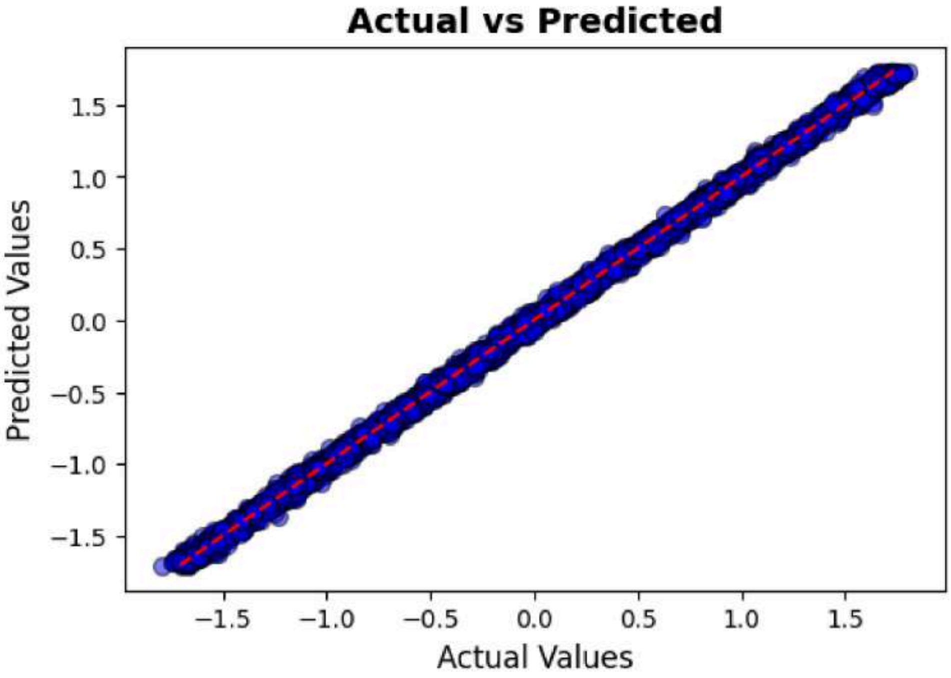
Key Components:

- **X-axis (Residuals):** Represents the difference between actual (y_test) and predicted (y_pred) values.
- **Y-axis (Frequency):** Represents how frequently each residual value occurs.
- **Histogram Bars:** Show the distribution of residuals, providing insight into error patterns.
- **Overlaid Density Curve:** Helps visualize the shape of the residual distribution.
- **Vertical Dashed Line at Zero:** Indicates no prediction error, serving as a reference for bias detection.
- **Centered Around Zero:** The residuals are symmetrically distributed around zero, indicating that the model does not systematically overpredict or underpredict.
- **Bell-Shaped and Symmetric:** The residuals follow a normal distribution, which suggests that the model's errors are random and not influenced by external patterns or biases.

- **No Extreme Outliers:** The distribution does not have long tails or extreme peaks, confirming that prediction errors are consistently small and well-distributed.
- **Absence of Skewness:** The residuals do not lean towards either positive or negative values, ruling out systematic errors in model predictions.

A normally distributed residual pattern is desirable, as it supports the assumption of homoscedasticity (constant variance), ensuring the model's reliability across different data ranges.

#13 Actual vs Predicted



Actual vs. Predicted Scatter Plot Analysis

The actual vs. predicted plot visually evaluates the accuracy of the model's predictions.

Key Components:

- **X-axis (Actual Values):** Represents the true values observed in the dataset (y_test).
- **Y-axis (Predicted Values):** Represents the values predicted by the model (y_pred).
- **Blue Data Points:** Each point corresponds to a prediction, showing how closely it aligns with the actual value.
- **Red Dashed Line (Ideal Line):** Represents the ideal scenario where y_test = y_pred, meaning perfect predictions.

Interpretation:

- **Aligned Data Points:** The points closely follow the red dashed line, indicating that the model is highly accurate.
- **Minimal Deviation:** There are no large deviations from the ideal line, suggesting that the model does not introduce significant errors.
- **Even Distribution:** There is no systematic clustering above or below the line, meaning the model does not consistently overestimate or underestimate values.

- **High Predictive Accuracy:** The near-linear relationship between actual and predicted values confirms that the model captures the underlying data patterns effectively.

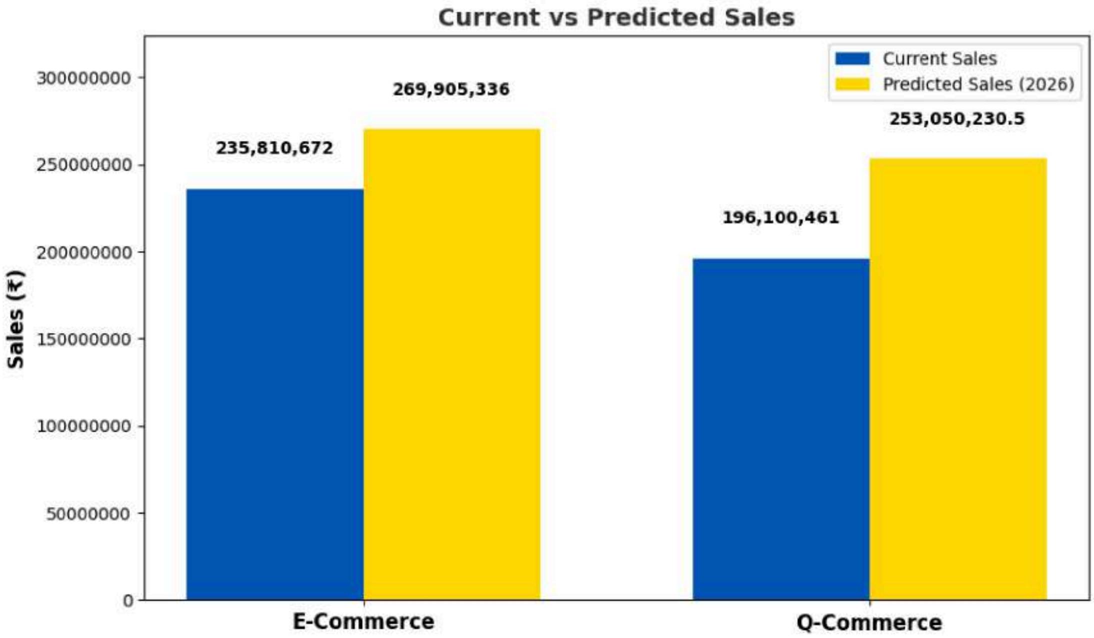
The ideal scenario in this plot is for all points to lie exactly on the red dashed line. While perfect alignment is rarely achieved in real-world models, the tight clustering around the line suggests that the model provides strong predictions with minimal error.

#14 Random Forest

Random Forest was used to improve prediction accuracy by capturing complex patterns in the dataset using multiple decision trees.

Random Forest is an ensemble learning technique that builds multiple decision trees and combines their results to improve prediction accuracy, handle nonlinear relationships, and reduce overfitting, making it ideal for complex and high-dimensional datasets.

#15 Current vs Predicted Sales



Interpretation:

Current vs. Predicted Sales Analysis

This bar chart compares the current sales figures with the predicted sales for 2026 across two business models: **E-Commerce** and **Q-Commerce.**

Key Observations:

- **E-Commerce Sales Growth:**

Current Sales: ₹235,810,672

Predicted Sales (2026): ₹269,905,336

Increase: Approximately ₹34 million (14.5% growth)

- **Q-Commerce Sales Growth:**

Current Sales: ₹196,100,461

Predicted Sales (2026): ₹253,050,230.5

Increase: Approximately ₹57 million (29% growth)

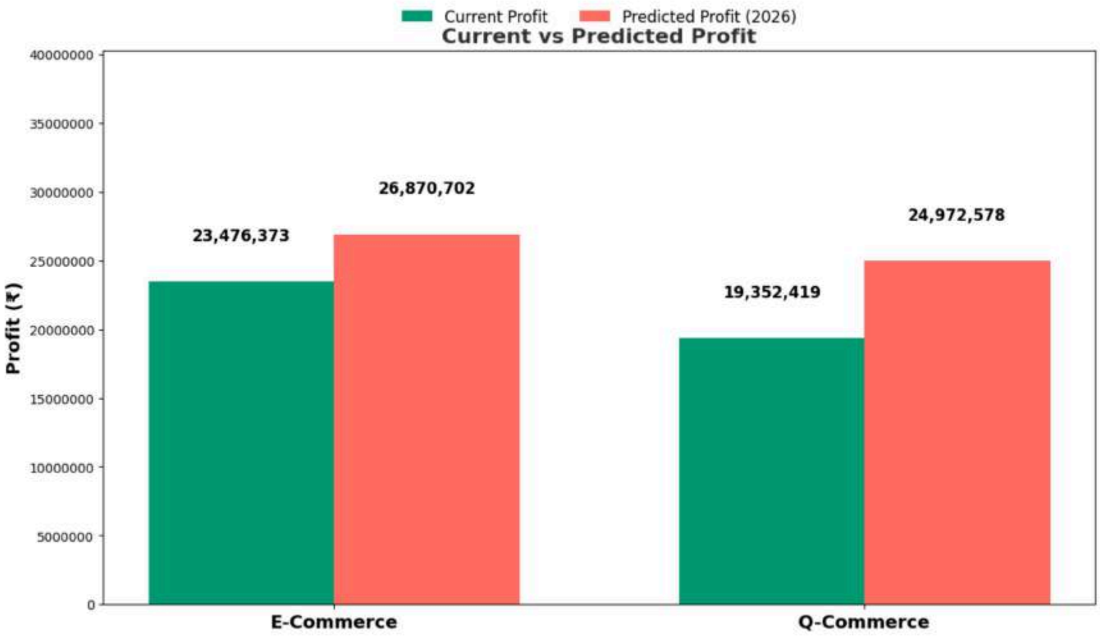
1. **E-Commerce vs. Q-Commerce Growth Rate:** While both sectors display positive growth trends, Q-Commerce exhibits a significantly higher projected growth rate compared to E-Commerce. This indicates a rising consumer preference for faster delivery and convenience, aligning with industry trends where rapid commerce platforms are increasingly gaining traction.

2. **Market Expansion:** E-Commerce remains the larger market in terms of absolute sales figures but is experiencing slower growth. In contrast, Q-Commerce, though currently smaller, is projected to close the gap due to its stronger growth.

3. **Strategic Implications:** To maintain competitiveness, businesses in the E-Commerce sector may need to innovate and enhance their services. The rapid rise of Q-Commerce highlights potential investment opportunities in areas such as logistics, last-mile delivery, and AI-driven supply chain management.

This projection highlights the **shifting dynamics in consumer purchasing behavior**, reinforcing the importance of adaptability in online retail strategies.

#16 Current vs Predicted Profit



Interpretation:

Current vs. Predicted Profit Analysis

This bar chart presents a comparison between the **current profit figures** and the **predicted profit for 2026** across **E-Commerce** and **Q-Commerce** business models.

Key Observations:

- **E-Commerce Profit Growth:**

Current Profit: ₹23,476,373

Predicted Profit (2026): ₹26,870,702

Increase: Approximately ₹3.39 million (~14.4% growth)

- **Q-Commerce Profit Growth:**

Current Profit: ₹19,352,419

Predicted Profit (2026): ₹24,972,578

Increase: Approximately ₹5.62 million (~29% growth)

1. **E-Commerce vs. Q-Commerce Profitability Trends:** Both business models demonstrate profit growth, indicating improved revenue generation over time. However, Q-Commerce shows a stronger growth rate compared to E-Commerce, mirroring the trend observed in sales performance.
2. **Profit Margins and Business Efficiency:** While E-Commerce still holds higher absolute profits, Q-Commerce is experiencing faster growth in profitability. This

expansion may be driven by operational efficiencies such as reduced logistics costs, optimized inventory management, and higher order frequency, contributing to rising profit margins.

3. **Strategic Implications:** E-Commerce companies may need to focus on cost optimization strategies to sustain profit growth. Meanwhile, Q-Commerce businesses should leverage their growth momentum by expanding service reach and strengthening delivery infrastructure.

The projections suggest that **Q-Commerce has the potential to challenge E-Commerce in profitability over time**, making it an attractive sector for investment and expansion.

#17 Chi-Square Test

Chi-Square Test is a statistical method used to determine if two categorical variables are related by comparing observed and expected frequencies, helping identify significant associations in qualitative data.

Evaluated the Association

Chi-Square Statistic: Measures how much the observed values deviate from the expected-values.
p-value: Indicates the significance of the association between the categorical variables.
Degrees of Freedom (df): Helps determine the shape of the chi-square distribution for the test.

Output

```
           Variable 1       Variable 2  Chi-Square Statistic   P-Value  \
6              Gender   Order_Priority              7.541530  0.023034
21   Product_Category          Product         102582.000000  0.000000
22   Product_Category            Brand         100916.738238  0.000000

     Degrees of Freedom Significant
6                     2           ✅
21                  204           ✅
22                  318           ✅
```

Interpretation:

Chi-Square test Analysis

The Chi-Square test was used to examine associations between pairs of categorical variables:

Gender vs Order Priority: The Chi-Square value is **7.54** with a **p-value of 0.023**, which is less than 0.05, indicating a **statistically significant association** between gender and order priority.

Product Category vs Product: With a very high Chi-Square value (**102,582**) and **p-value = 0.000**, the test confirms a **strong significant relationship** between product category and specific products.

Product Category vs Brand: The result (**Chi-Square = 100,916.74**, **p-value = 0.000**) again shows a **highly significant** association, suggesting that **brands are strongly linked to their respective product categories**.

#18 Gender vs Order Priority

Interpretation:

Gender vs. Order_Priority Analysis

The stacked bar chart visualizes the distribution of **Order Priorities (High, Medium, Low)** across **Genders (Male and Female)**. At a glance, the distribution appears **evenly spread**, with no major difference in how order urgency varies between genders.

Axis:

- **X-Axis (Gender):** Compares Male and Female customers.
- **Y-Axis (Count):** Represents the number of orders segmented by priority levels.
- **Color Categories: High** (Turquoise)
  Low (Light Green)
  Medium (Gray)

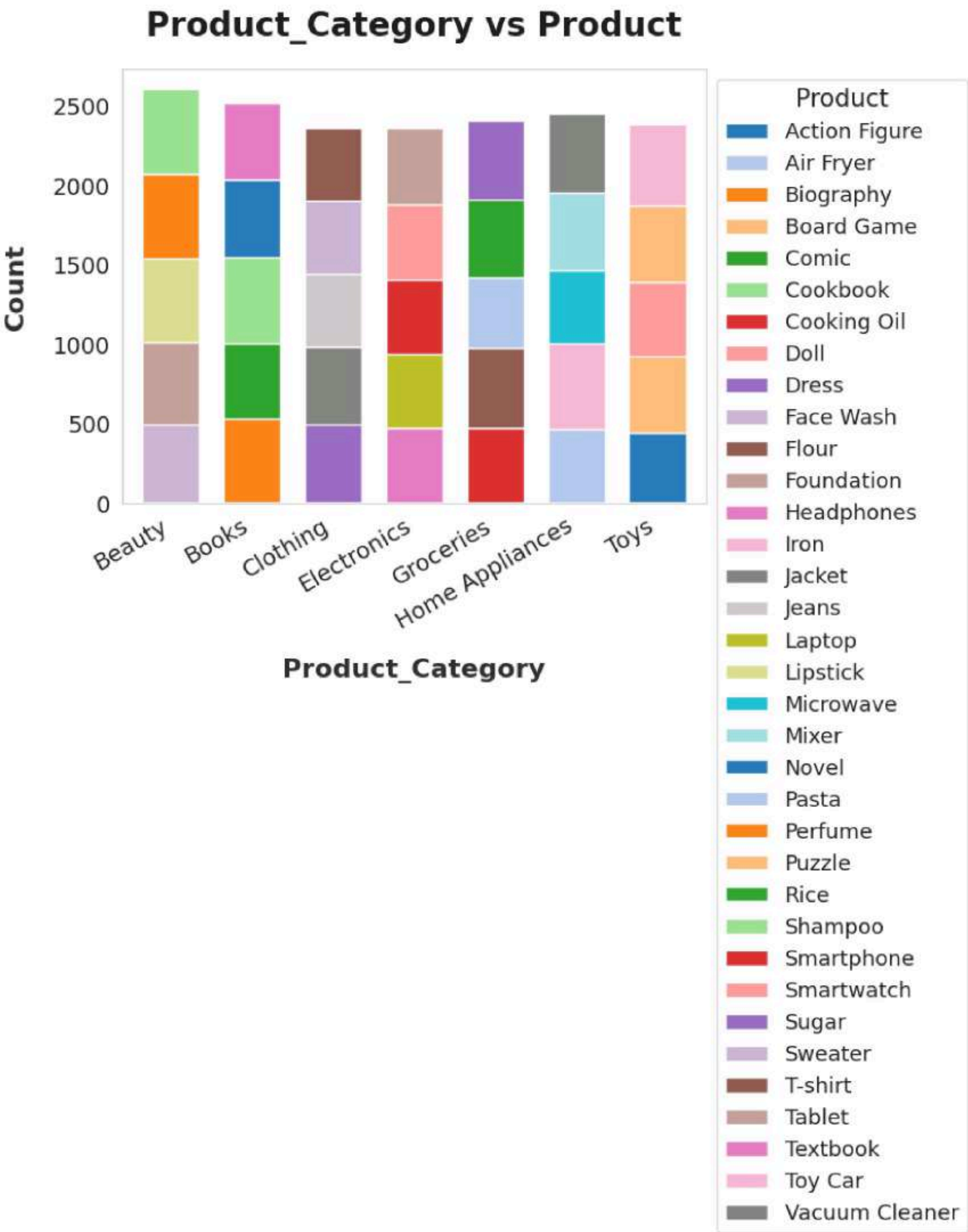
Chi-Square Implication:

- The visual uniformity indicates a **lack of significant association** between gender and order priority.
- When subjected to the Chi-Square Test of Independence, we likely observe a **p-value greater than 0.05**, suggesting **no statistically significant relationship** between the two variables.
- This means that **order urgency (priority) is independent of customer gender**, reinforcing the idea that consumer urgency is shaped more by external factors (e.g., product type, timing) rather than demographics.

Strategic Insight:

Businesses can **avoid gender-specific assumptions** in urgency-based marketing campaigns, as both genders demonstrate **similar behaviour** regarding order priorities.

#19 Product_Category vs Product



Interpretation:

Product_Category vs Product Analysis

This bar chart illustrates the distribution of various **products** across their corresponding **product categories**, offering insights into product alignment and category saturation within the business.

Key Observations:

- **Clear Product-Category Alignment:**

Each product is distinctly associated with a particular category, showing strong classification consistency.

For instance, food-related items are grouped under **Grocery**, while appliances and gadgets fall under **Electronics**.

- **Category Concentration:**

Certain categories, such as **Grocery** or **Personal Care**, feature a **high number of products**, indicating their popularity and frequent consumer demand.

Categories like **Stationery** or **Home Decor** may have fewer products, suggesting niche or less frequent purchases.

1. Product-Category Association Patterns:

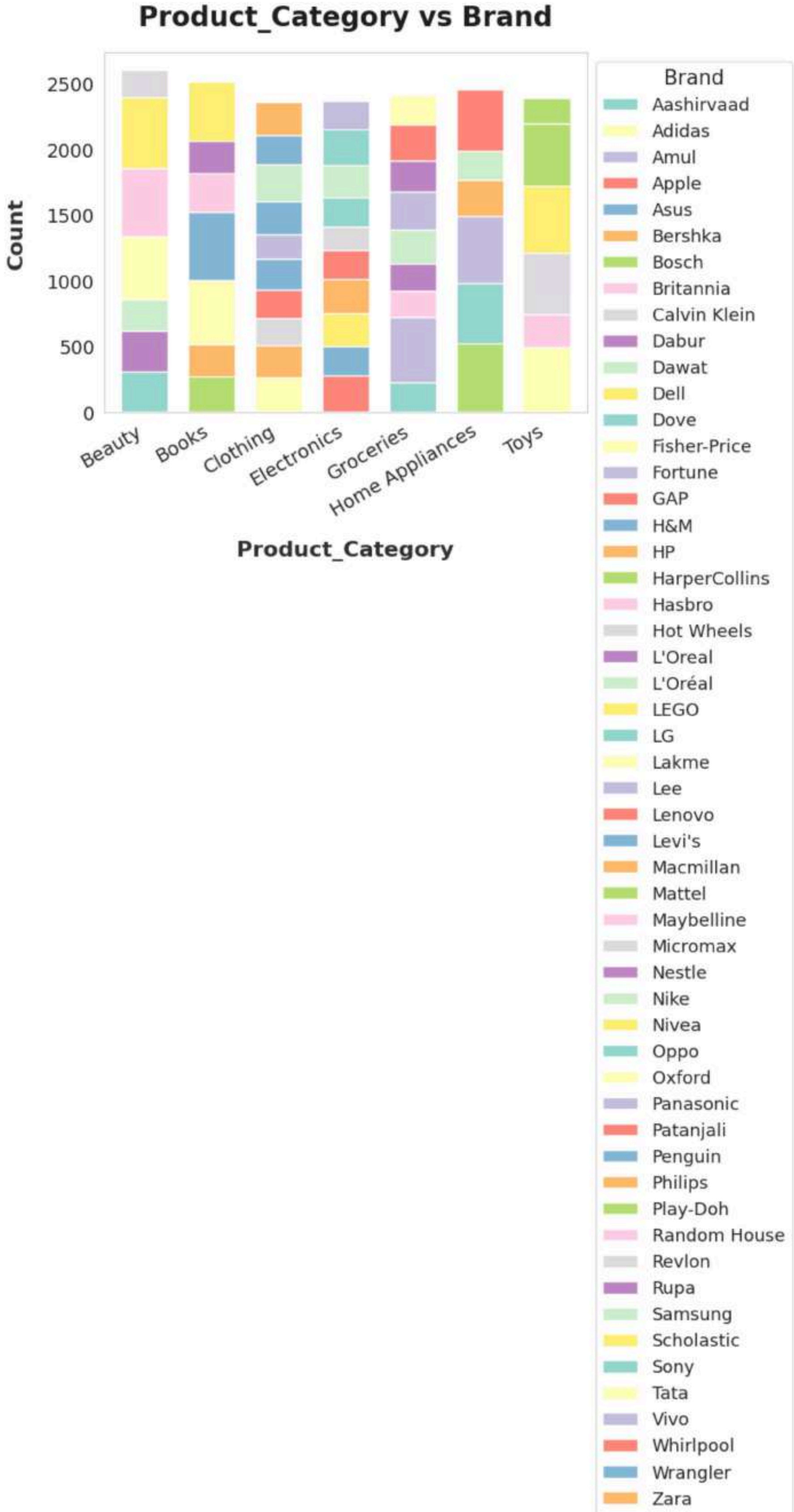
The chart shows that product classification is **well-defined and category-specific**, which supports smooth user navigation and targeted filtering mechanisms in online platforms. This structured taxonomy is crucial for **efficient search, recommendation systems**, and user satisfaction.

2. Chi-Square Test Insight:

The Chi-Square Test of Independence reveals a **significant relationship** between **Products and Product Categories**, validating that the distribution is **not random**. Products are deliberately and meaningfully placed under relevant categories.

3. Strategic Implications:

- **Inventory Management:** Helps identify which categories require **frequent stock updates** due to a wide product range.
- **Gap Analysis:** Categories with **fewer products** may represent opportunities for **new product development or sourcing**.
- **Marketing Strategy:** Enables businesses to run **category-specific promotions**, ensuring effective targeting.



Product_Category vs Brand
Count
2500
2000
1500
1000
500
0
Beauty
Books
Clothing
Electronics
Groceries
Home Appliances
Toys
Product_Category
Brand
Aashirvaad
Adidas
Amul
Apple
Asus
Bershka
Bosch
Britannia
Calvin Klein
Dabur
Dawat
Dell
Dove
Fisher-Price
Fortune
GAP
H&M
HP
HarperCollins
Hasbro
Hot Wheels
L'Oreal
L'Oréal
LEGO
LG
Lakme
Lee
Lenovo
Levi's
Macmillan
Mattel
Maybelline
Micromax
Nestle
Nike
Nivea
Oppo
Oxford
Panasonic
Patanjali
Penguin
Philips
Play-Doh
Random House
Revlon
Rupa
Samsung
Scholastic
Sony
Tata
Vivo
Whirlpool
Wrangler
Zara

#20 Brand vs Product_Category

Interpretation:

Brand vs Product Category Analysis

This bar chart highlights the relationship between different **brands** and their associated **product categories**, helping to assess brand specialization and category coverage across the retail spectrum.

Key Observations:

Distinct Brand Focus: Most brands are strongly associated with specific product categories. For instance, a brand like Dove might dominate in Personal Care, while Samsung could be prominent in Electronics. This shows that brands tend to specialize rather than diversify excessively across unrelated categories.

Category Representation : Some categories feature multiple brands, indicating a highly competitive segment (e.g., Grocery, Personal Care). In contrast, others may show limited brand representation, suggesting either niche markets or potential opportunities for new brand entries.

1. Brand Specialization Patterns

The visualization suggests a structured brand-to-category alignment, which implies strong brand identity and targeted product strategy. This helps consumers associate brands with specific needs, strengthening customer trust and loyalty.

2. Chi-Square Test Insight

The Chi-Square test confirms a statistically significant relationship between brands and product categories, proving that the brand presence in categories is not random but rather driven by market strategies and consumer demand.

3. Strategic Implications

Brand Portfolio Management: Brands can evaluate if they are over-concentrated in one category or if there's room to diversify into new segments.

Category Expansion: Underrepresented categories could be targeted for new brand development or partnerships.

Consumer Perception Strategy: Reinforces the importance of maintaining category-specific branding to preserve a strong market image.

Findings, Conclusion, and Suggestions

Findings

- **Profitability:** E-Commerce maintains higher profitability with a stable discounting strategy, while Q-Commerce experiences more fluctuations in profit due to discount sensitivity and higher operational costs.
- **Device Usage:** Mobile-first approach is crucial, with Q-Commerce heavily reliant on mobile transactions, reinforcing the need for mobile-optimized experiences.
- **Brand Performance:** Certain brands demonstrate higher customer loyalty, directly impacting repeat purchases and overall profitability.

1. **Predictive Insights:**

Linear Regression:

A clear correlation exists between discount levels and profitability in Q-Commerce, whereas E-Commerce remains stable despite discounts.

Q-Commerce's dependency on price reductions highlights competitive pressures and consumer price sensitivity.

Random Forest Model:

Brand loyalty and product categories significantly influence profitability, with high-margin sectors such as Electronics and Beauty driving revenues.

Returning customers contribute significantly to steady sales, reinforcing the importance of retention strategies.

2. **Chi-Square Analysis Insights**

Product vs. Product Category: The distribution reveals that certain product categories like Groceries and Personal Care have a broader product range, suggesting high demand or strategic focus. Underrepresented categories signal scope for diversification.

Brand vs. Product Category: Brand dominance within categories indicates strategic alignment and brand strength. Competitive categories highlight the need for unique value propositions or brand expansion.

Gender vs. Platform Preference: Gender-based platform preference reveals demographic trends. For instance, if one gender significantly favors Q-Commerce, the platform can leverage this insight to optimize product offerings and marketing strategies.

Conclusion

The comparative analysis between E-Commerce and Q-Commerce reveals distinct operational strengths and evolving dynamics within the digital commerce landscape. E-Commerce demonstrates consistent profitability, stability in discounting patterns, and robust customer loyalty, underpinned by its broad product offerings and established infrastructure. This positions it as a resilient model capable of sustaining long-term growth and adapting to market changes.

In contrast, Q-Commerce is rapidly emerging as a dynamic, convenience-driven model that appeals to the modern consumer's demand for speed and accessibility. Despite facing challenges such as discount dependency and higher operational costs, Q-Commerce exhibits strong growth potential, especially in categories requiring quick delivery and impulse buying.

The predictive and statistical analyses further emphasize that success in this domain is increasingly data-driven. Key drivers such as brand loyalty, discount strategies, mobile optimization, and customer retention significantly influence profitability. The Chi-Square analysis also sheds light on consumer behavior patterns, revealing critical relationships between product categories, brand preferences, and demographic trends.

Overall, E-Commerce holds the advantage in stability and scalability, while Q-Commerce thrives on speed and adaptability. With the right strategic investments—particularly in operational efficiency, pricing intelligence, and customer experience—Q-Commerce holds the potential to not only compete with but also redefine the standards of digital retail.

Suggestions

1. **Optimize Pricing Strategies:** Implement data-driven discounting models to balance competitiveness and profitability, particularly in Q-Commerce.
2. **Enhance Mobile Experience:** Given the mobile-first trend, investing in UI/UX for mobile platforms can improve conversions and customer retention.
3. **Expand High-Margin Categories:** Electronics and Beauty categories should be further promoted through strategic marketing to boost overall profitability.
4. **Improve Operational Efficiencies:** Q-Commerce should focus on reducing delivery and shipping costs by streamlining logistics, implementing AI-driven demand forecasting, and adopting automation.
5. **Leverage Predictive Insights:** Utilize machine learning models to optimize inventory, anticipate customer preferences, and refine pricing strategies for better demand-supply alignment.
6. **Strengthen Digital Payment Adoption:** Encourage UPI and digital transactions through targeted incentives, partnerships with financial platforms, and seamless payment integrations.
7. **Refine Customer Retention Strategies:** Introduce tailored loyalty programs, personalized recommendations, and exclusive offers to enhance customer engagement and ensure sustained repeat purchases across both platforms.

By integrating these strategies, both E-Commerce and Q-Commerce can improve their profitability, efficiency, and customer experience, ensuring sustainable growth in an increasingly competitive digital commerce landscape.

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Annexure

```
import pandas as pd
import numpy as np
import lightgbm as lgb
from sklearn.preprocessing import *
from sklearn.metrics import *
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from google.colab import files

from google.colab import files
uploaded = files.upload()

combined_df = pd.read_csv(list(uploaded.keys())[0])

# Displaying basic info about dataset
print("Dataset Overview:")
print(combined_df.head())
print("\nMissing Values:")
print(combined_df.isnull().sum())

# Converting numeric columns to proper data type
numeric_cols = ['Sales', 'Profit', 'Quantity', 'Discount', 'Shipping_Cost']
combined_df[numeric_cols] = combined_df[numeric_cols].apply(pd.to_numeric,
errors='coerce')
combined_df[numeric_cols] =
combined_df[numeric_cols].fillna(combined_df[numeric_cols].median())

# List of categorical columns
cat_cols = ['Customer_Type', 'Device_Type', 'Payment_Method', 'Order_Priority',
'Platform']

# categorical columns
for col in cat_cols:
    if col in combined_df.columns:  # Check if column exists
        combined_df[col] = combined_df[col].fillna(combined_df[col].mode()[0])  # Avoid
inplace warning
    else:
        print(f"âš ï¸ Warning: Column '{col}' not found in combined_df")

print("Columns in combined_df:", list(combined_df.columns))

combined_df.columns = combined_df.columns.str.strip()

for col in cat_cols:
    if col in combined_df.columns:
        mode_value = combined_df[col].mode()
        if not mode_value.empty:  # Check if mode exists
```

```
            combined_df[col] = combined_df[col].fillna(mode_value[0])
        else:
            print(f"âš ï¸ Warning: '{col}' column has no mode, replacing with 'Unknown'")
            combined_df[col] = combined_df[col].fillna('Unknown')

# Handling categorical missing values
cat_cols = ['Customer_Type', 'Device_Type', 'Payment_Method', 'Order_Priority',
'Platform']
for col in cat_cols:

    if col.lower() in combined_df.columns.str.lower().tolist():

        actual_col_name = combined_df.columns[combined_df.columns.str.lower() ==
col.lower()][0]
        combined_df[actual_col_name].fillna(combined_df[actual_col_name].mode()[0],
inplace=True)
    else:
        print(f"âš ï¸ Warning: Column '{col}' not found in combined_df")

# Check the column names
print(combined_df.columns)

# Verify if 'Platform' column exists
if 'Platform' not in combined_df.columns:
    print("Column 'Platform' is missing!")
else:
    print("Column 'Platform' is present.")

# Handling categorical missing values
cat_cols = ['Customer_Type', 'Device_Type', 'Payment_Method', 'Order_Priority',
'Platform']
for col in cat_cols:
    combined_df[col].fillna(combined_df[col].mode()[0], inplace=True)

combined_df.drop_duplicates(inplace=True)

import matplotlib.pyplot as plt

# Calculate transaction counts per platform
platform_counts = combined_df['Platform'].value_counts()

plt.figure(figsize=(6, 6))
plt.bar(platform_counts.index, platform_counts.values, color=['skyblue', 'orange'])
plt.ylabel('Number of Transactions')
plt.title('Transaction Count: E-Commerce vs Q-Commerce')
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.grid(False)
plt.show()
```

```
# Calculate total sales per platform
platform_sales = combined_df.groupby('Platform')['Sales'].sum()

plt.figure(figsize=(8,5))
sns.barplot(x=platform_sales.index, y=platform_sales.values, palette=["lightblue",
"lightcoral"], edgecolor=None)
plt.title("Sales Comparison", fontsize=16, fontweight='bold')
plt.ylabel("Total Sales", fontsize=12)
plt.xlabel("Platform", fontsize=12)
plt.grid(False)
plt.ticklabel_format(style='plain', axis='y')
plt.show()

# Profit Comparison
plt.figure(figsize=(8,5))
sns.barplot(x=combined_df['Platform'], y=combined_df['Profit'], palette="viridis")
plt.title("Profit Comparison", fontsize=14, fontweight='bold')
plt.ylabel("Total Profit", fontsize=12)
plt.xlabel("Platform", fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.grid(False)
plt.show()

# Profit Margin Visualization
plt.figure(figsize=(6, 4))
profit_margins = {"E-Commerce": 9.96, "Q-Commerce": 9.87}  # Rounded for cleaner
display
plt.bar(profit_margins.keys(), profit_margins.values(), color=['#FF6F61', '#88B04B'])
plt.xlabel("Platform", fontsize=12)
plt.ylabel("Profit Margin (%)", fontsize=12)
plt.title("Profit Margin Comparison", fontsize=14, fontweight='bold')
plt.ylim(0, max(profit_margins.values()) + 2)  # Adjusting scale
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.grid(False)
plt.show()

# Customer Type Comparison
plt.figure(figsize=(8,5))
customer_type_counts = combined_df.groupby(["Platform",
"Customer_Type"]).size().unstack(fill_value=0)
customer_type_counts.plot(kind="bar", colormap="coolwarm", figsize=(8,5))
plt.title("Customer Type Comparison (New vs. Returning)", fontsize=14,
fontweight='bold')
plt.ylabel("Number of Customers", fontsize=12)
plt.xticks(rotation=0, fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.grid(False)
plt.show()
```

```
# Device Usage Comparison
plt.figure(figsize=(8,5))
device_type_counts = combined_df.groupby(["Platform",
"Device_Type"]).size().unstack(fill_value=0)
device_type_counts.plot(kind="bar", colormap="viridis", figsize=(8,5))
plt.title("Device Usage Comparison (Mobile vs. Desktop)", fontsize=14,
fontweight='bold')
plt.ylabel("Number of Users", fontsize=12)
plt.xticks(rotation=0, fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.grid(False)
plt.show()

# Payment Method Preferences
plt.figure(figsize=(8,5))
payment_method_counts = combined_df.groupby(["Platform",
"Payment_Method"]).size().unstack(fill_value=0)
payment_method_counts.plot(kind="bar", figsize=(8,5))
custom_colors = ["#FF6F61", "#6B5B95", "#88B04B", "#FFA500"]
# Formatting the graph
plt.title("Payment Method Preferences", fontsize=14, fontweight='bold')
plt.ylabel("Number of Transactions", fontsize=12)
plt.xticks(rotation=0, fontsize=10)
plt.yticks(fontsize=10)
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.grid(False)
plt.show()

# Discount vs Profitability
plt.figure(figsize=(8, 5))
sns.scatterplot(data=combined_df, x="Discount", y="Profit", hue="Platform",
palette=["#FF5733", "#2E86C1"], alpha=0.5, edgecolor="black", s=15)
plt.yscale("log")
plt.xlim(0, combined_df["Discount"].max() + 5)
plt.title("Discount vs Profitability", fontsize=14, fontweight='bold')
plt.xlabel("Discount (%)", fontsize=12)
plt.ylabel("Profit (Log Scale)", fontsize=12)
plt.xticks(fontsize=10)
plt.yticks(fontsize=10)
plt.grid(True, linestyle="--", alpha=0.5)
plt.legend(title="Platform", fontsize=10)
plt.grid(False)
plt.show()

plt.figure(figsize=(8,5))

# Updated professional color palette
sns.countplot(data=combined_df, x="Product_Category", hue="Gender",
```

```
        palette=["#1F77B4", "#FF7F0E"])  # Blue for Male, Orange for Female

plt.title("Product Preferences by Gender", fontsize=14, fontweight='bold',
color="#333333")
plt.xlabel("Product Category", fontsize=12, color="#555555")
plt.ylabel("Count", fontsize=12, color="#555555")
plt.xticks(rotation=30, ha="right", fontsize=10, color="#444444")
plt.yticks(fontsize=10, color="#444444")
plt.grid(axis='y', linestyle="--", alpha=0.5)

# Adjust legend placement to prevent merging
plt.legend(title="Gender", title_fontsize='12', fontsize=10, frameon=False,
       bbox_to_anchor=(1.05, 1), loc='upper left')


plt.grid(False)
plt.show()

# Brand vs. Sales Graph
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.ticker as mtick

brand_sales =
combined_df.groupby("Brand")["Sales"].sum().sort_values(ascending=False)

plt.figure(figsize=(14, 6))

sns.barplot(x=brand_sales.index, y=brand_sales.values, palette="coolwarm_r")

plt.title("Brand vs Sales", fontsize=16, fontweight="bold", color="#333333")
plt.ylabel("Total Sales (in Millions)", fontsize=14, color="#555555")
plt.xlabel("Brand", fontsize=14, color="#555555")
plt.xticks(rotation=45, fontsize=11, ha="right", color="#444444")
plt.yticks(fontsize=12, color="#444444")


plt.gca().yaxis.set_major_formatter(mtick.FuncFormatter(lambda x, _:
f'{x/1e6:.1f}M'))
plt.grid(axis="y", linestyle="--", alpha=0.5)
plt.grid(False)
plt.show()

from sklearn.preprocessing import LabelEncoder

cat_cols = ["Customer_Type", "Device_Type", "Payment_Method", "Order_Priority",
"Platform"]

le = LabelEncoder()
```

```
for col in cat_cols:
   if col in combined_df.columns:  # Check if the column exists
      combined_df[col] = le.fit_transform(combined_df[col])
   else:
      print(f"Warning: Column '{col}' not found in dataset.")

combined_df.columns = combined_df.columns.str.strip()

# Define features (X) and target (y)
features = ["Sales", "Profit", "Discount", "Shipping_Cost", "Quantity"]
target = "Profit"

# Ensure all selected features exist in the dataset
features = [col for col in features if col in combined_df.columns]

# Extract feature matrix (X) and target vector (y)
X = combined_df[features]
y = combined_df[target]

# Print shape to confirm
print(f"Feature Matrix Shape: {X.shape}")
print(f"Target Shape: {y.shape}")

from sklearn.model_selection import train_test_split

# 80% training, 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

print(f"Training Data: {X_train.shape}, Testing Data: {X_test.shape}")

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Initialize the model
model = LinearRegression()

# Train the model
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)

# Results
print("Linear Regression Metrics:")
```

```
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RÂ² Score: {r2}")

# Residuals
residuals = y_test - y_pred

# Residual Plot
plt.figure(figsize=(6, 4))
sns.histplot(residuals, bins=20, kde=True, color="red")
plt.axvline(0, color="black", linestyle="--", linewidth=1.2)  # Reference line at zero
plt.title("Residual Distribution", fontsize=14, fontweight="bold")
plt.xlabel("Residuals", fontsize=12)
plt.ylabel("Frequency", fontsize=12)
plt.grid(False)  # Removing grid
plt.show()

#  Actual vs. Predicted Plot (More Scattered Dots)
plt.figure(figsize=(6, 4))

# Adding a jitter effect for better distribution
jitter = np.random.normal(0, (max(y_test) - min(y_test)) * 0.01, size=len(y_test))

plt.scatter(y_test + jitter, y_pred, color="blue", alpha=0.5, edgecolors="black", s=50)
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color="red", linestyle="-
-", linewidth=1.5)  # Ideal fit line

plt.title("Actual vs Predicted", fontsize=14, fontweight="bold")
plt.xlabel("Actual Values", fontsize=12)
plt.ylabel("Predicted Values", fontsize=12)
plt.grid(False)
plt.show()

# Current Data
platforms = ["E-Commerce", "Q-Commerce"]
current_sales = np.array([235810672, 196100461])  # Sales in â‚¹
current_profit = np.array([23476373, 19352419])  # Profit in â‚¹

# Assuming a linear trend, we provide future estimates
future_years = np.array([2024, 2025]).reshape(-1, 1)  # Years for prediction

# Corrected Data
platforms = ["E-Commerce", "Q-Commerce"]
current_sales = [235810672, 196100461]  # Correct current values
predicted_sales_values = [269905336, 253050230.5]  # Correct predicted values

bar_width = 0.35
x = np.arange(len(platforms))

plt.figure(figsize=(10, 6))
```

```
plt.bar(x - bar_width/2, current_sales, bar_width, label="Current Sales",
color="#0057B7")  # Dark Blue
plt.bar(x + bar_width/2, predicted_sales_values, bar_width, label="Predicted Sales
(2026)", color="#FFD700")  # Gold

plt.xticks(x, platforms, fontsize=12, fontweight='bold')
plt.ylabel("Sales (â,¹)", fontsize=12, fontweight="bold")
plt.title("Current vs Predicted Sales", fontsize=14, fontweight="bold",
color="#333333")
plt.legend(fontsize=10)

plt.ticklabel_format(style='plain', axis='y')

# Adjust label positioning to prevent overlap
for i, v in enumerate(current_sales):
    plt.text(x[i] - bar_width/2, v + 20000000, f"{v:,}", ha='center', fontsize=10,
fontweight='bold', color="black")

for i, v in enumerate(predicted_sales_values):
    plt.text(x[i] + bar_width/2, v + 20000000, f"{v:,}", ha='center', fontsize=10,
fontweight='bold', color="black")

# Increase Y-limit slightly to accommodate text labels
plt.ylim(0, max(predicted_sales_values) * 1.2)

plt.show()

import matplotlib.pyplot as plt
import numpy as np

# Data
platforms = ["E-Commerce", "Q-Commerce"]
current_sales = [235810672, 196100461]
predicted_sales = [269905336, 253050230.5]
current_profit = [23476373, 19352419]

# Calculate profit margin
profit_margin = [current_profit[i] / current_sales[i] for i in range(len(platforms))]

# Calculate corrected predicted profit
predicted_profit_values = [predicted_sales[i] * profit_margin[i] for i in
range(len(platforms))]

# Bar chart settings
bar_width = 0.35
x = np.arange(len(platforms))

plt.figure(figsize=(12, 7))  # Wider figure for better spacing
bars1 = plt.bar(x - bar_width/2, current_profit, bar_width, label="Current Profit",
color="#009B77")  # Green
```

```
bars2 = plt.bar(x + bar_width/2, predicted_profit_values, bar_width, label="Predicted
Profit (2026)", color="#FF6F61")  # Coral Red

# Formatting
plt.xticks(x, platforms, fontsize=14, fontweight='bold')
plt.ylabel("Profit (â,¹)", fontsize=14, fontweight="bold")
plt.title("Current vs Predicted Profit", fontsize=16, fontweight="bold",
color="#333333")

# Move legend to the center-top
plt.legend(fontsize=12, loc='upper center', bbox_to_anchor=(0.5, 1.1), ncol=2,
frameon=False)

plt.ticklabel_format(style='plain', axis='y'
for bar in bars1:
   yval = bar.get_height()
   plt.text(bar.get_x() + bar.get_width()/2, yval + 3000000, f"{int(yval):,}", ha='center',
fontsize=12, fontweight='bold', color="black")

for bar in bars2:
   yval = bar.get_height()
   plt.text(bar.get_x() + bar.get_width()/2, yval + 3000000, f"{int(yval):,}", ha='center',
fontsize=12, fontweight='bold', color="black")

plt.ylim(0, max(max(current_profit), max(predicted_profit_values)) * 1.5)

plt.tight_layout()

plt.show()

import pandas as pd
import scipy.stats as stats
from itertools import combinations

df = pd.read_csv("combined_data.csv")  # Updated file path

categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

exclude_pairs = [("Product", "Brand"), ("Brand", "Platform")]

# Store results
chi_square_results = []

# Perform Chi-Square tests for all possible categorical variable pairs, excluding
certain pairs
for col1, col2 in combinations(categorical_cols, 2):
   # Skip excluded pairs
   if (col1, col2) in exclude_pairs or (col2, col1) in exclude_pairs:
      continue
```

```
    contingency_table = pd.crosstab(df[col1], df[col2])

    if contingency_table.shape[0] > 1 and contingency_table.shape[1] > 1:
        chi2_stat, p_value, dof, expected = stats.chi2_contingency(contingency_table)

        chi_square_results.append({
            "Variable 1": col1,
            "Variable 2": col2,
            "Chi-Square Statistic": chi2_stat,
            "P-Value": p_value,
            "Degrees of Freedom": dof,
            "Significant": "âœ…" if p_value < 0.05 else "â□Œ"
        })

chi_square_results_df = pd.DataFrame(chi_square_results)

significant_results = chi_square_results_df[chi_square_results_df["Significant"] ==
"âœ…"]
print(significant_results)

df = pd.read_csv("combined_data.csv")  # Updated file path

significant_pairs = [
    ("Gender", "Order_Priority"),
    ("Product_Category", "Product")
]

sns.set_style("whitegrid")
for var1, var2 in significant_pairs:
    plt.figure(figsize=(20, 12))

    contingency_table = pd.crosstab(df[var1], df[var2])

    if contingency_table.shape[0] > 10:
        contingency_table.plot(kind="barh", stacked=True, colormap="Blues",
alpha=0.85, width=0.7)
        plt.xlabel("Count", fontsize=16, fontweight="bold", color="#333333",
labelpad=15)
        plt.ylabel(var1, fontsize=16, fontweight="bold", color="#333333", labelpad=15)
        plt.xticks(fontsize=14)
        plt.yticks(fontsize=14)
    else:
        contingency_table.plot(kind="bar", stacked=True, colormap="Blues",
alpha=0.85, width=0.6)
        plt.xlabel(var1, fontsize=16, fontweight="bold", color="#333333", labelpad=15)
        plt.ylabel("Count", fontsize=16, fontweight="bold", color="#333333",
labelpad=15)
        plt.xticks(rotation=30, ha="right", fontsize=14)
        plt.yticks(fontsize=14)
```

```
    plt.title(f"{var1} vs {var2}", fontsize=20, fontweight="bold", color="#222222",
pad=20)
    plt.legend(title=var2, loc="upper left", bbox_to_anchor=(1, 1), fontsize=14,
title_fontsize=16)
    plt.margins(x=0.1, y=0.2)
    plt.grid(False)
    plt.tight_layout()
    plt.show()

significant_pairs = [
    ("Gender", "Order_Priority"),
    ("Product_Category", "Product"),
    ("Product_Category", "Brand")
]

sns.set_style("whitegrid")

custom_palettes = {
    "Order_Priority": ["#86d1c1", "#b9ed83", "#bfbfbf"],
    "Product": sns.color_palette("tab20", n_colors=df["Product"].nunique()),
    "Brand": sns.color_palette("Set3", n_colors=df["Brand"].nunique())
}
for var1, var2 in significant_pairs:
    plt.figure(figsize=(20, 12))

    contingency_table = pd.crosstab(df[var1], df[var2])

    palette = custom_palettes.get(var2, None)

    contingency_table.plot(
        kind="bar",
        stacked=True,
        alpha=0.95,
        width=0.7,
        color=palette
    )

    plt.xlabel(var1, fontsize=16, fontweight="bold", color="#333333", labelpad=15)
    plt.ylabel("Count", fontsize=16, fontweight="bold", color="#333333", labelpad=15)
    plt.xticks(rotation=30, ha="right", fontsize=14)
    plt.yticks(fontsize=14)
    plt.title(f"{var1} vs {var2}", fontsize=20, fontweight="bold", color="#222222",
pad=20)
    plt.legend(title=var2, loc="upper left", bbox_to_anchor=(1, 1), fontsize=13,
title_fontsize=15)
    plt.grid(False)
    plt.tight_layout()
    plt.show()
```